NIST Advanced Manufacturing Series 100-24

Proceedings of the 10th Model-Based Enterprise Summit (MBE 2019)

Thomas Hedberg, Jr.
Mark Carlisle

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Systems Integration Division
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Introduction

The National Institute of Standards and Technology (NIST) hosted the tenth installment of the Model-Based Enterprise Summit (MBE 2019) on April 2-4, 2019 in Gaithersburg, Maryland. The MBE 2019 witnessed another year-over-year registration and attendance growth. The MBE Summit saw 340 attendees gather over three days to share their experiences with Model-Based Enterprise (MBE). This speaks to the growing interest of MBE within the community and the importance of the Summit output.

The MBE 2019 Program Committee continues to believe that the MBE Summit is the best place for gathering and sharing information dedicated to the digital transformation across the product lifecycle. The goal of the MBE Summit is to identify challenges, research, implementation issues, and lessons learned in design, manufacturing, quality assurance, and sustainment of products and processes where a digital three-dimensional (3D) model of the product serves as the authoritative information source for all activities in a product's lifecycle. The theme of MBE 2019 was *Democratizing the Implementation of MBE*. The model-based community moved beyond the question of "why is MBE important?" to "how do we deploy MBE?". The tenth MBE Summit was focused on highlighting the long history of MBE and real-world implementations of MBE in practice.

Authors from academia, government, and industry submitted papers on topics related to this year's theme using the following tracks: 1) Systems Engineering and Lifecycle Management; 2) Design; 3) Manufacturing; 4) Quality and Inspection; and 5) Operations, Logistics, and Sustainment. This volume contains the papers presented at MBE 2019. There were 58 submissions. Each submission was reviewed by experts and decided upon by the program committee. The committee decided to accept 30 papers. The MBE 2019 program also included five invited talks and three panels.

Program Committee

The Program Committee was responsible for the functional organization and technical content of MBE Summit 2018. It prepared the final list of conference topics and invited speakers, selected contributed papers, presentations and posters from amongst the submitted abstracts and refereed contributed papers. The PC consists of:

Thomas Hedberg, *Summit Chair* National Institute of Standards and Technology

Mark Carlisle, *Summit Coordinator* National Institute of Standards and Technology

Fred Constantino American Society of Mechanical Engineers

Daniel Finke The Pennsylvania State University

Bryan Fischer TDP360 LLC

Gregory Harris Auburn University

Anthony Holden U.S. Army

Paul Huang U.S. Navy, Office of Naval Research

Bruce Kaplan LMI

Ben Kassel LMI

Troy Peterson System Strategy, Inc., on behalf of INCOSE

Mark Sampson Siemens, on behalf of INCOSE

Tony Still U.S. Army

Steve Weinman American Society of Mechanical Engineers

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SUMMIT PROGRAM

Invited Speakers

Papers

Track 1: Systems Engineering and Lifecycle Management

Track 2: Design

Navy Digital Engineering Blueprint

Rear Admiral Lorin Selby
Chief Engineer and Deputy Commander for Ship Design, Integration and Naval Engineering
Naval Sea Systems Command (NAVSEA 05)

Biography

Rear Adm. Lorin Selby is a native of Baltimore, Maryland and graduated from the University of Virginia with a Bachelor of Science in Nuclear Engineering and earned his commission through the Naval Reserve Officers Training Corps program. He also holds a Master of Science in Nuclear Engineering and Nuclear Engineer degree from the Massachusetts Institute of Technology.

His shipboard tours include USS Puffer (SSN 652), USS Pogy (SSN 647) and USS Connecticut (SSN 22). From July 2004 to May 2007 he commanded USS Greeneville (SSN 772) in Pearl Harbor, Hawaii. During these assignments, Selby conducted several deployments to the Western Pacific, Northern Pacific, Northern Atlantic and Arctic Oceans.

Ashore, Selby's staff assignments include duty as a company officer and instructor at the U.S. Naval Academy, service as the deputy director of the Navy Liaison Office to the U.S. House of Representatives and duty as the Submarine Platforms and Strategic Programs branch head in the Submarine Warfare Directorate on the Navy Staff. Following selection as an acquisition professional, he served as the program manager for both the Submarine Imaging and Electronic Warfare Systems Program Office (PMS 435) and the Advanced Undersea Systems Program Office (PMS 394).

Selby served as commander, Naval Surface Warfare Center (NSWC) from October 2014 to August 2016. In this position, he led more than 17,000 scientists, engineers, technicians and support personnel, both civilian and active duty, within eight NSWC divisions located across the country.

As the Navy's chief engineer and the Naval Sea Systems Command (NAVSEA) deputy commander for Ship Design, Integration and Naval Engineering (SEA 05), Selby leads the engineering and scientific expertise, knowledge and technical authority necessary to design, build, maintain, repair, modernize, certify and dispose of the Navy's ships, aircraft carriers, submarines and associated combat and weapons systems.

Selby is authorized to wear the Legion of Merit (three awards), Meritorious Service Medal (four awards), the Navy and Marine Corps Commendation Medal (six awards) and the Navy and Marine Corps Achievement Medal (three awards) in addition to various unit awards.

Open Model-Based Engineering Environments

Mr. Christopher Delp
Manager, Computer Aided Engineering Systems and Software Environments
NASA Jet Propulsion Laboratory

ABSTRACT

Technical endeavors have always used the concept of models. Models are fundamental to the way humans think and solve problems. Efforts around modeling with software attempt to capture and reflect the abstract nature of human reasoning and memory. As engineering modeling languages and analysis capability evolve, engineering organizations are approaching a transformative condition where Engineering Environments enable modeling as a basis for Engineering work. These environments incorporate sophisticated collaboration and configuration control on top of massively scaled computing, promising a modern digital experience known as a Model-Based Engineering Environment or MBEE.

There are challenges for making MBEEs successful. Economically viable implementations are needed to enable organizations to operate MBEEs successfully. MBEEs must be able to evolve in scale to meet the insatiable appetite for compute and data handling that accompany their use. And possibly most important, Engineers using an MBEE are being driven by the requirements for the product they are Engineering. Thus, an MBEE must provide significant advantages for the Engineer by both increasing the quality of the creative experience and removing obstacles to productivity.

Open MBEE exists to address these challenges and empower Engineers through the phenomena of the open source collaborative software movement. The community that comes with open source provides a large-scale mechanism for developing consensus that is captured as concrete technical products. These technical products represent invariants that can propel Model-Based Engineering Environments to success in adopting organizations. Commodity access is crucial in maintaining the strong pace of innovation and technical capability necessary for MBEEs to evolve quickly enough to meet the needs of Engineers. This vision begins to form a projection of a substantial transformation in the world of collaborative engineering modeling such that MBEEs can be sophisticated, productive, and cost-effective.

Biography

Christopher Delp is the Manager of the Computer Aided Engineering Systems and Software Environments (CAE SSwE) at JPL. CAE SSwE provides a cutting-edge Engineering Environment for modeling systems, analysis and a software development based on Open MBEE. Previously he led the Model Environment Development effort on Europa Clipper which built the Model-Based Engineering Environment and the Open MBEE community of open source Model-Based Engineering software and models. He has worked in a variety of roles on JPL Flight Projects in Systems Engineering and Software Engineering. His experience includes Architecture and Design of Systems, Safety Critical software development and testing, and the application of Systems Engineering across the lifecycle. He is recognized as an industry leader in MBSE and Model-Based Engineering Environments.

Integrating Sustainment Throughout the Model Based Enterprise

Dr. Marilyn Gaska
LM Fellow and Chief Engineer, Logistics and Sustainment
Lockheed Martin

ABSTRACT

This presentation will highlight the importance of a model-based enterprise (MBE) to sustainment and across the life cycle. Model-based X where "X" is sustainment needs to be considered as part of the systems of systems engineering starting early in the life cycle. Computer-aided manufacturing, inspection tools, and approaches should be planned for use in sustainment to include repairs and ease of mods and upgrades to update capabilities. The complexity of managing the digital thread or tapestry is greater when sustainment is considered, with the need to linking and management the "as maintained" bill of materials for each delivered system. Application of data analytics and artificial intelligence (AI)/machine learning (ML) supports prognostics and health management and performance feedback. System of systems modeling methods that include application of the Affordable Systems Operational Effectiveness (ASOE) framework to help organize the sustainment considerations for both the primary and enabling systems to reduce life cycle costs and improve reliability and support return on investment (ROI) case studies. There are several opportunities for leveraging digital thread for sustainment as a concentration area. The first is application of augmented/virtual/mixed reality for maintenance opportunities and supported by global subject matter expert networks. The sustainment community pull for application of advanced manufacturing approaches to include additive manufacturing also relies on distributed access to technical data packages to support manufacturing at the point of need for parts that can be printed. A third focus area is on acquisition reform focus on capability management for legacy systems to meet the challenges of the National Defense Strategy. Systems designed with standards-based architectures and interfaces can support lower cost and more agile modifications and upgrades of both hardware and software in a system.

Biography

Dr. Marilyn Gaska is currently the Corporate Logistics and Sustainment Chief Engineer and Fellow in the Office of the CTO organization at Lockheed Martin Corporation, Bethesda, Maryland. At Lockheed Martin, she is responsible for the sustainment vision and technology roadmap, and she leads the Full Spectrum Capability Management™ initiative. She has led collaboration with the Services for the Logistics Future Operating Concepts and Logistics and Sustainment Enterprise 2040 to include additive manufacturing leverage for sustainment, initial collaboration on confined space monitoring, and Innovation Center concept collaboration. She is the Lockheed Martin lead for the Sustainment Innovation Collaborative Competition among the three Service Academies. Externally she is the chair of American Makes Additive Manufacturing Maintenance and Sustainment Advisory Group started in 2015. In that role she had worked with the OSD Additive Manufacturing for Maintenance and Sustainment Working Group to co-chair three Additive Manufacturing Business Model Wargame and Workshops events. In 2017 she was a recipient of an America Makes Ambassador Award. She is the lead for corporate coordination of Lockheed Martin participation in the America Makes Maturation of Advanced Manufacturing for Low-Cost Sustainment (MAMLS) projects managed by Air Force Research Lab. Marilyn also led the Manufacturing Environment Team for the NDIA Cybersecurity for Advanced Manufacturing (CFAM) 2016 effort. She is a qualified Program Manager, with sustainment program profit and loss responsibility. Marilyn has also held positions as Capture Manager, Systems Engineering Manager, and Advanced Technology Manager. She is the author of over 60 papers and presentations, including co-author of an article in the Defense Acquisition University AT&L Magazine Special Edition on Additive Manufacturing. She is also on the planning committee for the Aircraft Airworthiness and Sustainment Conference. Marilyn's Ph.D. degree in Systems Science and Industrial Engineering was received from Binghamton University in 1999. She also earned a Master's Degree in Advanced Technology at Binghamton. Marilyn graduated from Cornell University in Ithaca, NY with Bachelor's and Masters of Science degrees.

Towards Self-Aware Manufacturing

Dr. Tony Schmitz
Professor and Assistant Director, Energy Production and Infrastructure Center
University of North Carolina, Charlotte

ABSTRACT
This presentation will describe the application of artificial intelligence to precision part manufacture and measurement. Specifically, it will summarize current efforts toward self-aware operation, or the ability of a production or measuring machine to understand its current state and surroundings and respond accordingly. The innovation is the combination of data-driven and physics-based models to provide hybrid physics-guided data learning approaches that improve the accuracy, physical consistency, traceability, and generalizability of model predictions. Ongoing research efforts leverage artificial intelligence, machining process modeling, measurement science, and design and ultraprecision machining of freeform optics.

The research capitalizes on the adoption of new digital technologies that establish the digital thread, or communication framework that enables seamless data flow and an integrated view of manufacturing processes. This digital thread links every phase of a manufactured part's life cycle – from design, production, and testing through end use. For example, parts are described using a digital solid model that is developed using computer-aided design (CAD) software. Computer numerically-controlled (CNC) machine instructions for subtractive manufacturing, as well as other processes, are produced using computer-aided manufacturing (CAM) software. This data is partnered with the physical part as its digital twin, which accompanies the part throughout its lifetime. While these digital connectivities represent an evolutionary leap forward, human intervention is still required at nearly all stages. For example, the CAM part program is manually produced for every part in every factory by a specially trained, high wage programmer. To further complicate these issues, high volumes of data are available at each step through the IIoT that must be manually interpreted and implemented to improve the factory's productivity. This presentation will describe current research that addresses these challenges with the end goal of self-aware operation.

Biography
Tony Schmitz received his BS in Mechanical Engineering from Temple University in 1993, his MS in Mechanical Engineering from the University of Florida in 1996, and his PhD in Mechanical Engineering from the University of Florida in 1999. Schmitz completed a post-doctoral appointment at the National Institute of Standards and Technology (NIST) and was then employed as a Mechanical Engineer from 1999-2002. During this time, he was also a lecturer at Johns Hopkins University. Schmitz accepted an appointment in the University of Florida's Department of Mechanical and Aerospace Engineering (UF MAE) in 2002 and joined the Mechanical Engineering and Engineering Science Department at the University of North Carolina at Charlotte in 2011.

His professional recognitions include: 2019 UNC Board of Governors Award for Teaching, 2018 51st Annual Bank of America Award for Teaching Excellence, 2017 NAMRI/SME David Dornfeld Manufacturing Vision Award, 2016 SME College of Fellows, UNC Charlotte Lee College of Engineering 2013 Undergraduate Award in Teaching Excellence, 2012 Temple University Alumni Fellow, 2011 Sports Emmy Award (NBC Learn) for the Science of NFL Football video series, 2010 North American Manufacturing Research Institute/SME Outstanding Paper, 2009 UF MAE Teacher of the Year, 2005 SME Outstanding Young Manufacturing Engineer award, 2004 Journal of Tribology Best Paper Award, 2003 Office of Naval Research Young Investigator Award, 2003 National Science Foundation CAREER Award, 1999 Measurement Science and Technology Highly Commended Article, 1999 National Research Council Postdoctoral Research Associateship (NIST), 1999 Temple University Gallery of Success Inductee, 1998 Department of Energy/National Academy of Engineering Integrated Manufacturing Predoctoral Fellowship, and 1994 National Science Foundation Graduate Traineeship. Schmitz also serves as an associate editor for the ASME Journal of Manufacturing Science and Engineering.

Proc. of the 10th Model-Based Enterprise Summit (MBE 2019), Gaithersburg, Maryland, USA, April 2-4, 2019

MxD 15-11-08: Capturing Product Behavioral and Contextual Characteristics through a Model-Based Feature Information Network (MFIN)

Rosemary Astheimer
Purdue University
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Daniel Campbell
Capvidia
Houston, TX, USA

ABSTRACT
Computer Aided Design (CAD) software that is used to design mechanical components continues to evolve, as well as the Product Lifecycle Management (PLM) processes that manage this data, but the transfer of this information to anyone in the enterprise that will interact with the product, has changed very little in the last few decades. On the horizon is Model-Based Definition (MBD) which entails designing not only the product geometry in CAD but also all of the information needed to manufacture, inspect and sustain the product. The MxD 15-11 project addresses the industry need for a way to meaningfully capture and connect such information at the CAD feature level, and across all the various domains of industrial manufacturing.

Background

Today product data comprises a combination of electronic and paper documents spread across many files and multiple formats. The format that is used is based on who is receiving the data, the technology that they do or don't have and how the data will be used. Below is a list of a few examples of who might receive the data, what they will do with it, and the format that it may be captured in.

Task	Purpose	Format
Analysis	Material Properties	Granta MI, MSC Material Center
	Analysis Results	MSC Nastran
Procurement	Acquiring Materials	Material Properties Quantity
Manufacturing	CNC Machining	STEP, IGES
Inspection	Quality	QIF
Assembly	Bill of Materials	XSLX
	Assembly Instructions	PDF, JPEG
Maintenance / Repair	Service Investigation	PDF, JPEG, DOCX, XLSX
Marketing	Product Cost	Material Properties Manufacturing & Inspection Time Assembly Time Shipment Costs

The task of Model-Based Definition has begun by collecting Product and Manufacturing Information (PMI) – including Geometric Dimensioning & Tolerancing (GD&T) annotations, Bill of Material (BOM) and limited processing information stored as metadata – but the remaining assortment of delivery formats is not linked to the CAD geometry. The multitude of formats introduces risk the that data is not passed with 100% accuracy each time data is translated between formats, which makes design intent open to the interpretation of the receiver of the data. In addition to this, there is the simple and burdensome task of the manual transcription of data by a skilled engineer. According to The Model Based Enterprise (MBE) Study[1], an average of 6.4 hours per week per engineer are spent clarifying drawing information and another 5.5 hours per week per engineer generating additional documentation. With this amount of rework required, it's no surprise that errors are made during this manual process and aren't caught until late in the design process – which is costly. This study also compared respondents across several key metrics and showed that when a Model Based approach was used, engineers spent 6.6 fewer hours per week on documentation, and had 2.5 fewer emergency issues with 4.9 fewer assessments of why parts don't fit together.

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Project Purpose

The need for unambiguous transfer of data to these multiple file formats and configurations is clear. The technology innovation from this project will allow industry to leverage digital data more seamlessly throughout the enterprise and will help facilitate the automation of manufacturing planning and data retrieval, making the United States a competitive option to overseas manufacturing. The removal of the potential erroneous human-in-the-loop also allows for quicker turnaround times and lower cost when design changes are needed.

The objectives of this project are twofold. First, this project seeks to enable to systemization and automation of business logic associated with manufacturing operations in the domains of Design, Analysis, Manufacturing Process Planning, Quality, and Maintenance/Repair/Overhaul (MRO). This is accomplished by leveraging the MBD model and the strict semantic data definition inherent in the MFIN data model. The second objective of the project to establish data traceability of all data generated in the various domains mentioned above to the “single source of truth” – the master MBD model in PLM. By doing this, one can draw a single undirected graph of data that links all industrial data created via the MFIN, with the MBD model as the main hub.

Implementation

The MFIN concept is built around the idea of data semantics and connectivity at a Feature level. This is a higher level of data resolution than is currently common practice, where the entire CAD model itself is treated as an atomic entity. It also allows for the particulars of a given modelling technology to be abstracted out of the data model – for instance, a Hole feature in a part, where the hole is commonly represented by 2 hemi-cylindrical topological surfaces. In various downstream processes, this same feature may be represented by a single cylindrical surface, or tessellated into a bag of triangles, but the functional essence of the feature remains the same – it is a Hole.

At this point, it is probably necessary to clarify a key distinction – the difference between the MFIN concept, and typical PLM System implementations. These are entirely different categories of things; residing in different layers in the technology stack of manufacturing. The MFIN is a data model, along with a proposed methodology for how it is to be used. A PLM System is a software tool which organizes and stores data, and manages data workflows. Since an MFIN is at a lower level than a PLM Software system, it is entire possible (and encouraged!) to use the MFIN approach within the context of a PLM deployment. During the course of this project, technology demonstrators will be carried out which involve the use of the MFIN with a PLM system.

The MFIN draws from various standards; in particular, XML and the Quality Information Framework (QIF). XML is a modern platform for data modeling (particularly with the use of the XML Schema Definition Language, XSDL), and provides the additional benefit of easy manipulation with simple source code auto-generation and standard tools like XPath. QIF was used as a base for the MFIN because of its modern XML-based design, it’s semantic MBD data model, and its feature-based approach to data modeling. Because of this, the Quality domain of the MFIN data model is considered to be extremely robust.

The MFIN data model is rigorously defined with XSDL schemas, which allow for software tools to easily implement the format. During this project, we have seen software implementations in the Siemens NX and PTC Creo environments, as well as software implementations from Capvidia and MSC which make use of the MFIN. In addition to this, students at Purdue University made heavy use of Python and C# to write their own scripts that were able to read and write MFIN data. It is worth noting that these students are mechanical engineering students and *not* software engineering students – a fact which shows the true accessibility of the MFIN approach to manufacturing data. We foresee that a standards-based approach to data such as this will enable a marketplace of best-in-class software vendors who will be able to “plug into” enterprise-level manufacturing data systems and add tremendous value. In an era of ever-increasing technological specialization, this accessibility becomes paramount.

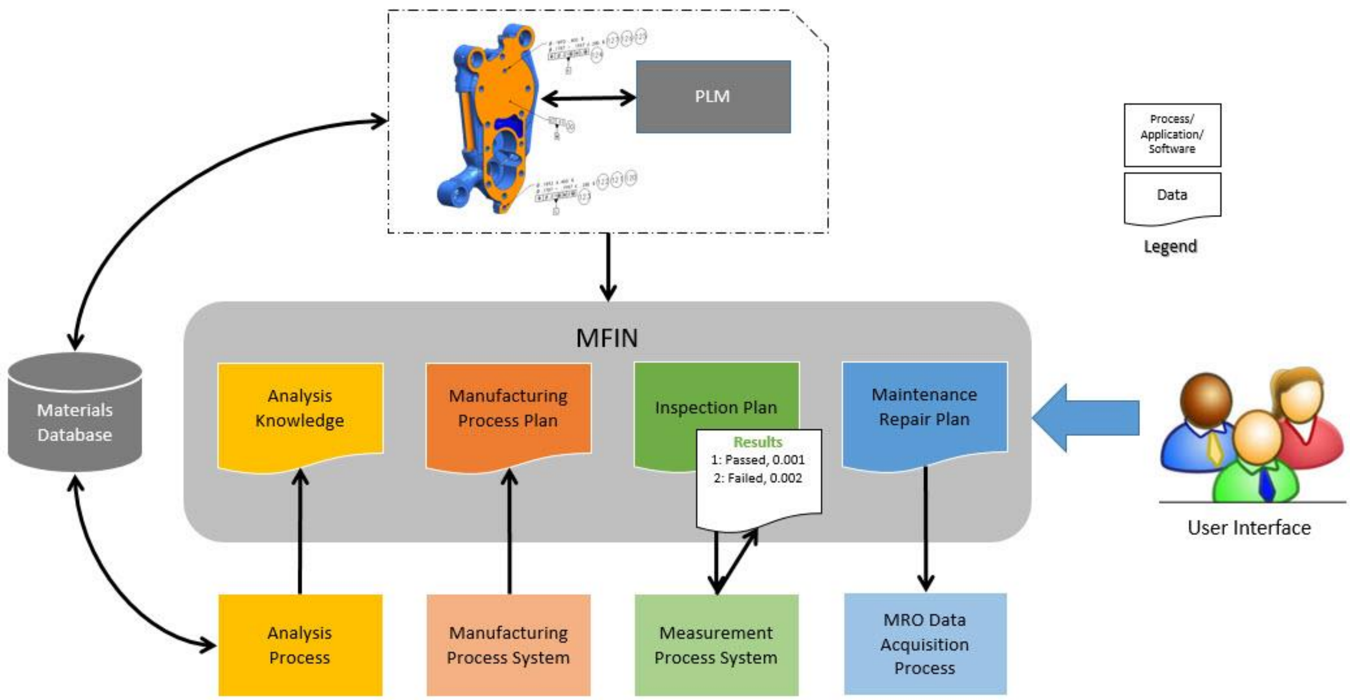

Figure 1: MFIN Architecture and example data links

The project innovates on many fronts including geometric representations, taxonomies and ontologies, metadata in the form of preservation descriptive information, data translation and certification, and information schema. The focus is on the digital thread from design to manufacturing to quality to sustainment with a feedback loop back to design. The framework creates a virtual or software linkage between CAD model features and related data elements in any data sets with the goal of creating a complete digital thread through a product’s lifecycle. Figure 1 above shows examples the data which is suitable for each of the MFIN application areas.

As additional information is associated with the MBD, the need for a comprehensive framework that will help facilitate standard methods of indexing, cataloging, storing, searching and retrieving the relevant information, as it is required across the product life cycle. In this context, the MFIN can be seen as a key enabler to Big Data and Advanced Analytics.

Conclusions

The MFIN concept is a proposed data model and methodology for implementing Model Based Enterprise (MBE) in a modern manufacturing environment. Developed under the direction of the MxD, and created by end users, technology providers, and leaders in academia, it reflects the latest thinking on how MBE can be implemented effectively across multiple domains, including design, analysis, manufacturing, quality, and MRO. It encourages process systemization and automation, which allows manufacturers to create products at lower cost, faster, and with greater and more repeatable quality. In addition to this, is provides the data traceability to enable meaningful, advanced data analytics on industrial data. In 2017, the Economist magazine declared that “The world’s most valuable resource is no longer oil, but data”[2]. It’s time for manufacturing to take data seriously, and the MFIN is how it can be done.

References

[1] Jackson, Chad (2014, June). *The Model Based Enterprise (MBE) Study.* Retrieved from, http://www.lifecycleinsights.com/finding/average-time-spent-authoring-clarifying-and-amending-documentation/

[2] Unknown authors (2017, May). The world's most valuable resource is no longer oil, but data. *The Economist*. Retrieved from https://www.economist.com/leaders/2017/05/06/the-worlds-most-valuable-resource-is-no-longer-oil-but-data

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The Case for Integrated Model Centric Engineering

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Abstract

Ten plus years after its introduction, the practice of Model-Based Systems Engineering (MBSE) has yet to be widely adopted across the industry. Amongst several reasons, a few stand out: the lack of a formalism with well-defined semantics to create system model, the lack of a methodology to create system model across tools, disciplines, and organizations, the lack of rigor to analyze system model continuously, the lack of comprehensive content-based version control to support provenance, traceability and reproducibility, the lack of best practices in managing configuration and change of system model, and the inability of different kinds of stakeholders to access the system model and provide feedback on it. We call a practice that addresses these challenges Integrated Model Centric Engineering (IMCE). This paper overviews the challenges facing MBSE, discusses desirable characteristics of SE practice, outlines the IMCE principles needed to improve them, and summarizes the impact of adopting IMCE.

1. Introduction: Challenges of MBSE

Models are at the heart of science and engineering. A system model is a simplified version that represents some details of interest about the system while suppressing others. System models facilitate understanding and inform decision making, explaining, and predicting events of such systems.

However, for a system model to enable these analytical features, it must be expressed in a language with sufficiently expressive syntax and precise semantics. The Systems Modeling Language (SysML [1]) standard from the Object Management Group (OMG) is a popular choice among MBSE practitioners. SysML allows modeling systems from different viewpoints including requirements, structure, behavior, and parametrics, while its standard graphical notation facilitates communication with stakeholders about such viewpoints. Until recently, SysML's informal semantics made it poorly suited for rigorous analysis. Thanks to OMG's executability roadmap, several SysML viewpoints including: activity diagrams [2], state machine diagrams [3] and composite structure diagrams [4], now have operational semantics useful for simulation-based analysis. OMG's Object Constraint Language [5] further complements the analysis landscape for well-formedness analysis. However, OMG offers poor support for logical analysis such as consistency (no contradictions) and satisfiability (no incompatible constraints).

In principle, MBSE ought to enable transitioning the systems engineering (SE) practice from document-centric to model-centric on the premise that traditional documents foster misunderstanding, because of tacit assumptions and implicit semantics, whereas descriptive models facilitate precise communication because of standardized semantics. This transition requires complementing MBSE with a methodology. Well-known methodologies include OOSEM [6], State Analysis [7], CESAM [8] and Arcadia [9]. The effectiveness of a methodology requires tool support and extensible modeling languages for tailoring methodology-specific vocabularies, viewpoints, analyses and guidance. Unfortunately, this flexibility is seldom available for many methodologies; some of which conversely lack in methodology-specific logical analysis criteria for enacting useful guidance and encouraging reuse of best practices for supported domains.

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Since systems engineering is inherently a collaborative endeavor, involving multiple teams with distinct responsibilities, it makes sense to organize a system model as a logical aggregate of model fragments assigned to different teams. In practice, significant problems arise due to mismatches between the collaboration flexibility needed for a desired organization and the collaboration capabilities available from modeling tools and applicable standards. This mismatch often results in a substantial level of artificial complexity due to the tool-specific accommodations needed to work around the limitations of the tools. For example, while SysML modeling tools typically support splitting a model into fragments cross-referencing each other, intrinsic limitations in SysML preclude the properties of a SyML element in one fragment to be assigned values in another fragment. Collaboration mismatches are further exacerbated across multiple tools due to poor interoperability/interchange. Progress in standards, such as OMG's MIWG [10] and OASIS's OSLC [11], is notoriously lagging behind the level of collaboration support needed in practice, while emerging tool-specific solutions, such as Syndeia [12] and ModelBus [13], underscore the depth of the problem, which is currently tackled at the low-level of discrete model elements, instead of high-levels of methodology-specific patterns.

Furthermore, relating model fragments is insufficient for managing information represented in different ways across multiple kinds of elements and models with partial overlap. For example, intrinsic differences in domain-specific modeling practices (e.g. mechanical, thermal, electrical) in CAD modeling tools preclude a common representation of system-level components. Poor standards and limited capabilities for interchange and interoperability further exacerbate the problem of relating these heterogenous representations. Ontological notions of identity criteria have yet to be embraced in these standards organizations, yet are fundamental to establishing robust correspondence principles. Worse, current MBSE methodologies fail to address the challenge of identity management across the diversity of concerns involved (e.g., risk management, project management, operations and maintenance) to ensure a continuity of identity across viewpoints. Not surprisingly, MBSE practitioners face many challenges in managing the identity criteria used in different models, and sometimes across multiple viewpoints, where legacy practices for naming and identifying engineering elements may turn out to be computationally inadequate for robust identification across models.

For many reasons, MBSE tools evolved from niche and isolated products to embrace the demand for distributed collaboration, with a corresponding shift away from managing models as individual files, that are uploaded/downloaded from servers, towards proprietary repositories and protocols that operate at the scale of individual model elements. The collaborative landscape in MBSE has become a complex web of proprietary repositories and protocols that defies the trends in software engineering where distributed content-based versioning paradigms, such as GIT, have simplified the collaborative landscape, with vendors embracing the mantra of "X-as-code" for managing concerns (e.g. X as infrastructure, deployment, configuration, operation).

Currently, "X-as-model" does not compute in MBSE; instead, poor configuration management (CM) practices exacerbate trust in MBSE. Without a notion of a GIT-like history of changes made across inter-related model fragments, MBSE practitioners face significant challenges to ensure that products derived from MBSE models are up-to-date with respect to planned changes. Conversely, MBSE practitioners lack GIT-like strong assurances from the collection of inter-related MBSE tools that declaring the current state of MBSE models as a baseline really means a GIT-like commit: an immutable state of affairs that can be retrieved at a later time. Without such strong assurances, it is understandably difficult for stakeholders to trust that MBSE reports really reflect the intended state of the MBSE models, as opposed to whatever the MBSE tools provided when those reports were produced.

In the rest of this paper, we discuss a vision to improve MBSE in practice. Specifically, in section 2, we discuss desired characteristics of modern systems engineering practice. We then introduce the Integrated Model Centric Engineering (IMCE) practice in section 3 by defining its architecture principles, which help improve these characteristics. In section 4, we reflect on the impact of adopting an IMCE practice. We review related works in Section 5. In section 6, we conclude and outline future works.

2. Characteristics of Modern Systems Engineering Practice

Systems Engineering is not merely any activity that concerns itself with systems. It must, by definition, be an *engineering* discipline, and therefore manifest those characteristics that distinguish engineering from other fields of endeavor. It must, for example, make effective use of concepts and knowledge from science and mathematics. To be considered modern, it must in addition make effective use of up-to-date techniques and technologies. It must not suffer from any deficiency for which effective remedies have been found in any field.

The following illustrate some desirable characteristics of modern systems engineering practice.

2.1 Clarity

By definition, SE is concerned with problems whose scale requires collaboration to solve. Clarity of communication, therefore, is of paramount importance. Systems engineers describe the world as it is, or might be, and propose approaches that can be shown by analysis to achieve some desired goal. Without precise language to describe these states, approaches, and analyses, however, it is impossible to reach consensus among collaborating parties.

2.2 Rigor

Engineering achieves rigor in part through its adoption of mathematical principles. Engineering analysis routinely makes use of mathematical abstractions such as differential equations, matrices, statistical distributions, etc. Also, concepts from abstract algebra (e.g., Galois Fields), formal logic, and graph theory, to name a few, have proven extremely valuable in engineering applications. Note that clarity in an engineering language is often achieved by reference to abstractions with definite properties. A *capacitor*, for example, demonstrates a relationship between voltage and current, specified by a first-order linear differential equation. The name is intimately linked to an abstraction.

2.3 Traceability

An SE process entails a large number of decisions, choices, and constraints that represent a creative exercise of design authority. In traditional SE doctrine, the Work Breakdown Structure documents the systematic delegation of this authority along discipline and/or organizational lines. A modern SE environment must preserve the association between an authority and its decisions, otherwise the system architecture becomes a disorganized collection of assertions with no way to determine who asserted what. Moreover, it must be possible, given any assertion in a model, to determine the authority context in which it was made, the rationale for that particular decision, and the relevance of other models that contributed to this assertion. In information management, this information is called *provenance*.

2.4 Repeatability

The analyses that support complex decision-making often require highly-specialized software and large inputs representing information about the system, its environments, customer requirements, operational strategies, risks, etc. As a consequence, these analyses are often expensive to specify, expensive to execute, and disturbingly easy to get wrong. It is important to formalize the complete specification of analyses, including their dependencies, so that once an analysis has been executed once, it can be executed again with minimum overhead and cost. This is important for maintaining confidence in analyses over long system development and operations periods, but also to ensure that trade studies carefully restrict variation to only those factors under study. It is also desirable to isolate the specification of an analysis from its computation.

2.5 Durability

Durability is closely-related to repeatability. If any operation is to be repeatable, then any information it requires must be available. The way to ensure this availability is to ensure that any information produced or needed by the SE process is stored once in an accessible location (assuming proper access controls) and never changed or deleted. Such information is said to be *immutable*. Of course, the iterative nature of SE implies that decisions and designs evolve over time, but this change is better managed by assigning a permanent identifier to every version of any pertinent information and keeping every version permanently.

2.6 Efficiency

It is rarely the case that all useful SE contributions for an endeavor have been achieved before resource limits are met. For that reason, efficiency is a key virtue. There are multiple avenues for pursuing efficiency, but one of the most important is automation. Computation has always been an important part of SE, but the recent emergence of powerful systems for logical reasoning, machine learning, data mining, etc., have expanded the opportunities to exploit computation to augment, and in some cases, replace human processes. As with storage, the cost of computation has dropped to the degree that endeavors with only modest budgets can deploy computing resources that would have dwarfed the largest supercomputers a few years ago. Of course, careful attention to repeatability and durability enhances the prospects of efficiency through automation.

3. Architectural Principles for Integrated Model-Centric Engineering

We call a practice that strives to improve the characteristics outlined above an Integrated Model Centric Engineering (IMCE) practice. The following sections describe a set of architectural principles that can guide implementation of an IMCE practice; they are chosen in the context of the desired characteristics described above. We claim adherence to these principles enhances the prospects of improving those characteristics, and we support the claims with rationale as space permits.

3.1 Adopt Linguistic Rigor

Because natural language understanding remains an open challenge, the only pragmatic alternative that promotes clarity of communication is formal language. The breadth of SE, however, precludes an all-encompassing controlled vocabulary; therefore, it is necessary to align controlled vocabularies with limited scopes of architecture viewpoints framing specific concerns of interest to homogeneous cohorts of stakeholders [14]. That is, the controlled vocabulary of a viewpoint should be sufficiently small to facilitate learning for proficient communication and sufficiently expressive to convey those concerns precisely.

3.2 Support Decisions with Analysis

Systems Engineering rigor and traceability require identifying stakeholders and concerns, specifying why the concerns matter (rationale) and what it means to address them adequately (conformance). A system model should not merely describe a design, but should also *explain* why a particular design is preferred. This explanation should involve computable figures of merit and constraints that link design decisions to outcomes and values meaningful in the stakeholder domain.

3.3 Analyze at the Right Level of Abstraction

Systems Engineering employs decomposition to transform a problem in one domain (e.g., planetary science) into a set of related problems, typically along engineering discipline (e.g., electrical, mechanical, attitude control etc.) lines. Separation of concerns suggests that we analyze each domain separately and each in its own terms: the science domain is concerned with data sets, coverage, resolution, etc., while the electrical domain is concerned with power allocations, battery state of charge, fault isolation, etc. Maintaining this separation is important for repeatability. Of course, traceability requires that we make a principled connection between domains in the form of analysis that shows, for example, that a coverage requirement mandates a minimum battery capacity, or that failure of a solar panel will reduce downlink data volume.

3.4 Define Patterns to Manage Complexity

Adopting linguistic rigor often implies making fine-grained distinctions; complex systems are described by large numbers of simple facts. It is also true, however, that more coarse-grained patterns recur in these descriptions. Modeling component interconnections, for example, makes use of multiple concepts (e.g., component, interface, junction) and multiple relationships (e.g., component presents interface, junction joins interface), but a complete description of a pairwise connection always involves two components, one interface presented by each, and one junction joining the interfaces. Patterns provide a bridge between the SE domain and the knowledge representation domain and support rigor, traceability, and efficiency.

3.5 Adopt CI/CD to Discover Issues Early

Repeatability and efficiency argue for automation of analysis. Continuous Integration (CI) and Continuous Delivery (CD) are modes of computing that map and order computing task dependencies to execute tasks as soon as possible, thereby achieving two useful goals: (1) providing early feedback on the analytical consequences of engineering decisions, and (2) regularly exercising analysis automation to ensure it’s ready when needed. Both goals provide systems engineering teams the capability for summarizing the impact of complex collaborative engineering activities and determining whether the predicted characteristics of the resulting design remain within acceptable margins for key stakeholder concern criteria.

3.6 Use Content-Based CM

Repeatability, durability, and efficiency argue for fine-grained configuration management of original data and intermediate results. Beyond mere management of versions, however, the ability to easily determine whether any two versions differ in the most minute detail is essential for strong guarantees of repeatability and traceability, as is the ability to quickly determine if a particular snapshot of content exists anywhere in the CM repository. These features are provided by configuration control systems that use hashes of content as version identifiers. Git is overwhelming the most widely-used and trusted such system today.

3.7 Use Deterministic Serialization of Model Content

Content-based CM systems can distinguish content instances based on syntactic differences, but the desired capability is to distinguish semantic differences. This capability can be achieved if each semantically-distinct model has one and only one syntactic serialization. Guaranteeing that is not difficult in practice but it requires conscious intent and care.

3.8 Record Provenance of Model Content

Systems Engineering is inherently collaborative, incremental, and iterative. That notwithstanding, there is a logical precedence to the process steps in that each step requires input data and processing capabilities (e.g., software) that transforms model content in some defined state into another defined state. Traceability and repeatability mandate recording the specific instances of all inputs and processing capabilities used to create each instance of every output. Recording provenance at every step creates a “chain of custody” for all information back to its origin. Combined with content-based CM, this capability elevates the guarantees of syntactic repeatability about versioning models in CM to guarantees of semantic traceability about all changes actually made between different versions of models in CM.

3.9 Define and Verify Process Invariants

A rigorous, traceable, and repeatable process is specified by unambiguous specifications of preconditions and postconditions. Every computation depends on predicates that must be true if the result is to be trustworthy. Explicit verification of these conditions at each step, integrated into the CI/CD system, helps to ensure that violations of asserted conditions are detected reliably and as early as possible, thereby ensuring that contaminate or otherwise untrustworthy artifacts are not produced. In addition, the thought required to formulate such conditions unambiguously forces clear thought about the definitions of processing steps and leads to deeper understanding of the engineering process.

3.10 Define Artifact Organization Strategy

A traceable, repeatable, and durable computational environment is going to produce large numbers of artifacts to be stored and indexed for later access. It is important to devote thought to the organizational scheme for these artifacts, giving due consideration to affinities regarding, among others, the following:

- **Concerns:** artifacts addressing related stakeholder concerns should be near each other in the artifact organization scheme and retrievable by concern.
- **Provenance:** Similarly, artifacts with related provenance should be similarly related in the organizational scheme. It particular, it should be convenient to locate and retrieve artifact by provenance attributes.
- **Access Control:** The nature of acquirer/supplier relationships mandates that cooperating parties control which of their partners can access the information they produce. Organizational schemes that account for this fact systematically simplify access controls and reduce the risk of unintended withholding or disclosure of information.

3.11 Account for Variation Explicitly

The collaborative and complex nature of systems engineering typically requires two canonical forms of design variation. One is classically called a *trade study*, in which multiple possibly-incompatible design options are considered and evaluated according to some preference criteria. The other is inherent in the notion of a *baseline*, a distinguished state of the design which is official in some sense but often expected to change at a designated milestone in the future. The engineering environment must expose the baseline but allow work to proceed toward the next milestone, including all necessary analysis, reporting, etc.

These situations require the engineering environment to maintain distinct variants and associate each with applicable metadata (e.g., trade option description, baseline status designation) in such a way that work in each branch is isolated from every other branch, but branches can be merged when desired. This approach to variation management is common in software development and is again one of the strengths of Git.

4. Impact of Adopting IMCE Practice

Meaningful adoption of the principles described above entails much more than mere endorsement of slogans. It requires honest and occasionally brutal examination of current practice and the will to change for the better when warranted.

For example, consider the impact of a commitment to linguistic rigor. Such a commitment would entail agreement within a community to use a consensus lexicon and grammar in both oral and written communications, in standard engineering products, and in interaction with information systems that support engineering analysis. Process guidance and training material may need to be updated. Software may need modifications. Similarly, a commitment to recording provenance would require practitioners to ask, whenever information is stored, to ensure that it is annotated with whatever data will be necessary for some future party to understand its meaning and judge its importance.

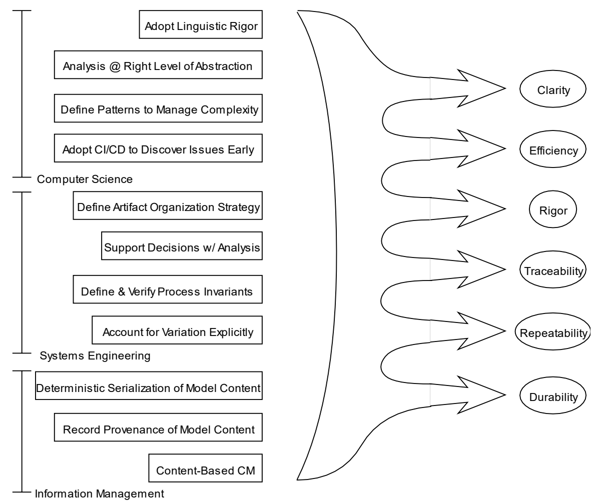

Figure 1 Adopting IMCE architecture principles helps improve the desired characteristics of MBSE practice

These principles may seem burdensome, and indeed they are when considered only as individual responsibilities. The cost to any individual, however, is more than made up by the benefits each individual realizes from his or her peers also meeting those responsibilities.

Systems engineering is increasingly driven by the need to curate large volumes of information representing a broad range of concerns and expressed in discipline-specific terms. Engineering, however, is by no means the only field being so driven, and powerful solutions to these drivers, applicable to many fields, are emerging from the computer science and information management disciplines, as shown on the left side of Figure 1. The architectural principles reflect this fact.

The principles also reflect the fact that computation and data storage costs have plummeted in recent years, to the point where it is economically feasible to preserve many versions of large data sets indefinitely, and to harness large numbers of processors for computationally-intensive tasks. This has profound implications for the practice of engineering.

Putting these principles into practice implies, among other things, that every valuable fact in the scope of systems engineering for a given program is expressed in standards-based language using established formalisms, stored such that it can be accessed using standard query protocols and languages, annotated with complete provenance data, and retained indefinitely. It implies use of scalable computing resources to perform any operation, for which machines are more reliable than humans. Most of all, it implies recognition that the primary product of systems engineering is knowledge in the form of information and a commitment to treating that knowledge at all times as valuable along multiple characteristics as shown on the right side of Figure 1.

5. Related works

Addressing the challenges of MBSE is on the agenda of several organizations in the industry. One such organization is INCOSE, which recently released their vision for using *Integrated Data as a Foundation for Systems Engineering* [15]. The vision outlines the MBSE challenges, how they should be addressed from a data-centric perspective, and how to transition organizations towards implementing the vision. We see the IMCE vision described in this paper as in-line with the INCOSE vision, sharing a similar strategy for practicing MBSE from integrated and data-centric perspectives. Moreover, we highlight the desired characteristics of such practice and enumerate the architecture principles needed to enable it.

Another relevant organization is the OMG, which has recently issued two requests for proposals (RFPs). The first is for SysML v2 that enables more effective application of MBSE by improving precision, expressiveness, interoperability, consistency and integration of the language concepts relative to SysML v1. The second RFP complements the first by requesting a set of APIs and services for SysML v2 that supports construction, query, viewpoint management, analysis, CM, and transformation of SysML v2 models. We view this effort as synergetic as it facilitates using SysML as a lingua franca by SE tools and improves the chances of success integrating them. We work closely with the OMG to influence submissions to these RFPs.

6. Conclusion and Future Works

This paper highlighted the challenges facing MBSE practitioners today and described the IMCE vision of addressing them. The approach was presented in terms of the desired characteristics of modern systems engineering practice (which are clarity, rigor, traceability, repeatability, durability and efficiency), and the architecture principles that are needed to improve each one of them.

In the future, we plan to define a reference architecture for a software platform that helps systems engineers adopt an IMCE practice. The architecture will propose ways to realize the IMCE principles in order to achieve the desired characteristics. We also plan to implement the architecture using state of the art technologies. Moreover, we plan to develop applications on the platform that focus on various SE disciplines and applications.

Acknowledgements

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References

[1] OMG, "SysML v1.5." Available: https://www.omg.org/spec/SysML/1.5/.
[2] OMG, "FUML v1.4." Available: https://www.omg.org/spec/FUML/1.4/.
[3] OMG, "PSSM v1.0 Beta 1." Available: https://www.omg.org/spec/PSSM/1.0/Beta1/.
[4] OMG, "PSCS v1.1." Available: https://www.omg.org/spec/PSCS/1.1/.
[5] OMG, "OCL v2.4." Available: https://www.omg.org/spec/OCL/2.4/.
[6] Friedenthal, S., Moore, A., Steiner, R., "A Practical Guide to SysML: Systems Modeling Language." Morgan Kaufmann/OMG Press, Elsevier Inc., Burlington, 2015.
[7] Ingham, M., Rasmussen, R., Bennett, M. and Moncada, A., "Engineering Complex Embedded Systems with State Analysis and the Mission Data System." Journal of Aerospace Computing, Information, and Communication, vol. 2, no. 12, pp. 507-536, 2005.
[8] CESAM-Community, "CESAM: Cesames systems architecting method." January 2017. Available: http://cesam.community/wp-content/uploads/2017/09/CESAM-guide_-_V12092017.pdf
[9] Voirin, J.-L., "Model-Based System and Architecture Engineering with the Arcadia Method." ISTE Press - Elsevier, London, 2017.
[10] OMG, "Model Interchange Wiki." Available: http://www.omgwiki.org/model-interchange/doku.php
[11] OASIS, "Open Services for Lifecycle Collaboration." Available: https://open-services.net/
[12] Intercax, "Syndeia." Available: http://intercax.com/products/syndeia/
[13] Fraunhofer, FOKUS, "ModelBus." Available: https://www.modelbus.org/

[14] ISO/IEC/IEEE 42010, "Systems and Software Engineering – Architecture Description." Available: https://www.iso.org/standard/50508.html.

[15] INCOSE, "Integrated Data as a Foundation of Systems Engineering." July 2018. Available: http://www.omgwiki.org/MBSE/lib/exe/fetch.php?media=mbse:rwg_data_as_a_foundation_of_se_draft_5_050218_review_copy.pdf.

Model Based Enterprise R&D at DLA

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ABSTRACT

Over the past several years the Defense Logistics Agency has participated with Engineering Service Activities and Sustainment Activities in pilot projects to study the acceptance of 3D Technical Data within the Department of Defense Supply Chain. The initial pilot projects focused on the use of embedded PRC geometry in a PDF file with other technical data attached as necessary. Subsequent pilot projects performed during 2018 have been expanded to include different formats. This paper will provide a short overview of the Defense Logistics Agency pilot project program, progress of the expanded pilots, and an introduction to an upcoming technical data project, "Connecting the MBE" which is a look at the issues facing the Defense Logistics Agency interfacing with a broad spectrum of PLM systems having dissimilar formats, product definitions, domains, and scope.

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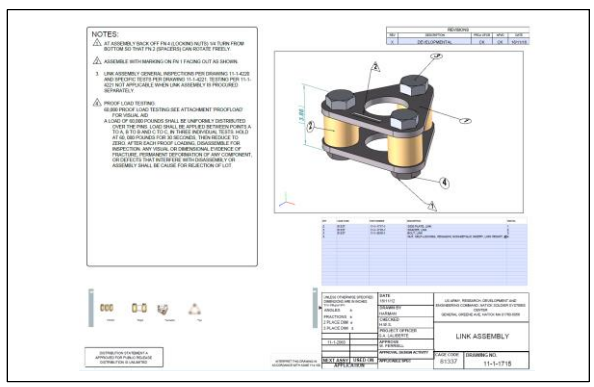

The initial purpose was to determine if traditional paper-based products could be replaced with a 3D Technical Data Package to support DLA sustainment processes. This research focused on the format of the technical data package and it was determined that PDF based technology was the most appropriate for DLA. Several pilot projects were completed and indicated the culture could withstand the transition to a PDF based Technical Data Package that included a 3D interactive view. DLA does not intend to require a specific format nor content from the engineering Service Agencies. DLA needs to be prepared to accept other mechanisms for viewing 3D geometry including JT, native CAD data, and the use of enhanced HTML5 graphical functionality.

The three most recently undertaken pilot projects include the use of ISO 14306: JT file format specification for 3D visualization; WebGL to enable the visualization of 3D product model data using an HTML5 compatible browser; and a third-party viewer to visualize data provided in native format, in this case, CATIA. This underscores the DLA position to not mandate a specific format. Results from the pilot project indicate that as an enterprise, DLA is most prepared to use data that can be visualized using an Acrobat reader. For all intents and purposes this has been limited to data encoded using either ISO 24517, U3D or ISO 14739, PRC. Although not currently part of any DLA pilot projects a joint ad-hoc committee was formed to include ISO 10303 Part 242 as a 3D stream for PDF.

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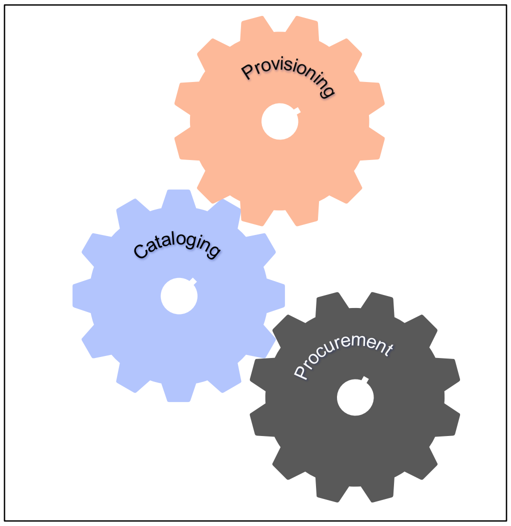


The primary sustainment processes the Technical Data Package needs to enable are cataloguing, provisioning, and procurement.

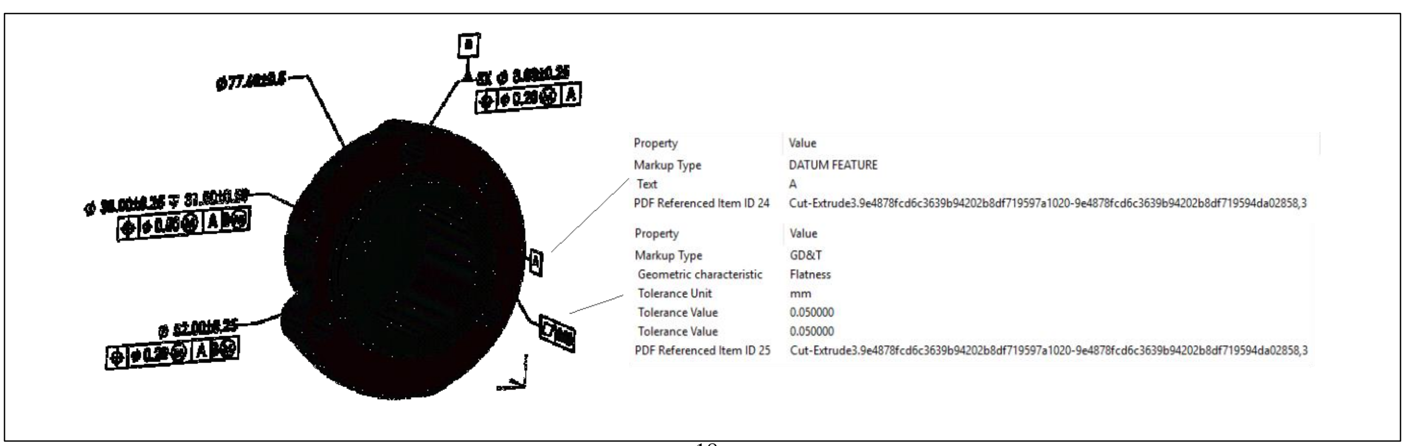
Cataloguing is the method by which the Defense Logistics Agency (DLA) creates and maintains a standardized record for parts that the Department of Defense (DoD) and other federal civilian agencies distribute, store, and procure on a recurring basis. A complete data package will enable the cataloguer to evaluate the item's form, fit, and function. Key elements that are catalogued are the physical features and materials that describe the part.

Provisioning is the process of determining and acquiring the range and quantity of spares and repair parts, and support and test equipment required to operate and maintain an end item of material for an initial period of service.

Procurement is the act of buying goods and services for the government. A National Stock Number (NSN) is created and assigned as a "first time buy" in the Enterprise Buyer System (EBS). The Purchase request is generated which includes all the technical data necessary provide a part. This technical data can vary from basic form, fit, and function to detailed manufacturing process with inspection criteria. The Product Specialist determines the adequacy of technical data including tolerances, materials, and QA requirements.

DLA does not normally create or modify the technical data but will access the technical data to discover the information necessary to support provisioning and cataloging. DLA is also responsible for managing the acquisition of parts for the services but is completely dependent on the services to provide the information necessary to specify the form, fit, and function of the product. In some cases, the services may provide detailed technical data to manufacture the part. In some cases, this may even specify manufacturing processes as well as acceptance criteria. For these pilot projects the usual technical data includes dimensioned 3D views, bills of material, engineering product structure, and lists. Sometimes the data provided to enable 3D visualization is provided in a format that provides sufficient precision and accuracy to enable downstream manufacturing processes. In some of the technical data packages the 3D visualization data is accompanied with STEP data that is commonly used with high confidence to define the shape of the product.

DLA is considering expanding their research beyond the replacement of the paper-based drawing with the 3D Technical Data Package. Research priorities include Data interoperability, exchange of data between PLM systems, Legacy data conversion, Digital rights management techniques, and the Modernization of the federal



catalog. Several research projects are being suggested for consideration. "Legacy and Missing Data" will study the alternatives that should be considered if suitable technical data is not available. The emphasis will be on the capture of shape and materials directly from an existing part and the conversion of legacy drawings. "Connecting the MBE" will examine issues related to obtaining data from information technology systems used by the OEM and Engineering Service Activity. This access could be direct connect, through the internet, file delivery to a standalone system, through a cloud, or access to a data repository. "Semantic with Visual" is a natural extension to the 3D Technical Data Package effort. The pilot projects have gone a great way in demonstrating the DLA workforce can obtain data visually from a 3D view. However, the greatest potential for process improvement lies in the advancement of machine to machine communication which will fundamentally rely on the availability of a semantic definition using a standardized taxonomy and ontology.

The Defense Logistics Agency is committed to leveraging advanced technologies and understands that technical data is a fundamental component.

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The Return of the Domain Specific Product Data Definition

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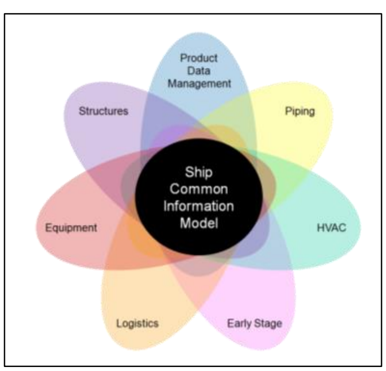
ABSTRACT

In recognition of "then and now to the future" this paper will look at what may have been the most extensive attempt to develop a set of application protocols by the US shipbuilding industry that truly embraced the promise of STEP. Two of the major reasons for the evolution from IGES to STEP were the adoption of a formal modeling language and an emphasis on the definition of products. STEP as a neutral file format for CAD geometry has been undeniably successful. However, this success has been limited to general purpose geometry and limited Product Manufacturing Information. But perhaps it may be time to take a fresh look at domain specific definition. From a review of the STEP Shipbuilding Application Protocols to a pilot project to determine the feasibility implementing domain specific data exchange using AP203 for geometry and AP239 for product attributes a case for why domain specific data exchange is a key component of the DoD Digital Engineering Vision will be presented.

In recognition of "then and now to the future" this is a look at what may have been the most extensive attempt to develop a set of related STEP application protocols that truly embraced the promise of STEP. Two of the major reasons for the evolution from IGES to STEP were the adoption of a formal modeling language and an emphasis on the definition of products. STEP as a neutral file format for CAD geometry has been undeniably successful. However this success has been limited to general purpose geometry and limited Product Manufacturing Information. But perhaps it may be time to take a fresh look at domain specific definition. From a review of the STEP Shipbuilding Application Protocols to a pilot project to determine the feasibility implementing domain specific data exchange using AP203 for geometry and AP239 for product attributes a case for why domain specific data exchange is a key component of the DoD Digital Engineering Vision will be presented.

The US Navy can be considered a pioneer in the development of domain specific data exchange. In the 1980's the US Naval Shipbuilding industry made several attempts to enable the exchange of information between partnering shipyards during the design and construction phases of the DDG51 program and the SEAWOLF program.[1] The entire range of data exchange methodologies were explored in including direct translators, IGES, IGES application subsets, and STEP. The DDG51 program went the route of the direct translator and developed the DDG51 Digital Data Transfer Program, a purpose built neutral file exchange of components between Computervision and CALMA. The SEAWOLF program took a standards based approach. Using standard IGES for the exchange of drawings and a modified IGES for ships structure and piping.

Experience with these customized exchange programs led to a decision to determine the feasibility of a standardized approach to data definition and exchange. Simultaneously the CAD industry was looking for an evolution from IGES to the next "step" in data exchange. This international effort resulted in ISO 10303, Industrial Automation Systems and Integration - Product Data Representation and Exchange or more commonly, STEP. The attraction of STEP was a combination of it being a schema based data exchange definition, an international standard, and the potential to define domain specific application protocols within a common infrastructure.



1 Murphy, J., NIDDESC - Enabling Product Data Exchange for Marine Industry, Proceedings of the Ship Production Symposium, New Orleans, Louisiana, September 1992

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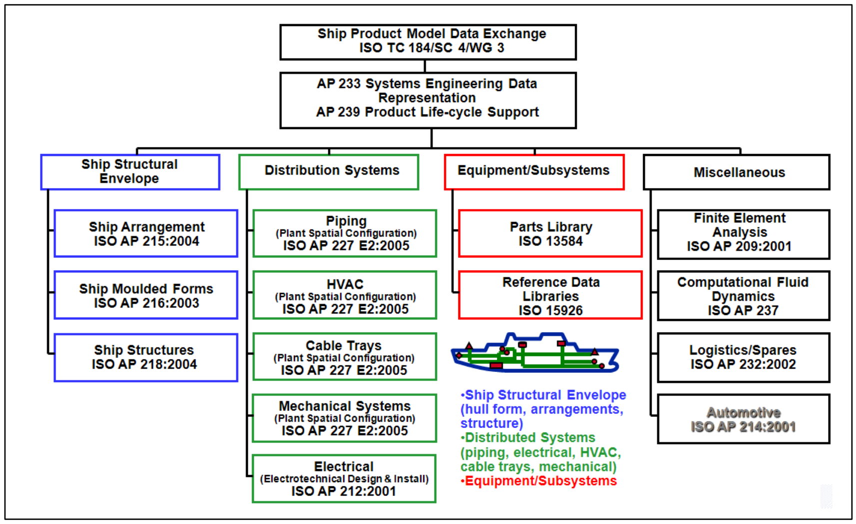
In order to facilitate the establishment of an industry consensus data exchange capability the Navy / Industry Digital Data Exchange Standards Committee (NIDDESC) was formed in 1986 as a joint effort between the US Navy and the member shipyards of the National Shipbuilding Research Program (NSRP). NIDDESC recognized that data exchange was more than just geometry. In order to define a system as complex as a ship required a multidisciplinary approach that considered the needs of more than one phase of the lifecycle. Initially the focus was on the disciplines that would have the greatest impact on early stage design, detail design, and construction. In retrospect greater consideration should have been given to logistics and those lifecycle phases beyond construction.

The NIDDESC efforts resulted directly in the development of four application protocols, AP215 - Ship Arrangement, AP216 - Ship moulded forms, AP217 - Ship piping, and AP218 - Ship structures. Participation in the ISO standards process led to a close collaboration with the European Shipbuilding industry. During the development of the Ships piping application protocol it became clear that there was substantial overlap of requirements between the marine and process plant industries. The resulting collaborative effort led to the deprecation of AP217 and a stronger and more inclusive Plant spatial configuration application protocol.

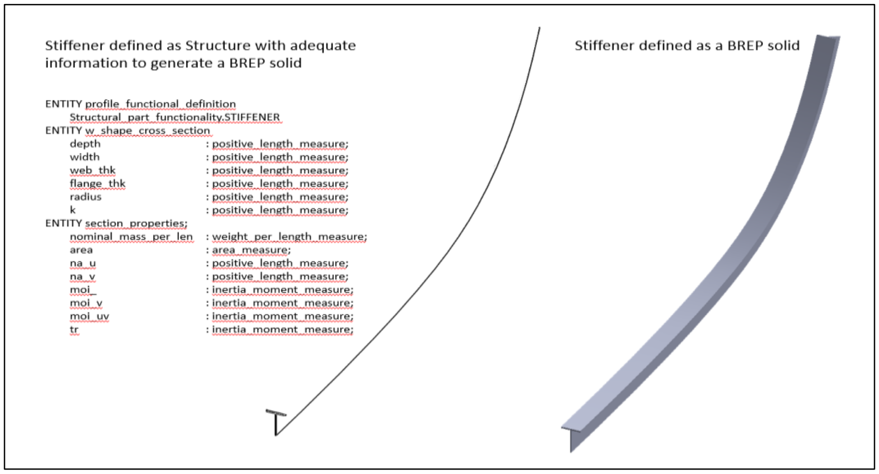


The common thread among what is referred to as the Shipbuilding application protocols is that these are all domain specific data exchanges in which the definition reaches far beyond geometry and a set of core product manufacturing information. Domain specific data definition provides an object definition which spans multiple lifecycle phases. It should be emphasized that the NIDDESC focus was the definition of objects through the combination of geometry, non-graphical attributes, and the relationships between entities.

The NIDDESC approach included an evaluation of marine industry requirements and through consensus determined moulded forms, arrangements, structures, and piping were major priorities of the design and construction phases of the ships lifecycle. An application activity model was created for each of these domains which were used to govern the definition of the information requirements. The application reference model was used to define the information to support an activity within a taxonomy understood by domain subject matter experts. It should be noted the emphasis of the team of subject matter experts was the application domain and not data exchange nor STEP. Eventually several of the team members became well versed in STEP. One of the most significant lessons learned is the definition of the product data has to be led by the domain experts not the data exchange experts!

It is widely considered that AP 203 was the impetus for the widespread use of STEP seen today. These days AP 203 and AP 214 are used interchangeably, with the majority of users not even aware that there is a difference. Even those first two widely used application protocols employed a set of conformance classes that define a subset of the application protocol.

One of the most widely stated reasons why STEP was developed was, "The IGES effort has not focused on specifying a standardized information model for product data. IGES technology assumes that a person is available on the receiving end to interpret the meaning of the product model data."[2] It can be inferred that one shortcoming that STEP would address was the need for a human in the loop to interpret the product data.



Shipbuilding STEP Application Protocols provided all of the information necessary to define arrangements, structures, and other objects used in the design and construction of ships. AP 242 defines shape and features but does not define the characteristics of the part. For example if using STEP to define a stiffener, AP 218 provides shape, functionality, and characteristics[3] whereas AP242 does not provide any of the information necessary for the system to differentiate a stiffener from a pump. The shape defined using AP218 may be in a form that is unconventional from the perspective of the mainstream mechanical CAD systems, but in reality is consistent with the concept of the sketch based feature modeling system. The stiffener may not be defined as a single BREP solid, but it is defined as a planar cross section swept along an explicit 3D curve. This trace can also be defined as an intersection between a surface and a plane thus providing the design intent inferred from a topological relationship between the geometry which most probably was defined using AP 216.

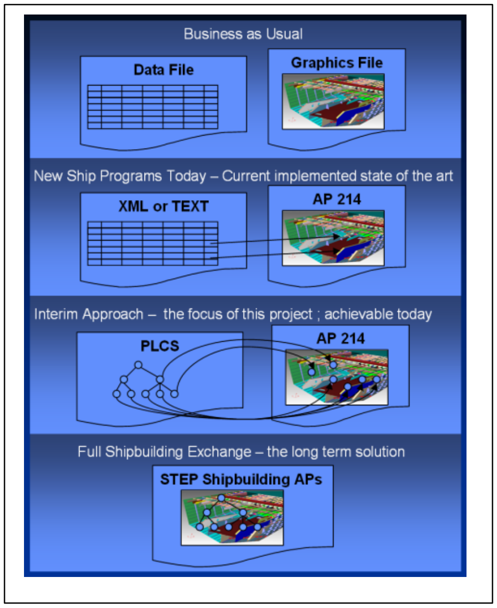
The collaborative effort in the shipbuilding community was so effective it resulted in interest from the European shipbuilding industry, NASA for the structures application protocol, and the elimination of the Piping application protocol because it was determined that the Plant Spatial application protocol, AP 227, was not only sufficient but provided a better solution for the marine industry. During the 1990's pilot projects were initiated for all four of the "Shipbuilding STEP application protocols". These pilot projects proved that STEP could be used to define objects and to provide a means of exchanging product model data both within an enterprise, across enterprise boundaries, and even between the shipbuilders and the government. Initial pilot projects identified a subset of entities that were required to satisfy a specific exchange scenario between a limited set of exchange partners. Since the objective of the pilot was a proof of concept a limited scope was necessary in order to able to achieve a demonstrable solution within a very short timeframe. Separate subsets of piping, hull forms and structures data interoperability were defined, test data was selected, and prototype translators between different CAD systems, simulation systems, and analysis systems were developed. Upon the successful demonstration of this domain specific data exchange additional pilot projects were undertaken that not only expanded the breadth of the domains into HVAC, electrical, and a common parts catalog, but also into other application areas including structural analysis and shipyard steel manufacturing processes. These pilots demonstrated that the information developed during the design phase could be leveraged by other disciplines.[4] It also proved a need that the neutral file definition include more than shape data. The last pilot project examined the integration of this product definition data into an Integrated Product Data Environment.

2 Furlani, C., Wellington, J., Kemmerer, S., Status of PDES-Related Activities (Standards & Testing), NISTIR 4432, Gaithersburg, MD, October 1990

3 ISO 10303-218:2004(E), Industrial automation systems and integration — Product data representation and exchange — Part 218: Application protocol: Ship structures, Geneva Switzerland, 2004.

4 Gischner, B., Integrated Logistics Environment (ILE) Project Final Report, NSRP, November 2012.

Unfortunately, for many reasons these application protocols were never integrated into the commercial CAD systems nor used in production. The CAD vendors supported the pilot projects but for reasons beyond this discussion were never really interested in developing a marine industry neutral file exchange capability. During the late 1990's alternate approaches surfaced including the use of the "mainstream" STEP translators provided by the CAD vendors to access the shape data and the use of AP239 to define product structure and the relationships between objects.[5] This approach did not gain traction either. Finally, the Navy and the NSRP member shipyards collaborated on the definition of a Ship Common Information Model (SCIM) in conjunction with a US shipbuilding Integrated Product Data Environment (IPDE) specification.[6] It is interesting to note that although the shipbuilding STEP development efforts have never been used in a production environment that the SCIM and IPDE specification have been consulted by some of the shipbuilders as they build their next generation model based environment.



This is not meant to minimize the benefits STEP has provided by enabling the exchange of shape data between a multitude of systems including the expected CAD, CAE, and CAM systems but a myriad of others as well. But the relationship of the application of STEP to its potential has been underwhelming. There has not been much of an incentive to extend STEP, and there are plenty of other impediments including an inability to reach consensus on the definition of products, a lackluster at best acceptance of data exchange by the CAD vendors, the lack of subject matter experts that understand data definition, and the perception that the upfront cost to enable this type of data exchange is cost prohibitive.

But even if we concentrate on the most prolific areas of STEP there are still several functionalities that should be available at a high level of maturity. The functions include a robust feature model, a consistent graph model, and of course the heart of AP242, Product Manufacturing Information. After over 30 years of use there can still be instances of errors due to the mathematical definition of curves and surfaces. It seems that with a robust feature model the mathematics of the nominal geometry could be adjusted to meet the functional definition of the geometry. These details are necessary to narrow the gap between providing a neutral geometry definition and a neutral model definition and the first steps toward providing a neutral definition of parts and systems.

In the summer of 2018 the Department of Defense released a Digital Engineering Strategy. The second goal of the strategy is, "Provide an enduring, authoritative source of truth".[7] The perspective of the DoD is to accomplish this goal the primary means of communication needs to evolve from being document based to being model based. STEP AP 242 can take great strides in providing this information but it can only provide a fraction of the information necessary to provide form, fit, function, behavior, and that most sought after information, design intent. The DoD focus on STEP has been the definition and exchange of the information required to manufacture the part, but very little has been done to address the functional and behavioral definition of the part. Perhaps that has been the domain of the sysML. Could it be we are beginning to see the bifurcation of product definition? And maybe that is not such a bad thing. It does not take a data exchange expert to see an ever increasing overlap in

[5] Kassel, B, Briggs, T., An Alternate Approach to the Exchange of Ship Product Model Data, Society of Naval Architects and Marine Engineers Ship Production Symposium, 2007.

[6] Kassel, B, Navy Product Data Initiative, American Society of Naval Engineers Engineering the Total Ship Symposium, 2008.

[7] Deputy Assistant Secretary of Defense, Digital Engineering Strategy, Washington DC, June 2018.

the scope of neutral standards. There is massive overlap between X3D, JT, 3D PDF, STEP. And even IGES can process solid geometry and define parts.

Is STEP the answer to our question of how to define, exchange, and archive the product data necessary to enable the Digital Engineering Strategy? It can be, but even more important than the file format is the existence of a definition of the product data. Call it a data dictionary, schema, taxonomy, or ontology, it really doesn't matter. Maybe it is not THE standard but A standard that matters. It would be great if there was a single neutral standard that could provide all the information required to define systems and parts in a way that can enable the Digital Engineering Strategy. Most people would be happy if there was an open schema based definition that accompanied product data in general.

When talking about the future, the conversation turns to all sorts of potentially disruptive technologies. Virtual reality, set based design, multidisciplinary analysis and optimization, being able to address all areas of the lifecycle simultaneously during the design phase. Close coupling manufacturing processes to the design model, adjusting the manufacturing processes based on feedback from the manufacturing systems, level loading both within and across enterprises during the manufacturing phase. Leveraging the digital sibling, a new operational paradigm with mixed reality, streamlining the supply chain with additive manufacturing, and improving reliability and inventory control with prognostics. There are two "must haves" that all of these technologies have in common; a robust digital thread and the timely access to a precise and accurate model based definition.

Over the past few years a group of people put a great deal of heart and sweat into modernizing MIL-STD-31000 to improve the definition and acquisition of the data necessary to produce machined parts. It was a good start and there is much left to do. But in order to realize the five goals in the Digital Engineering Strategy, actually lets look at them as challenges, we will need to look well beyond the data typically associated with CAD/CAM and realize we need to provide the data that can allow the behavior of those systems to be mimicked completely in the virtual environment.

It is too bad that we did not pay more attention to Dan Billingsley and that group of digital data pioneers that attempted and unfortunately were unable to reach their goal of widespread and regular use of neutral product model data within the US Navy shipbuilding market sector. And while we are waxing philosophical, lets not forget that it was not just NAVSEA and the shipbuilding industry that developed the concept of the shipbuilding domain specific data exchange, but we have seen three NIST employees, Kent Reed, Mark Palmer, and most recently Sharon Kemmerer who were instrumental in elevating an idea spawned by the US Navy to an international level retire before this could come to fruition. Just imagine where we would be today if we had been able to convince the CAD vendors to implement product data exchange technology, the shipbuilders to deliver the data, and our program offices to acquire that product model data to which we were entitled.

But lets only look back so that we do not repeat our mistakes. Lets look forward to enable a digital thread enabled model based environment that provides the data we need to do our jobs and operate our systems and accelerate new technologies in a way that is usable by the consumer while protecting the intellectual property of the author.

References

Murphy, J., NIDDESC - Enabling Product Data Exchange for Marine Industry, Proceedings of the Ship Production Symposium, New Orleans, Louisiana, September 1992

S. J. Kemmerer (ed.), STEP: The Grand Experience, NIST Special Publication SP 939, US Government Printing Office, Washington, DC 20402, USA, July 1999

Furlani, C., Wellington, J., Kemmerer, S., Status of PDES-Related Activities (Standards & Testing), NISTIR 4432, Gaithersburg, MD, October 1990

Deputy Assistant Secretary of Defense, Digital Engineering Strategy, Washington DC, June 2018.

ISO 10303-218:2004(E), Industrial automation systems and integration — Product data representation and exchange — Part 218: Application protocol: Ship structures, Geneva Switzerland, 2004.

Kassel, B, Briggs, T., An Alternate Approach to the Exchange of Ship Product Model Data, Society of Naval Architects and Marine Engineers Ship Production Symposium, 2007.

Kassel, B, Navy Product Data Initiative, American Society of Naval Engineers Engineering the Total Ship Symposium, 2008.

Gischner, B., Integrated Logistics Environment (ILE) Project Final Report, NSRP, November 2012.

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DATA-DRIVEN APPROACH TO ESTIMATE MAINTENANCE LIFE CYCLE COST OF ASSETS

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ABSTRACT
Different participants in the supply chain of an industrial asset, from original equipment manufacturer (OEM) to owner/operator (O/O), know more than others about significant aspects of the asset. Sharing of information between these participants is necessary to most effectively manage a product or asset for all stakeholders involved. In particular, one type of data generated about an asset during its lifecycle is maintenance data. Field maintenance data collected over the usage of a product provides valuable information about its failure patterns and performance in different operating contexts that can benefit all. However, maintenance data by itself typically has data quality issues and needs to be understood and processed in order for information of value to be extracted and used. In this article, we present a case study of how maintenance data from the CMMS/EAM can be processed to return information that can be used to benefit everyone in the supply chain.

INTRODUCTION

Lifecycle costs for industrial assets can mean different things from different perspectives of the supply chain. Product lifecycle management (PLM) is the activity of effectively managing products across the product lifecycle (which spans phases from design, to production, logistics, and maintenance to disposal/obsolescence of a product) (1). For the users of an industrial asset, lifecycle cost analysis (LCC) measures the total cost of ownership (TCO), taking many different factors into account from the stages of an asset's lifespan, such as initial costs, annual operating and maintenance costs, and decommissioning costs. These two perspectives are complimentary, but how information is used depends on the stakeholder.

Different stakeholders in the supply chain include the original equipment manufacturer (OEM), the owner/operator (O/O) of the asset, as well as middle parties such as dealers and suppliers. In practice, there is often an asymmetry of information between the different participants, which is characterized by each of the participants knowing more than others about significant aspects of the asset. For instance, OEM knows more about the design characteristics and performance capabilities about the equipment they manufacturer. The dealers knows more about parts and services as well as local and regional dynamics that affect the sale of new whole goods as well as overhaul records. The O/O will know more about how the fleet was operated, for how long, and the conditions under which it was operated, including dispatch and production data, utilization rate, scheduled and unscheduled downtime. Additionally, the O/O will know more about how the fleet was serviced and maintained including parts consumption and labor.

Effective PLM depends on collaboration among the different participants in the supply chain and the sharing of information from the data. OEMs can benefit from understanding the gap between how a product is intended to be used, and how it is actually used by the O/O. Information about an individual asset in its operating context throughout its useful life can inform the product lifecycle for the OEM such as for improving designs in new products or versions, improving the quality of product production, and for creating and validating pricing structures. From an O/O perspective, benefits of collectively using information include reducing unplanned downtime, optimal planned downtime, incremental capacity utilization, and improved certainty about the TCO. From a dealer perspective, benefits include increase in parts and services revenue as well as increased opportunity for managed services.

Maintenance work order data contains information about failure patterns and maintenance activities of an asset through its lifecycle. This data has the potential to generate actionable intelligence as well as field usage information which can be useful for all members of the supply chain. However, simply sharing raw data alone will not give anyone these rewards. Adaptable work processes in which actionable information can be shared

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across the supply chain effectively need to be developed (2) (3). To extract actionable information, the gap between the raw collected maintenance data and actionable insights needs to be addressed.

This paper discusses challenges in the maintenance data and proposes data-driven analytical approaches for addressing these challenges in order to extract relevant information from maintenance work orders that can shared between the different participants of the supply chain. This paper focuses specifically on estimating the annual costs around an asset from historical data and understanding the costs and reliability from different failure modes from observed field data. We illustrate these concepts with a simple case study comparing simulated life cycle costs between two comparable asset models in a system, which demonstrates both the challenges that need to be considered to extract actionable insights as well as showing what this information could look like and how it could benefit all stakeholders.

BACKGROUND - FIELD DATA FOR ANNUAL MAINTENANCE LIFECYCLE COSTS

Annual lifecycle costs include the costs of maintenance (both corrective and proactive), production losses from downtime, and other regularly occurring activities that could incur costs or lost opportunity to produce. Maintenance data from Enterprise Asset Management (EAM) or Computerized Maintenance Management systems (CMMS) contains information about work tasks such as planning, scheduling, and reporting (4). The information in the CMMS/EAM contains records of all maintenance activities and costs across asset fleets, but challenges from directly using this information arise due data quality and consistency issues. Discussions of different data quality challenges are well reviewed in (5) (6) (7) (8) (9) (10) (11). Some key data quality challenges relevant to this study include missing breakdown indicator (unknown which events are failure events), missing and inconsistent failure modes, and the unstructured nature of manufacturer and model nomenclature across a large registry.

In our case study, we show how historical maintenance data can be used to estimate annual lifecycle costs and the considerations and assumptions made along the way. The GE Asset Answers database aggregates work history data from many industrial facilities around the world by asset type, manufacturer, as well as many other characteristics. This data is anonymized and made available to subscribers who can compare themselves against peer data. This effort is part of the effort to develop ways that the maintenance data in Asset Answers can be made more valuable to all participants, and show how information sharing benefits all. We specifically compare two similar manufacturer and model of centrifugal pumps from different peer data, evaluate the data quality, use natural language processing to predict which events are failures and to structure the unstructured text. We use this information to estimate metrics to inform a system reliability model and run a Monte Carlo simulation to compare annual lifecycle costs by risk events. A similar workflow was used in (12) to estimate the contribution of a certain category of component failures on system reliability. To protect proprietary information, all variables have been anonymized and age has been scaled.

CASE STUDY

Out of over 65,000 repair events for over 6,200 centrifugal pumps at 22 different companies over a 4 year period of time from the Asset Answers database, we identified 2 comparable makes and models, AIC pumps and RELIABLE pumps. 8,000 repair records were identified against these two models. The next step is to identify which of these repair events are a failure. This process and considerations are described in (13), where we use a classifier in the GE Digital APM commercial software package which predicts if a repair event was a failure or not. Of the 8,000 repair events, about 5,800 of them were predicted as failure events. For this dataset, common themes among the repairs that were not predicted as failure events were either some undeterminable text, or routine procedures such as inspect, service, or service. A few examples are shown in Table 1.

Table 1 Example work order descriptions demonstrating failure classification of repair events for centrifugal pumps

Work description	Is A Failure?
Seal is leaking badly	True
Block valve is broken open and inoperable	True
00120-Pump 1 Work Request	False
Check impeller size	False

Once we had isolated which maintenance events corresponded to failures, text mining was utilized to characterize the failure mode information. From this dataset, we characterized failure events by maintainable item and failure mechanisms and used text matching to extract the information. Different types of approaches for structuring unstructured text are very well described in (14), and have been compared and studied in (15) (16). Challenges that arise with extracting failure information from maintenance work orders include naturally occurring class imbalance (certain components or failure events are going to happen at greater frequency than others), the possibility of multiple correct labels per observation, and the challenges of the transactional text such as misspellings and abbreviations.

In our case study, the objective is to use the structured data to estimate annual life cycle costs from field data by different risk events. We use a system reliability simulation to estimate the annual lifecycle costs throughout a 10-year period of time. The simulation tool used is a Monte-Carlo system reliability simulation in the GE APM Reliability commercial software package. We build a simple system reliability (reliability-availability-maintainability, or RAM) model to illustrate how these processes can be used as part of larger manufacturing process and other more detailed factors can also be incorporated. The block diagrams are shown in Figure 2.

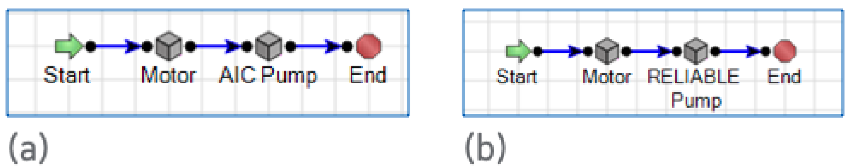


Figure 1 System reliability scenario models for the two pumps. The system is simplistic but illustrates the framework, and we assume the risks are all on the Pump subsystem

Reliability factors are incorporated using the failure mode information extracted from the data. Availability factors come from the unplanned downtime over the course of the 10-year simulation due to these failure modes. Maintainability is modeled using the time-to-repair (TTR) distribution estimated from the field data. The Society of Maintenance and Reliability (SMRP) defines TTR as the time needed to restore an asset to its full operational capabilities after a failure (17). We estimate TTR as the difference between the maintenance start and maintenance completion date on the work order, as an estimate of when the maintenance work was done. TTR distribution is typically right skewed, and we model it using the lognormal distribution.

To map the RAM simulation results to the financial implications, we use costs per repair event estimated from the data and assume a user-specified production loss quantity. We use the average repair cost from the maintenance work orders as measures of unplanned fixed corrective costs. We make the user-specified assumption that any loss of pump function will interrupt production that is valued at $5,000 per 24 hour day to get estimates of the lost production losses.

We assume both the cost to repair and the time to repair do not vary between the two pump models, but do vary by the failure mode. We assume that these factors are more specific to the site-specific maintenance and reliability practices than to the asset make and model but do depend on the nature of the failure. Make and model independent estimated parameters used in our simulation are in Table 2(a).

We identified that the 3 most common failure mode groupings to use as risk events. The common risk events were seal failures, valve failures, and bearing failures, accounting for 46% of the total failures. For each population (for the 2 make and models), 2-parameter Weibull distribution parameters were estimated using the probability distribution fitting tool in GE APM Reliability Analytics with maximum likelihood estimation. Estimated shape β and scale η parameters are summarized in Table 2(b).

Simulating the RAM model over 10 years produces an estimate of the cost of unreliability per year for each vendor scenario. We ran 1,000 iterations. The cost of unreliability in this scenario is a combination of the unplanned corrective costs and the lost production costs (Table 3). We apply the Net Present Value (NPV) functions using an initial investment of $0 and a discount rate of 10%. The results of the NPV represents the sequence of cash flows in today's dollars and shows AIC Pumps is projected to incur lower costs over a 10 year period of time than RELIABLE pumps. Estimated annual costs can be used with other information, such as comparison to the purchase price. For example, if AIC pumps has a higher acquisition price, this information can be used to justify its purchase to the O/O.

Table 2 Extracted parameters from field data for use in estimating 10 year asset lifecycle costs for two comparable pump models. (a) Maintainability measures dependent on failure mode, but we assume independent across the different asset make and model numbers, (b) comparison of estimated reliability (Weibull distribution) parameters between the two asset make and models.

Measure/parameter	Seal failure	Valve failure	Bearing failure
Average Corrective Work Cost (USD)	$4096	$2557	$5873
MTTR (days)	1.15	1.13	1.00
TTR Distribution - μ	1.26	0.82	1.34
TTR Distribution - σ	1.6	1.8	1.2

(a) Make and model independent estimated metrics and distribution parameters for RAM simulation

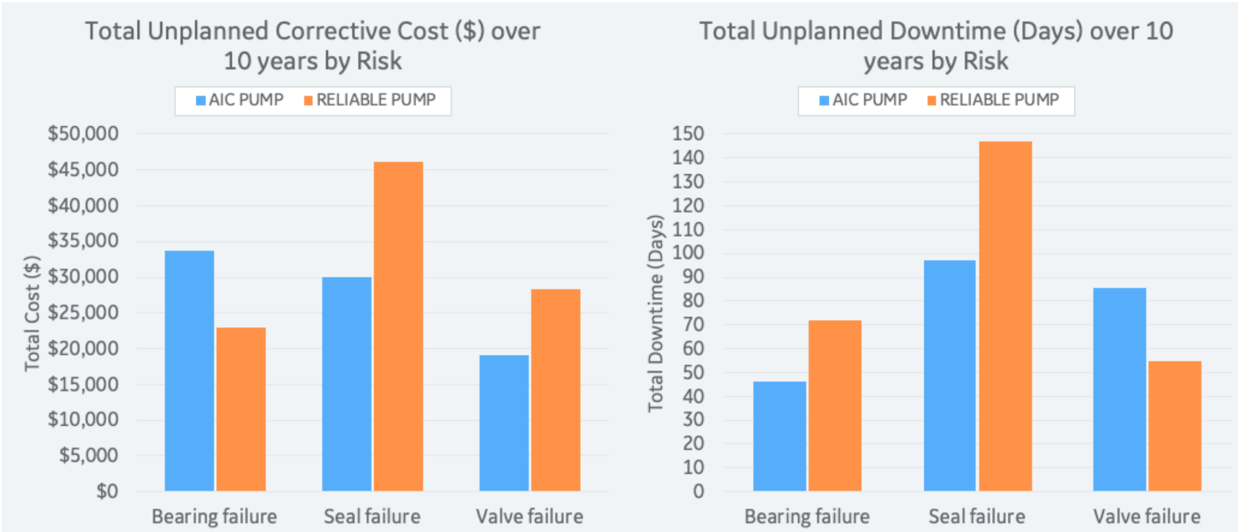
Failure mode	Parameter	AIC PUMP	RELIABLE PUMP
Seal Failures	Shape β	0.68	0.58
	Scale η (days)	397	213
Bearing failure	Shape β	0.88	1.24
	Scale η (days)	582	400
Valve failure	Shape β	0.71	0.71
	Scale η (days)	424	633

(b) Make and model dependent estimated metrics and distribution parameters for RAM simulation

Table 3 Annual cost of unreliability as a sum of production losses

Year	AIC PUMP	RELIABLE PUMP
2018	$7,088	$10,057
2019	$130,462	$160,024
2020	$118,755	$148,669
2021	$125,740	$158,307
2022	$127,608	$157,620
2023	$129,818	$142,474
2024	$121,852	$141,726
2025	$120,593	$138,163
2026	$115,824	$146,259
2027	$121,992	$129,293
2028	$108,041	$134,457
TOTAL	$1,227,773	$1,467,049
NPV	$764,159	$919,263

In this simulation, the costs are driven by the lost production, which is determined by the availability. We can compare the corrective costs as well as the total downtime by failure mode for the two scenarios in Figure 3. Figure 3 shows that the unreliability and unavailability incurred by seal failures is worse for RELIABLE pumps. However, the corrective cost from bearing failures is worse for AIC pumps, but there is greater total unplanned downtime for RELIABLE pumps. Which pump model will incur the most cost annually depends on the production losses.



(a) (b)

Figure 2 Comparison of 10-year risks from simulation model for 2 pump models (a) Comparison of corrective costs over 10 year by failure mode (b) Total unplanned downtime. Production losses are driven by unplanned downtime. AIC pumps have greater costs with valve and seal failures than Reliability pumps, but more downtime associated with seal failures and bearing failures. The cost trade-off of unreliability is determined largely by the production losses.

CONCLUSIONS

The case study in this paper illustrates steps and processes that can be used to process field maintenance data into actionable information. The outputs from the study were comparative metrics for different failure modes for different models, as well as the output from simulation models that can be used to make decisions.

Decisions often made based on upfront costs, but they have long lasting impacts on the life cycle cost of the system. RAM modeling has been available to support these decisions for many years, but it has traditionally relied on the information available within organizations or from published reference materials. Asset Answers provides a wealth of data that can be used to build high quality reliability models of operating cost based on actual field performance data.

REFERENCES

1. Stark, J. (2015). ***Product lifecycle management.*** **Springer, Cham, 1-29.**

2. Prajogo, D., & Olhager, J. (2012). ***Supply chain integration and performance: The effects of long-term relationships, information technology and sharing, and logistics integration*****. International Journal of Production Economics, 514-522(1).**

3. Li, J., Tao, F., Cheng, Y., & Zhao, L. (2015). ***Big data in product lifecycle management.*** **The International Journal of Advanced Manufacturing Technology, 667-684.**

4 Gulati, Ramesh and Smith, Ricky. (2013). ***Maintenance and Reliability Best Practices Second Edition.*** **Industrial Press, Inc., New York.**

5. Lukens, S., Naik, M., Hu, X., Doan, D. S., & Abado, S. (2017). ***The role of transactional data in prognostics and health management work processes.*** **Proceedings of the Annual Conference of the Prognostics and Health Management Society. St. Petersburg, FL, 517-528.**

6. Meeker, W. Q., & Hong, Y. (2014). ***Reliability meets big data: opportunities and challenges.*** **Quality Engineering, 102-116.**

7. Hodkiewicz, M., Kelly, P., Sikorska, J., & Gouws, L. (2006). ***A framework to assess data quality for reliability variables.*** **Engineering Asset Management. Springer, London. 137-147.**

8. Koronios, A., Lin, S. & Gao. (2005). ***A data quality model for asset management in engineering organisations.*** **Proceedings of the 10th International Conference on Information Quality (ICIQ), Cambridge, MA, 27-51.**

9. Lin, S., Gao, J., Koronios, A., & Chanana ***(2007). Developing a data quality framework for asset management in engineering organisations*. International Journal of Information Quality, 100-126.**

10. Lukens, S. & Markham, M. (2018). ***Data science approaches for addressing RCM challenges.* SMRP Conference Proceedings, Orlando, FL.**

11. Naik, M. & Saetia, K. (2018). ***Improving Data Quality By Using Best Practices And Cognitive Analytics*. SMRP Conference Proceedings, Orlando, FL.**

12. Hodkiewicz, Melinda, Batsioudis, Z., Radomiljac, T., and Ho, Mark T.W. (2017)**. *Why autonomous assets are good for reliability - the impact of 'operator-related component' failures on heavy mobile equipment reliability.* PHM Society Conference, St. Petersburg, FL.**

13. Lukens, S. & Markham, M. (2018). ***Data-driven application of PHM to asset strategies.* Proceedings of the Annual Conference of the Prognostics and Health Management Society, Philadelphia, PA.**

14. Hodkiewicz, M., & Ho, M. T. W. (2016). ***Cleaning historical maintenance work order data for reliability analysis*. Journal of Quality in Maintenance Engineering, 146-163(2).**

15. Sexton, R., Hodkiewicz, M., Brundage, M. P., & Smoker, T. (2018). ***Benchmarking for Keyword Extraction Methodologies in Maintenance Work Orders.* PHM Society Conference, Philadelphia, PA.**

16. Sexton, R., Brundage, M. P., Hoffman, M., & Morris, K. C. (2017). ***Hybrid datafication of maintenance logs from AI-assisted human tags.* Big Data (Big Data), 2017 IEEE International Conference on.**

17. ***SMRP Best Practices. (2017).* Society for Maintenance & Reliability Professionals (SMRP) Atlanta, GA.**

Standard APIs and Link prediction for the Digital Thread

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ABSTRACT
Addressing cross-cutting concerns such as traceability, change management, and trade-off studies is complex in multi-disciplinary engineering. These aspects can only be addressed efficiently if organizations take a global level perspective on data and view data from many different sources as a whole.

Traditionally, enterprise software applications are coupled to a specific data store. The application layer communicates with the data layer through an interface to perform basic create-read-update-delete (CRUD) operations. These operations are common to most applications. By standardizing the interface between application and data layers through a standard API, enterprise software applications can be decoupled from specific data stores. APIs in general have 2 aspects: the API protocol and the semantics of the data being consumed and produced by the API. The latter aspect is independent of technology and is based on reaching a consensus between domain experts, which can be much harder than standardizing the API protocol using common technology.

Standardizing the API protocol can help organizations access data from various sources, reuse old data with new applications, and connect data to establish a digital thread. Several technologies such as REST, Linked Data, Hypermedia APIs, GraphQL, or collections of standards such as OSLC and Solid can be used to standardize the API protocol. The main ideas of these technologies as well as their adoption levels are presented. The impact of a standard API protocol for organizations, application vendors, and standardization organizations is explained. The opportunities as well as remaining challenges related to a standard API ecosystem are described.

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Digital thread is viewed as a game changer by the US Air Force [DigitalThreadUSAF2013] to increase product development speed and reduce risk. The digital thread is sometimes called digital continuity, or even simply traceability. From a technical perspective, the digital thread is very simply about connecting data across the product life cycle. Even though this may seem very simple, achieving the digital thread is currently a challenge. PLM vendors may claim that they are offering digital thread solutions, but existing solutions have incomplete coverage of product data and do not scale. As PLM vendors are traditionally hesitant to support standards, which are necessary to connect data from 500+ data sources, and as PLM vendors prefer to use proprietary integration approaches in order to achieve vendor lock-in, the coverage of existing digital thread solutions from PLM vendors is limited to CAD-related data and is improving very slowly.

Simultaneously, product manufacturers are trying to get the most value from IoT data as it offers many new business opportunities. IoT data on its own can be analyzed to better understand how products are actually being used in the field. However, IoT can also be used to improve the physics-based models which were used during design and manufacturing [GE-AI-Future-2016]. For example, models predicting the end of life of a product can gain accuracy based on IoT data. As a result, products could potentially be operated longer and their value could significantly increase. In order to improve a specific physics-based model based on some specific IoT data, it is necessary to keep track of what IoT data relates to what physics-based model. Both data sources need to be connected. In other words, the digital thread is necessary for getting the most value from IoT data. As PLM vendors are innovating very slowly to support the digital thread, some organizations are looking at open standards and architectures inspired by the World Wide Web to connect data, and achieve the

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digital thread independently of PLM vendors, in order to innovate at their own speed. In this context, this white paper will explain the value of standard APIs and link prediction for the digital thread.

Systems engineers, who need to understand the big picture, are also interested in connecting various engineering data. Instead of calling it the digital thread, they call it traceability. Traditional traceability activities in systems engineering are typically performed at the end of a design activity, to document how requirements relate to tests, and how these tests were performed. Traditional traceability activities involve describing the trace links in a single tool, or in spreadsheets, or in a PLM system. These links are then traditionally inspected during certification activities or when the cause of an accident or malfunction needs to be found.

Modern traceability activities in contrast are meant to be used in a more active way [Future-of-traceability-2016]. The trace links are meant to used during the design activity, in addition to using the trace links after the design activity. The trace links are used to help engineers gain a better understanding of the design in order to take better design decisions. The trace links are meant to be frequently created, modified, navigated, in addition to being inspected. As this modern traceability activity becomes more common, engineers will more easily and more precisely understand what they can reuse across projects.

The trace links become the map which helps engineers navigate through the complexity of product design. The links can be followed, similar to discovering related web pages when browsing. The links can be queried, for example to know how artifacts which are separated by multiple links are connected, similar to asking a navigation system like Google Maps for the route to go from A to B. The links can be commented for improved collaboration, similar to having a discussion thread in social media. The links can support change management by quickly making visible artifacts impacted by a change. The digital thread is meant to support this kind of modern traceability activities. In contrast, current solutions to manage trace links are siloed, and cannot be queried nor analyzed at a global level, in a tool-agnostic way. Current traceability solutions are tied to a specific systems engineering application, PLM solution, or to spreadsheets, and don't support modern traceability activities.

A tool-agnostic way to achieve the digital thread supporting modern traceability activities is based on standards, especially API standards. With over 500 different applications being used in engineering, more than 500 different application programming interfaces (APIs) exist to access data in these different applications or databases. A higher level of abstraction is required for accessing data independent of its storage solution.

Web APIs have gained a lot of adoption in the last decade. Some say that we live in an API economy. Among Web APIs, REST APIs have become the de facto standard. Even though REST APIs provide a significant level of standardization, many aspects still need to be standardized. REST APIs use different identifiers for data, different schema definitions, different machine-readable descriptions of their web services which is necessary for machine-based discoverability, different ways to describe data versions and updates, and last but not least different ways to describe links between data.

All these aspects can be standardized as shown for example by Open Services for Lifecycle Collaboration (OSLC). Over 50 OSLC APIs have been developed for engineering applications. IBM and Mentor Graphics are large vendors supporting OSLC. Recently, interest in OSLC has grown among smaller vendors who want to take advantage of this new technology. Vendors like Contact-Software (PLM), Sodius and MID (systems engineering) are creating solutions supporting OSLC. Approaches similar to OSLC exist such as Solid and Hydra. However, these approaches have not yet reached the same level of adoption and maturity as OSLC. It is likely that a mix of these approaches will ultimately gain broad adoption.

Standard APIs are necessary for creating a new kind of application which can work with data from different sources independent of storage location or storage solution. For example, a "Google Search" for data is only possible if data is accessible through a standard API. Current Web search engines can index documents on the Web saved on different servers because they can access documents through a common interface, in this case the HTTP protocol.

A common interface for data decouples application logic from data storage, in the same way that the HTTP protocol decouples Web applications (e.g. search engines, browsers) from document storage. This decoupling allows organizations to mix-n-match applications with datasets as they choose. For example, an organization can easily run the latest AI algorithm on old existing data without having to deal with the traditional difficulties of having to use multiple different APIs to access the data in the first place. Taking into account the high speed of innovation in AI, and the resulting short half-life of AI algorithms, it becomes critical for organizations to quickly benefit from the latest AI algorithms. Standard APIs are disrupting traditional software solutions by breaking apart the traditional proprietary APIs. Standard APIs enable new opportunities for faster and more holistic data analysis. Standard APIs can therefore be considered an important enabler for innovation in organizations undergoing digital transformation efforts.

Following Metcalfe's Law on the value of networks, the impact of standard APIs is proportional to the square of the number of standard APIs. Trace links as described earlier, which are the foundation for modern traceability activities, can be defined between more data as more standard APIs exist. As more links exist, navigating through links becomes more interesting to engineers.

Engineers may initially define links simply for the purpose of traceability, and over time realize that the links can actually be used for a second purpose, namely as building blocks for the definition of model transformations. In this second use case, the digital thread can help support semantic interoperability. Links can be used to identify semantic correspondences between data elements. As engineers use many different vocabularies related to specific domains, and as these vocabularies continuously evolve, it becomes very hard to keep track of how these different vocabularies relate to each other. Some vocabularies may have semantic overlaps. For example, some vocabularies may share concepts with the exact same meaning but with a different name, in which case a one-to-one mapping would describe the semantic correspondence between these concepts. In some cases, the mapping may be one-to-many. These mappings can be collected in a model transformation in order to automatically translate data conforming to one language into data of another language. Running these data translations from one language to another is useful for the purpose of reuse and synchronization.

It is a challenge to know what the correct mappings between languages are. First, it is challenge of scalability as there are many different vocabularies used in engineering, possibly in the hundreds within large organizations. By trying to find a translation between each possible language, this would require tens of thousands (100x100) of model transformations to be defined. The number of required model transformations can be reduced by using a universal language which is the superset of all possible domain-specific concepts that need to translated. In such an approach, only hundreds of model transformations would need to be defined. If domain-specific languages were static and would not contain additional concepts over time, nor have the meaning of concepts change over time, then the definition of a stable universal language and related model transformations would be a one-time effort. Unfortunately, domain-specific languages continuously evolve requiring continuous updates to the universal language and model transformations.

Another challenge is that different model transformations may exist between different languages. For example, a Modelica model can be mapped into a SysML parametric diagram or a SysML internal block diagram. After 2 years for the Modelica and SysML communities to agree on an official standard for the mapping between Modelica and SysML, many engineers were nevertheless choosing a different mapping from the standard mapping. This means that the definition of model transformations cannot be imposed in a top-down approach, but in practice bottom-up. Based on how engineers agree to use domain-specific languages, and related mappings, model transformations can be defined to support the automatic translation of concepts exactly as intended by engineers. As links can describe a semantic mapping between concepts, or a mapping between instances of concepts, they form the atomic unit of model transformations between languages. Multiple links describing semantic mappings can then be combined into a single model transformation for automatically translating data between different languages.

Creating trace links manually can be time-consuming and error-prone. An engineer first needs to find both data elements to be linked. This may require checking the context of data elements to be sure about the right selection of data elements. Even if engineers spend a lot of time creating links, as with any human activity, some of the defined links will be wrong and some will be missing.

Based on patterns in manually defined links, several automatic approaches exist to predict missing links. The investigated approaches were deep learning on graphs, heuristics, and graph mining. Deep learning has gained a lot of popularity in recent years and it is often considered the most advanced machine learning technique. Heuristics based approaches for link prediction are considered old yet reliable. Graph mining is typically not considered for link prediction but it can identify complex patterns, and be used for link prediction even though it requires a lot of computation.

In the academic literature, an increasing amount of papers are published on the application of deep learning for graphs. The papers often cite good prediction results. However, most academic literature inflate the quality of link prediction results by selecting a very specific test dataset for evaluating the link prediction model, namely a dataset which only includes the links to be predicted. In general, a link prediction model receives as input a set of possible links, and for each one, the model will output a boolean true/false value indicating if the link exists or a likelihood between 0 and 1 of the link existence. The choice of dataset to evaluate a link prediction model is critical. It will influence the number of true positive vs false positive predictions. If the model predicts too many false positives compared to true positives, the model becomes useless as the objective of the link prediction model is to help engineers in identifying highly probable links. By recommending false positives, the link prediction model is actually giving more work to engineers and this needs to be avoided. In the academic literature, link prediction models using deep learning are evaluated using a dataset containing only links to be predicted. The link predictions may then be accurate to 80% or even 90%.

However, in reality, a link prediction model needs to be evaluated for a dataset describing all possible links as engineers have no idea which links can be predicted. In that case, the dataset will contain a very high number of link candidates which the model should predict as non-existent. The evaluation results are then very different. The ratio of true positives to false positives predictions is then too low and the model is not considered useful. Another drawback of deep learning on graphs is that it is currently not able to clearly identify complex patterns composed of a chain of multiple nodes in a graph. Most trace links in engineering will follow some complex patterns covering multiple nodes. A second drawback is that trace links used in engineering will form a graph of relatively small size, compared to the size of graphs used to describe social networks. Deep learning only works with a lot of data. The size of engineering graphs, as used in the digital thread, may be too small for deep learning algorithms. It can be concluded that link prediction using deep learning is currently not suitable for graphs as used in the digital thread. However, this assessment may change as a lot of research is currently being performed on the application of deep learning on graphs.

A simpler alternative to deep learning is to use a heuristics-based model for link prediction. Such a model will predict links between nodes, based on nodes having common neighbor nodes. This approach is simple yet it can produce useful results as many patterns in graphs involve nodes having common neighbors. In many graphs, this may be the most common pattern. Heuristics-based link prediction models work on small graphs, and can thus be applied on graphs describing the digital thread.

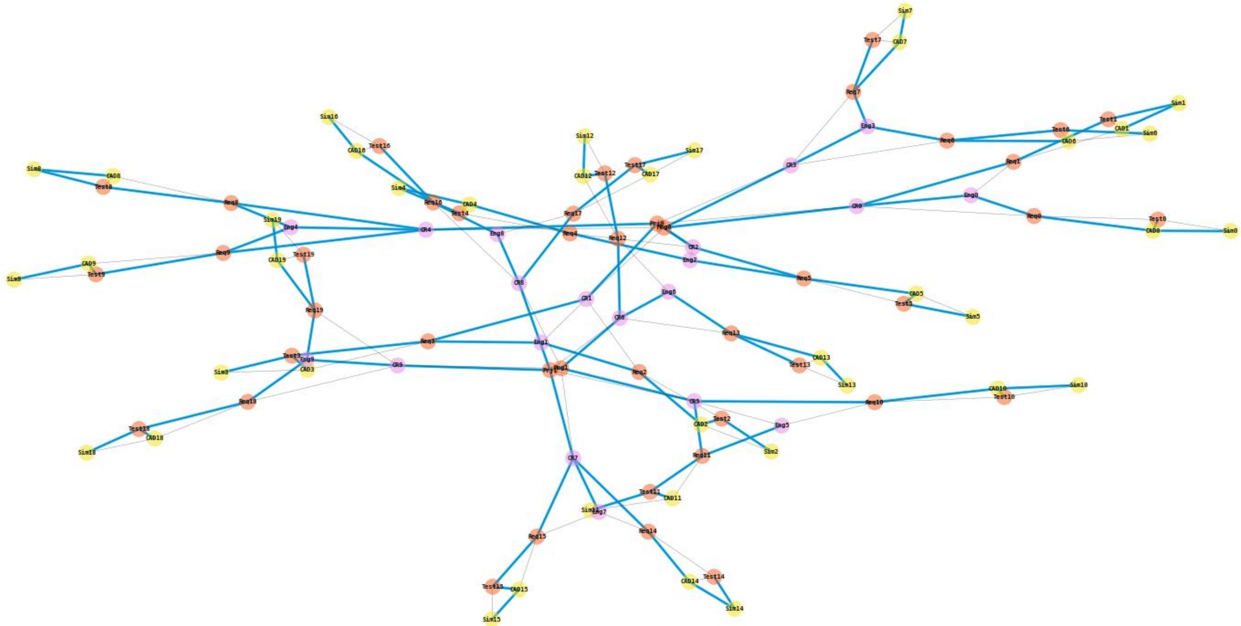

Fig. 1: Initial graph for heuristics-based link prediction model. Blue edges are existing known links. Grey edges are the links to be predicted.

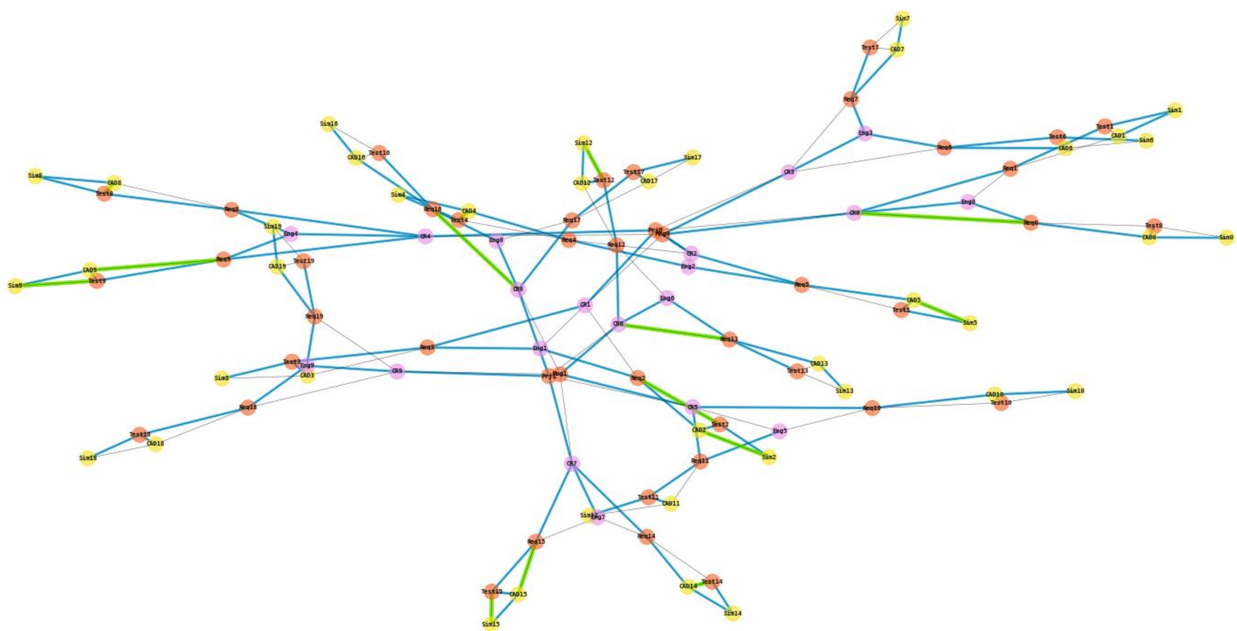

Fig. 2:Graph containing links predicted by heuristics-based model. Blue edges are existing known links. Grey edges are the links to be predicted. Green edges are the predicted links

A third alternative is to apply a (semi) brute-force approach to identify patterns in a graph. This is called graph mining. It is computationally-intense but it can identify very complex patterns in a graph very accurately. After identifying patterns, a link prediction model can then use these patterns to see if additional pattern instances can be found by adding links to the graph. If so, the link prediction model would output these links as probable links. Graph mining can be performed on small graphs. The subsequent activity of trying to find additional pattern instances through additional links is very computationally intense, and ideally requires distributed computing resources, even for small graphs.

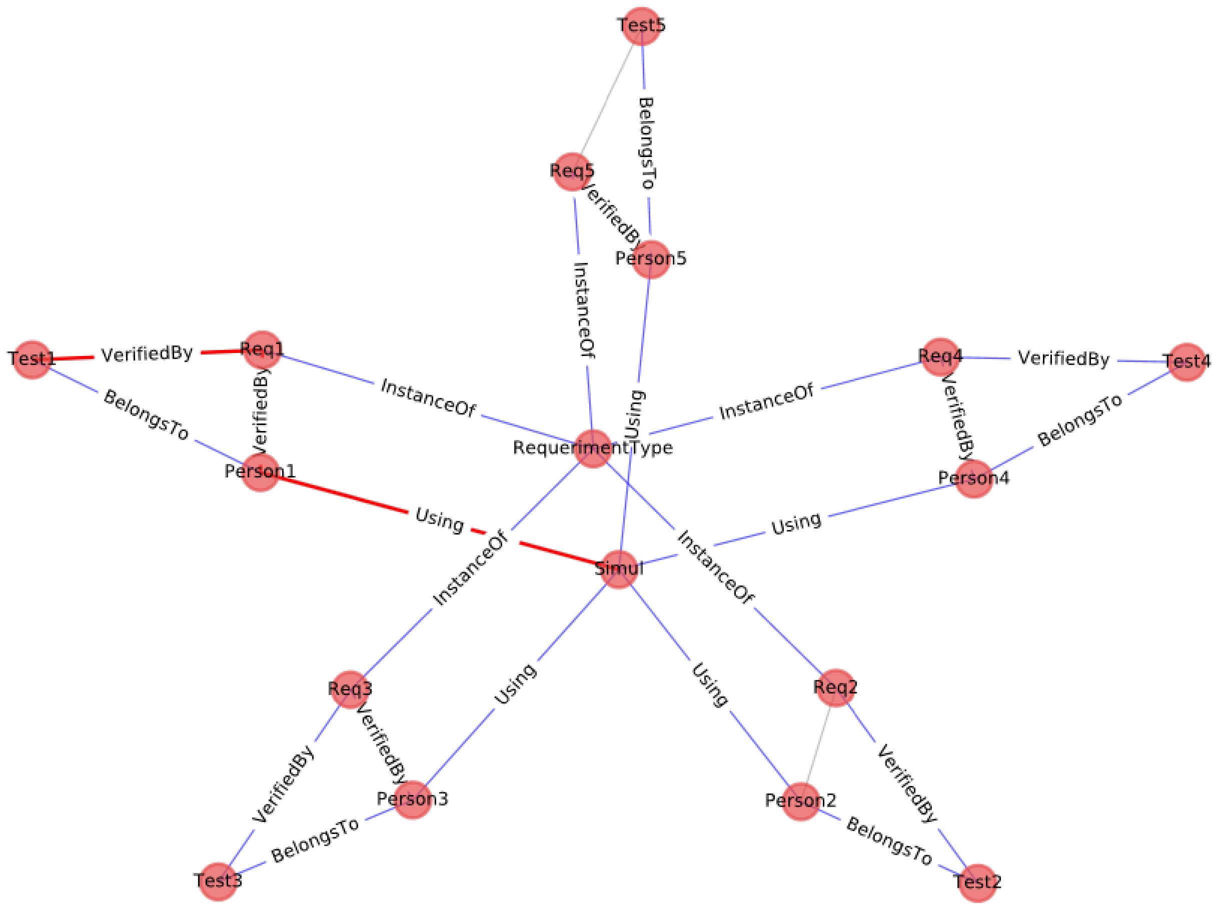

Fig. 3: Initial graph for link prediction model based on graph mining. The pattern identified through graph mining is shown through red links. It is composed of 4 nodes.

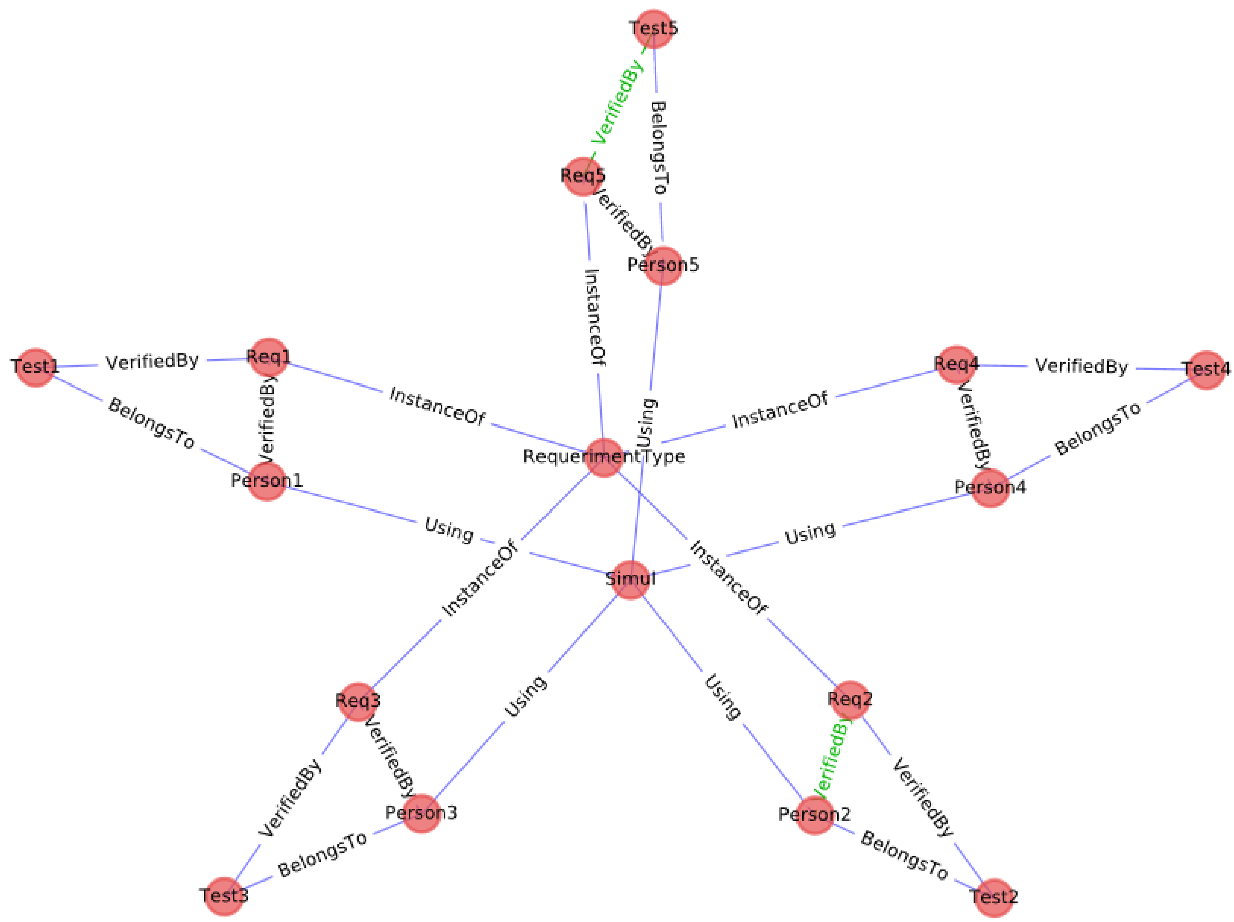

Fig. 4: Predicted links are additional links creating additional pattern instances. Predicted links are shown in green.

CONCLUSION

New ways of connecting data allow engineers to better understand the big picture and to better analyze IoT data. Connecting data requires easy data access, enabled by standardized Web APIs for data sources. Connected data should be viewed as a graph, on which additional analysis can be performed for example for link prediction. Existing approaches for link prediction are not perfectly suitable for graphs used in engineering which are relatively small and have complex patterns. Different approaches for link prediction using deep learning, heuristics and graph mining have been investigated. Better results could be obtained by combining different link prediction approaches, and by taking into account additional information such as string values associated to graph nodes for natural language processing.

REFERENCES

[DigitalThreadUSAF2013] Why Digital Thread? USAF 2013,
https://www.dodmantech.com/ManTechPrograms/Files/AirForce/Cleared_DT_for_Website.pdf

[GE-AI-Future-2016] Four of GE's top engineers talk about business, competition and the future
https://www.businessinsider.com/top-ge-engineers-on-business-competition-and-future-2016-10

[Future-of-traceability-2016] Future of traceability, Jama, 2016
https://www.youtube.com/watch?v=2Fp35S2a1gU&list=PLIk9my-nIqejgSWGzm87trLx_3oX4njy6

Configuration Management and Data Management Challenges in a Model-Based Enterprise or a Universe of Data

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One of the challenges often overlooked by companies trying to become a true Model-Based Enterprise (MBE) is the management of the massive amounts of data it generates. It is easy to become overwhelmed by the volume and variety of data that must be generated, collected, monitored and hopefully reused. This becomes even more daunting when one realizes that all the data generated throughout a product's lifecycle must now be looked at as a single set of related elements, not a set of siloed data sets.

Perhaps an analogy can be used to put this amount of data into perspective. If one thinks of the data generated by an organization's extended enterprise as a universe of data, the complexity quickly becomes apparent. Each buisness unit or in smaller organizations each location in the enterprise is not unlike a galaxy where all the departments generate constellations of data, that in turn generate systems of data, etc. All these bodies of data are held into their proper place by gravity or a Configuration Management/Data Management (CMDM) process.

By stepping back and visualizing the problem in an abstract way such as described above we have started the first step in solving our data management problem, characterization. Characterization is the process of breaking down the massive amount of data into similar categories that serve a common purpose. It is important to note that each category contains several layers of abstraction or subcategories. For example, we can continue the universe analogy where each galaxy is a business unit or location in the organization's extended MBE. Next, we begin to look at each department as a cluster or constellation of stars. Now each group or major buisness process is its own star system and each person their own planet of data. Finally, the gravity that keeps each in their proper place is the CMDM group and their processes.

The next step in better managing the data is to assign each group its own repository of data. A repository can be a controlled network storage disk or an access-controlled container in a Product Lifecycle Management (PLM), Enterprise Resource Planning (ERP), or similar enterprise level tool. Every subcategory would then have its own repository under the main container. Next, we can assign various rules and workflows to govern how each of these containers work and control data. Continuing this process ends up with a unique and ordered universe.

Now that we have tackled the easy part of managing the MBE data universe it is time to move on to the more difficult aspects. That is understanding the relationships between the data elements themselves and their structure. In other words, defining the natural laws of the MBE data universe.

Again, we can use the analogy approach to better understand the workings of the data management problem. By looking at our universe from the bottom up this time we can get a better look at what types of data make up the universe. At the lowest level are the various file formats and the files themselves, these can be compared to the atoms that comprise the various elements of our MBE universe. Files of different types are combined in a data set to provide a definition of the product. A data set is akin to molecules that combine atoms to form something greater then they are. These data sets are then modified and added to document the product's evolution through production and sustainment. Again, this is not unlike the combination of various molecules to create new compounds and alloys.

The alchemy of elements and molecules are the foundation of the universe's natural laws. Once this is understood one can decipher all of the magic of chemistry and physics. The same is true of management of data for the MBE data universe. By understanding structure and evolution of a data set through its lifecycle one can create a data management strategy.

Next, we need to discuss what a data set really is. It is far more than just the Computer Aided Design (CAD) model and/or drawing that many think defines a product. A data set contains many items that are contained within the model (i.e. parameters, attributes, relations, etc.), there are many other things that are contained in external files (i.e. standards, external notes, revision and effectivity data, etc.). This collection of data continues

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to grow as a product goes through its lifecycle. Items like manufacturing analysis data, material data, process data, visualizations such as 3D PDFs, technical instructions, etc. are encountered along the way. Each item that makes up the actual product has its own data set and many of these are not physical components but are software and operation instructions. These items and the other components then combine into subassemblies and systems, finally into the product itself. These derivations have data uniquely associated with it. Finally, each data set and/or item within it is also translated many times into derivative copies to be used by a specific process (i.e. STEP files for manufacturing). These derivatives are technically part of the data set, but like the by products of a chemical reaction they also have a use of their own.

The use of the derivatives and the evolution of the data sets are perhaps the biggest challenge to data management, because many of the derivatives become authoritative definition for those who use them. This means that the original data set is no longer the single authoritative source. Each of these point of use data sets (POuDS or PODS) represent a new configuration or to further an analogy, a new molecule that must be managed.

As the product evolves through its lifecycle these PODS are created with more and more frequency. Typically, their useful life span is short, especially when compared to the life span of the original definition data sets. This fact makes their management even more critical. If not managed, the out of date PODS could be mistakenly used and thus potentially introduce a flaw into the product. This could be even more of an issue if this occurs during the sustainment phase which could also cause the users of the product to lose confidence in the product itself.

To address these issues the CM/DM plan must include a process that places emphasis on the control and revision of the data sets as a whole. In other words, each data set is a configured baseline unto itself. Each data set would then retain the master revision and its components allowed to iterate under that revision. In the case of the PODs, I am recommending that they too have their own revision. However, their revision level should start at the level of the original data set at the time of their creation. This would make it very clear at what point the POD was created from the master. Overall this approach would let every data set be tracked and controlled.

Furthermore, by managing the data sets as distinct baselines or objects unto themselves the CM/DM strategy can be simplified. By looking at a group of files as a single object the relationships of that group can be readily defined and managed. At the same time the objects that make up the data set can be managed in their own context. Do not misunderstand, while this simplifies the effort, it is still a very complex issue. For instance, even if the item that makes up the data set is used in another data set, they will need to be managed by the original data set and the relationship must be managed as well. This could cause a rippling set of changes that must be evaluated as a whole.

In conclusion, the objective of this paper is to show both the complexities of the MBE data environment and a foundational approach on how to break it down and thus manage it.

MIL-STD-31000B Update and 3Di pdf Technical Data

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ABSTRACT
DOD has traditionally procured, created, and maintained Technical Data Packages (TDPs) based on 2-Dimensional (2D) engineering drawings. While the source of these drawings has transitioned to 3D Computer Aided Design (3D CAD) over the last 15 years or so, the legally binding technical data is still largely 2D, black line art, third angle projection, "front, top, side" drawings. Various organizations in DOD have recently begun the transition to 3D intelligent (3Di) pdf based technical data as the core of our technical data packages. 3Di based technical data provides a superior means to define products compared to traditional drawings. DOD is developing the training, standards, templates and infrastructure to transition to this better technical data of the future. Part of this transition is the update of MIL-STD-31000 to incorporate 3Di based technical data. DOD intends to work with our industry partners on this transition to a superior technical data package to improve communication, lower costs and provide improved support to the warfighter.

BACKGROUND

The Technical Data Package is the single authoritative technical description of an item which supports the acquisition, production, inspection, engineering, and logistics and defines the required design configuration. In October 2018, DOD released a new revision of MIL-STD-31000 B-revision, (MIL-STD-31000 is the military standard which defines a Technical Data Package), which incorporated 3D intelligent pdf (3Di pdf) as a suitable format of the TDP. The goal of this update is to allow DOD to transform to a modern technical data infrastructure based on 3Di pdf models.

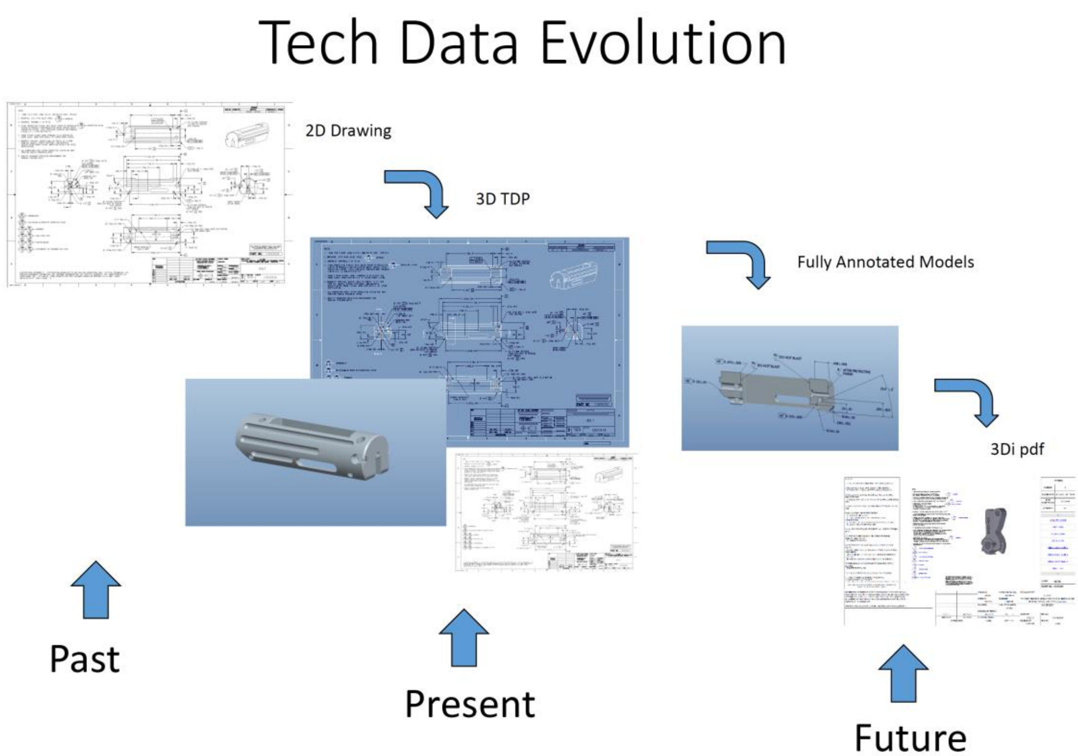

Figure 1. The Evolution of Technical Data Packages.

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DISCUSSION

In DOD, despite advances in 3D CAD, the official, legally binding TDP is still largely defined by black line art, third angle projection, “FRONT-TOP-SIDE” view, 2D engineering drawings. With recent advances is the 3D pdf format, this format has the ability to form the core of the TDP. MIL-STD-31000B defines a 3D intelligent pdf viewable as: “*A 3-dimensional viewable CAD representation which details the complete technical description of the required design configuration of an item provided in a widely available software format (e.g. ISO 32000-1 Portable Document Format (PDF)).”* The 3Di pdf provides better method to convey design intent over traditional black line art, 3rd angle projection “front-top-side” 2D drawings. The 3Di pdf provides the following benefits:

- Can provide a complete, authoritative engineering definition.
- Is CAD agnostic.
- The 3Di pdf does not require training (to use) and can be opened without special software.
- The 3Di pdf is interactive, allowing user to select annotations with visible surfaces and features highlighted.
- The 3Di pdf utilizes feature-based view states for more logical presentation of the design features.
- The technology is here today, all we need are the standards, business processes, and training to implement it.

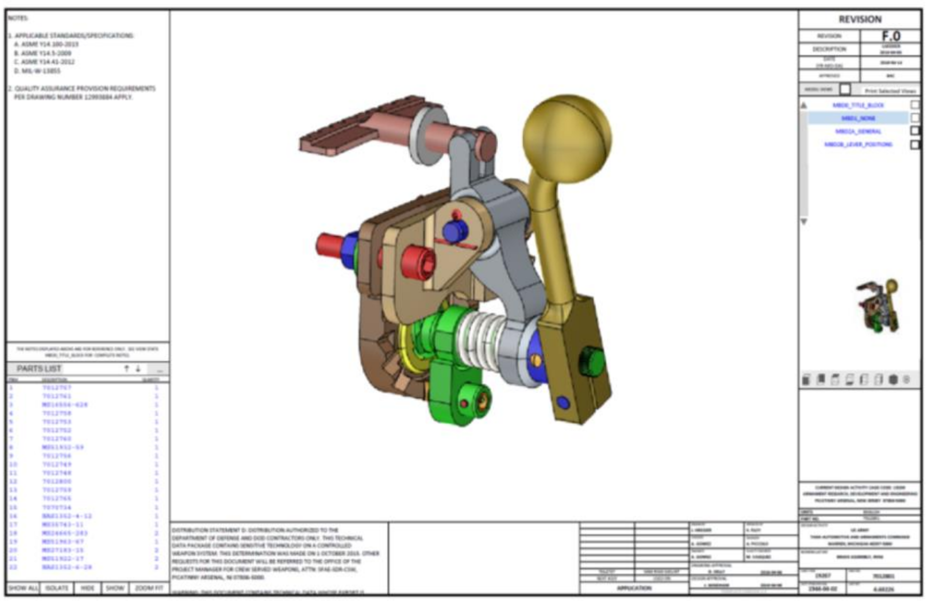

Figure 2. Screen shot example of a 3Di pdf.

With this release of MIL-STD-31000, there are now two types of TDP allowable: 2D and 3D. The type 3D TDP has 4 sub-options: 1) 3D native models only, 2) 2D drawings derived from the 3D native models, 3) 3Di pdf viewable data derived from the 3D native models, and 4) neutral files derived from the 3D native models (see Figure 3).

The B revision also establishes and clarifies terminology related to 3D based technical data (see figure 4). It establishes three format types for 3D CAD data:

Native CAD Data. CAD data as created in its original authoring software format. In general, only the original authoring software format is capable of reading, editing and interpreting native CAD data. (Examples: CREO, CATIA, Autodesk, SolidWorks, etc.) Generally native CAD data is the only format suitable to serve as master technical data. Native CAD data may also serve as authoritative technical data.

Neutral CAD Data. CAD data which is derived from the native format and converted into a format which can be imported into another CAD software. Neutral CAD data is created to a widely available national or international standard (e.g. STEP, IGES, etc.). In general, Neutral CAD data cannot serve as master technical data but may serve as either reference or authoritative technical data.

Viewable CAD Data. CAD data which is derived from the native format and converted into a format which can be displayed by a widely available software and for purposes of defining design intent in a human readable format (e.g. 3Di PDF). In general, viewable CAD data cannot serve as master technical data but may serve as either reference or authoritative technical data.

Technical Data Origin:

Master Technical Data. A set of technical data which is the controlling source for any subsequent technical data output. All changes to the technical data must originate on the master technical dataset. There can be only one instance of the master technical data which is typically in the native CAD format and maintained by the current design activity.

Derivative Technical Data. A set of technical data generated from master technical data. Typically derivative technical data is created to change its format to suit a different purpose. For example converting master, native format data to neutral or viewable data (e.g. STEP, IGES, PDF, etc.) so as to allow it to be read by a wider range of software applications. Changes to derivative technical data originate on the master technical dataset.

Technical Data Validation Status:

Authoritative Technical Data. A set of technical data which has been released and validated as adequate and complete for its intended purpose.

Reference Technical Data. A set of technical data which is provided for information, but is not necessarily validated as accurate, adequate and complete.

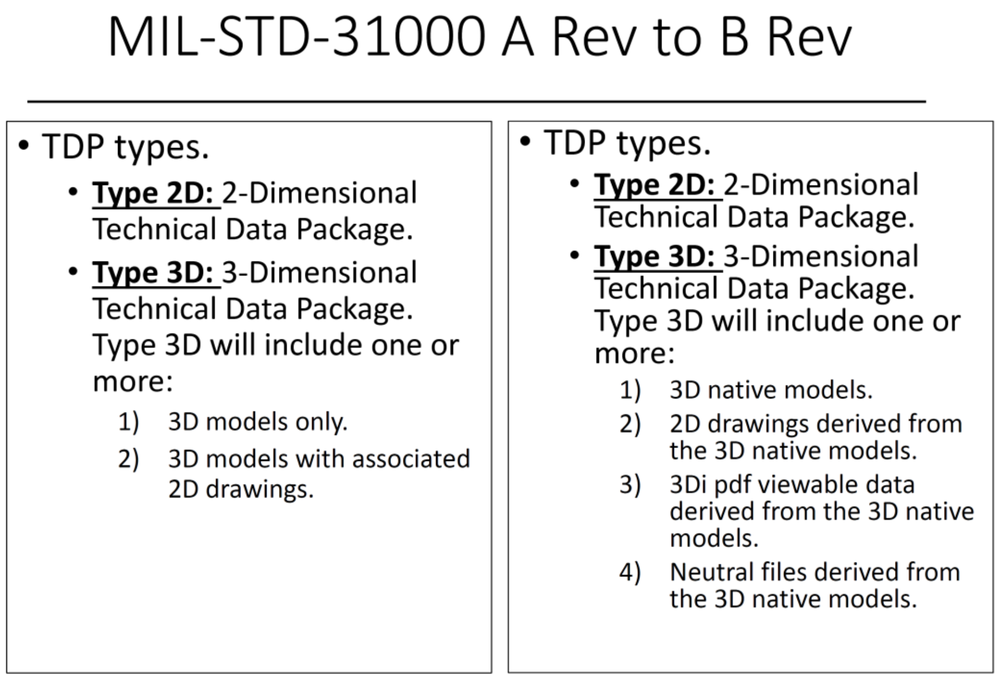

Figure 3. Types of TDPs: Revision A vs Revision B of MIL-STD-31000.

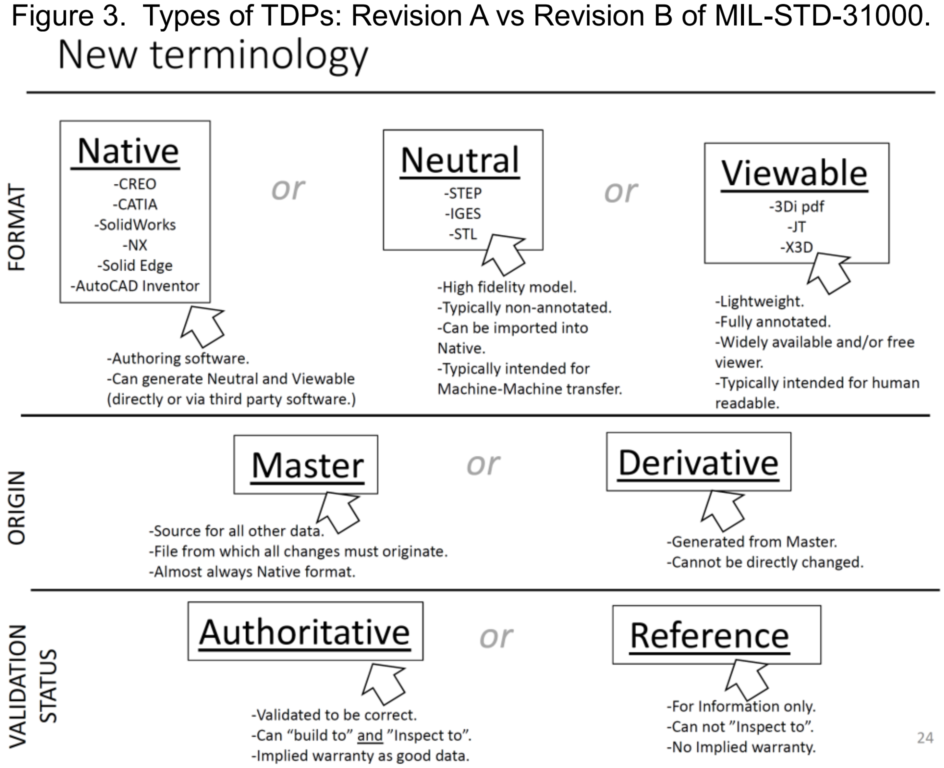

Figure 4. 3D TDP Terminology

SUMMARY

DOD is moving to a modern Technical Data infrastructure based on 3Di models. The release of MIL-STD-31000 supports this effort. The 3Di model based TDPs are better than 2D, black line art, third angle projection, "front-top-side" and Government and industry teams need to engage early and often on best TDP solution for their programs. Be advised, requirement to deliver 3Di pdf based TDP may be coming soon to a contract near you.

EXCHANGING DIGITAL ENGINEERING INFORMATION IN A GLOBAL SUPPLY CHAIN

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ABSTRACT
As part of the Department of Defense (DoD) effort to advance digital engineering, the Department seeks to evolve from document-based artifacts to exchanging work products digitally. In response, the community has begun an effort to articulate the exchange of digital artifacts across stakeholders and digital technologies. Ongoing work is presented by the Digital Engineering Information Exchange Working Group (DEIX WG), a collaboration among the International Council on Systems Engineering (INCOSE), the National Defense Industrial Association (NDIA) Modeling and Simulation (M&S) Subcommittee, and the DoD Office of the Under Secretary of Defense for Research and Engineering (DoD/OUSD(R&E)). This paper describes products the DEIX WG is developing to exchange digital engineering information in a global supply chain.

THE CHALLENGE

The current DoD engineering approach is stove-piped, linear, and can cause years of effort to conceive, design, and deliver systems. In addition, the current acquisition process relies heavily on documents that use large amounts of data in acquisition activities and decisions. The professionals involved with the acquisition process communicate and store static documents separately and in a disjointed manner across organizations, tools, and environments [1]. Examples of the static documents may include diagrams, spreadsheets, text documents, and two-dimensional drawings. Many engineers base their activities and decisions on information that is spread across multiple document-based artifacts, which require tedious and time-consuming methods to ensure engineering rigor, consistency, and coherency. Despite advances in digital technologies, there are significant inefficiencies in cost, schedule, and performance of the acquisition activities when suppliers and acquirers exchange information following a traditional document-based approach.

THE OPPORTUNITY

The heart of digital engineering is incorporating digital technologies into a model-based approach. The primary means of communication moves from documents to digital models and data. This enables access, management, analysis, use, and exchange of information from a common set of digital models and data. As a result, authorized stakeholders have access to current, authoritative, and consistent information over the lifecycle [2].

To address the challenges defined in DoD's Digital Engineering Strategy [2], the International Council on Systems Engineering (INCOSE), the National Defense Industrial Association (NDIA) Modeling and Simulation (M&S) Subcommittee, and the Department of Defense Office of the Under Secretary of Defense for Research and Engineering (DoD/OUSD(R&E)) have established the Digital Engineering Information Exchange Working Group (DEIX WG pronounced "DEX WIG"). The purpose of the DEIX WG is to identify standard ways to define, request, offer, and exchange information among stakeholders across the entire lifecycle. The WG activities and products span the systems engineering lifecycle as it relates to the inputs and outputs of ISO/IEEE 15288. The DEIX WG is developing the following four products:

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1. **Digital Engineering Information Exchange Model (DEIXM):** The DEIXM product is a conceptual framework for exchanging digital artifacts. According to the Defense Acquisition University (DAU) glossary, a digital artifact is "an artifact produced within, or generated from, the digital engineering ecosystem. These artifacts provide data for alternative views to visualize, communicate, and deliver data, information, and knowledge to stakeholders" [3]. The goal of the DEIXM product is to define a set of constructs and conventions for exchanging digital artifacts. This product provides the primary input that informs the narrative for the DEIX Primer (product 3).

2. **Digital Viewpoint Models (DVM):** Stakeholders will use the DVM as a generic template to describe the information they want to view. This product offers practitioners a common way to repeatedly and consistently describe digital engineering information to exchange. Figure 1 illustrates a high-level concept for creating digital views and viewpoints. Typically, a system of interest is represented by a number of digital artifacts that together provide a description of the system. The DVM product will define the semantics and syntax for creating digital viewpoints, which provide a template for assembling the digital artifacts into digital views. The artifacts are selected and assembled using any combination of digital presentation technologies.

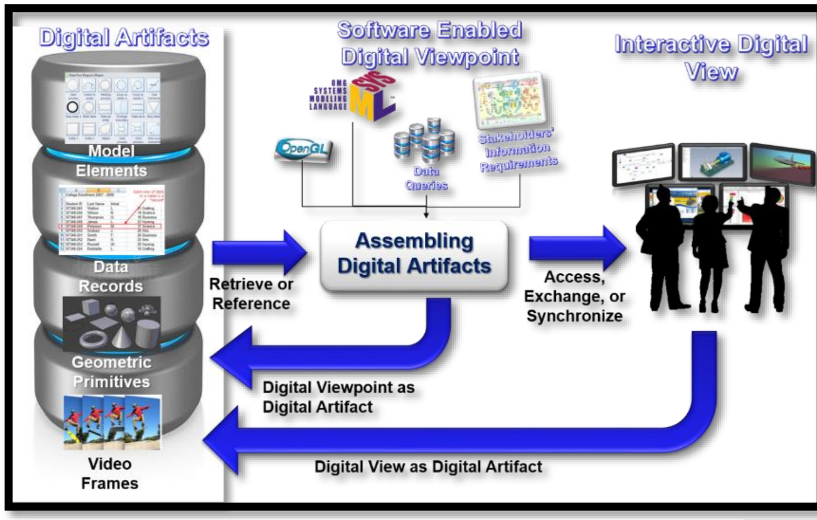

Figure 1: Concept for Creating Digital Views and Viewpoints

3. **Digital Engineering Information Exchange (DEIX) Primer:** The DEIX Primer provides a concept of operations for exchanging digital information in order to achieve community acceptance and encourage adoption of the DEIX concepts. The primer is a narrative that introduces the digital engineering information exchange terminology and models to new and current practitioners of digital engineering practices. To the extent possible, the content will be sufficiently general to accommodate diverse disciplines, domains, industries, and the international community. An encyclopedia of DEIX's related topics is the initial step in building the DEIX Primer [5]. The primer will leverage any new knowledge from the DEIXM and DVM product teams and translate their modeling language to natural language narratives.

4. **Digital Engineering Information Exchange Standards Framework (DEIX-SF):** The objective is to identify and build a consensus-based standards framework for the DEIX. By evaluating existing standards and identifying standards gaps, this product will assist formalized, consensus-based standards bodies to pursue the development of needed standards. Finally, in coordination with the INCOSE Standards Initiative, the results of this product will be used as a basis to coordinate with national and international standards organizations to incorporate DEIX concepts.

CONCLUSION

The digital era provides the opportunity to leverage new digital technologies, forms of media, and means of interaction to provide new ways to visualize, communicate, and deliver data, information, and knowledge to stakeholders. This DEIX WG is chartered to provide standard and conventional ways to define, request, offer, and exchange information among stakeholders across the lifecycle. The products are intended to improve the upstream and downstream supply chain inefficiencies and help the community to address significant challenges and goals defined in the DoD Digital Engineering Strategy.

REFERENCES

[1] P. M. Zimmerman, T. W. Gilbert and F. J. Salvatore, "Digital engineering transformation across the Department of Defense," The Journal of Defense Modeling and Simulation, 2017.

[2] Office of the Deputy Assistant Secretary of Defense for Systems Engineering, "Digital Engineering Strategy," U.S. Department of Defense, Washington, DC, 2018.

[3] Defense Acquisition University (DAU), "Digital Artifact," DAU Glossary, 2019. [Online]. Available: https://www.dau.mil/glossary/Pages/Glossary.aspx#!both|D|27344. [Accessed 05 March 2019].

[4] J. H. Coleman, F. J. Salvatore, C. Schrieber and T. A. Peterson, "INCOSE Digital Engineering Information Exchange Working Group Charter," International Council on Systems Engineering, San Diego, CA, 2018.

[5] Digital Engineering Information Exchange (DEIX) Community of Interest (COI) Members, "DEIX Topical Encyclopedia Entries," OMG MBSE Wiki, 28 December 2018. [Online]. Available: https://www.omgwiki.org/MBSE/doku.php?id=mbse:topical_encyclopedia_for_digital_engineering_information_exchange_deixpedia. [Accessed 05 March 2019].

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DIGITAL ENGINEERING STRATEGY AND IMPLEMENTATION

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ABSTRACT
The U.S. Department of Defense (DoD) Digital Engineering Strategy [1] introduced digital engineering as the catalyst to transform the design and delivery of complex systems. DoD defines digital engineering as "an integrated digital approach that uses authoritative sources of system data and models as a continuum across disciplines to support lifecycle activities from concept through disposal" [1]. The Office of the Under Secretary of Defense for Research and Engineering [OUSD(R&E)] and the Armed Services are currently rolling out initiatives to implement digital engineering. This paper provides an overview of the digital engineering strategy and implementation efforts that will advance the state of practice.

BACKGROUND

Historically, DoD has relied on robust engineering practices and the use of modern weapon systems to defeat the Nation's adversaries. In an era of growing threats, tight budgets, aggressive schedules, and global digitalization, it is more imperative than ever that DoD maintain its technological superiority [1] [2].

In the National Defense Strategy of 2018 [3], the Secretary of Defense encourages the defense workforce to adopt new practices to achieve greater performance to meet future challenges. Our adversaries are realizing next-generation capabilities across key technological domains. To maintain our global competitive advantage, DoD must adopt the use of 21st century technology to modernize the way it engineers weapon systems. Without sustained and predictable investments to restore readiness through cutting-edge technology, our military forces could lose their competitive advantage. To meet the National Defense Strategy's lines of effort, DoD must modernize its defense systems and prioritize speed of delivery to fight and win future wars [1] [2].

DIGITAL ENGINEERING VISION

DoD's vision for digital engineering is to revolutionize how the Department designs, develops, delivers, operates, and sustains systems. Digital engineering seeks to securely and safely connect people, processes, data, and capabilities across an end-to-end digital enterprise. This approach will enable the use of models throughout the lifecycle to digitally represent the system of interest (i.e., system of systems, systems, processes, equipment, products, and parts) in the virtual world.

Digital engineering will enable stakeholders to interact with digital technologies (e.g., advanced computing, big data analytics, artificial intelligence) to improve the engineering practice and solve problems in new and groundbreaking ways. Through increased computing speed, storage capacity, and processing capabilities, digital engineering has empowered a paradigm shift from the traditional design-build-test methodology to a model-analyze-build methodology. This approach can enable DoD programs to prototype, experiment, and test decisions and solutions in a virtual environment before they are delivered to the warfighter.

Using models is not a new concept; however, digital engineering emphasizes continuity of the use of models across the lifecycle. Transitioning to digital engineering will address long-standing challenges associated with complexity, uncertainty, and rapid change in deploying and using U.S. defense systems, by providing a more agile and responsive development environment. Expected benefits of digital engineering include better informed decision making, enhanced communication, increased understanding of and confidence in the system design, and a more efficient engineering process [1] [2].

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FIVE STRATEGIC GOALS

The strategy was developed around five strategic goals to define the vision for what the Department wants to achieve. The goals are based on an extensive review of the literature and input from across the Services, industry, academia, the National Defense Industrial Association (NDIA), the International Council on Systems Engineering (INCOSE), and our interagency partners. **Error! Reference source not found.** illustrates the five goals that make up the Digital Engineering Strategy [1]:

Figure 1: Digital Engineering Goals

1. **Formalize the development, integration, and use of models to inform enterprise and program decision making.** The first goal establishes the formal planning, development, and use of models as an integral part of performing engineering activities as a continuum across the lifecycle. Such ubiquitous use of models results in a continuous end-to-end digital representation of the system of interest. This supports consistent analysis and decision making for programs and across the enterprise [1].

2. **Provide an enduring, authoritative source of truth.** This goal moves the primary means of communication from documents to digital models and data. This approach enables access, management, analysis, use, and distribution of information from a common set of digital models and data. As a result, authorized stakeholders have the current, authoritative, and consistent information for use over the lifecycle [1].

3. **Incorporate technological innovation to improve the engineering practice.** This goal extends beyond the traditional model-based approaches to incorporate advancements in technology and practice. Digital engineering approaches also support rapid implementation of innovations within a connected digital end-to-end enterprise [1].

4. **Establish a supporting infrastructure and environments to perform activities, collaborate, and communicate across stakeholders.** This goal promotes the establishment of robust infrastructure and environments to support the digital engineering goals. It incorporates an information technology infrastructure and advanced methods, processes, and tools, as well as collaborative trusted systems that enforce protection of intellectual property, cybersecurity, and security classification [1].

5. **Transform the culture and workforce to adopt and support digital engineering across the lifecycle**. The final goal incorporates best practices of change management and strategic communications to transform the culture and workforce. Focused efforts are needed to lead and execute the change, and to support the organization's transition to digital engineering [1].

IMPLEMENTATION NEXT STEPS

Digital engineering transformation efforts are already in progress across DoD. OUSD(R&E) and the Armed Services are moving toward implementing the digital engineering goals collectively. The Digital Engineering Strategy describes what is necessary to foster the use of digital engineering practices. OUSD(R&E) is collaborating with the Services and Agencies to develop the how—digital engineering practices in appropriate stages and levels for each respective enterprise.

Although DoD Components own their digital engineering implementation plans, OUSD(R&E) will coordinate efforts to ensure the DoD engineering enterprise stays on track to improve the engineering practice. As DoD Components create, share, and execute their implementation plans, OUSD(R&E) will work to close gaps, eliminate duplication, and share best practices.

The specific next steps are outlined below:

- **Coordinate DoD Digital Engineering Effort**
  OUSD(R&E) convened a Digital Engineering Summit with representative leaders from DoD Components to discuss Service implementation plans. OUSD(R&E) will continue to collaborate with DoD Components as part of the Digital Engineering Working Group (DEWG). The DEWG will address common practices and concerns, facilitate information exchange and collaboration, align technical initiatives, propose policy and guidance, and pursue cross-cutting issue resolution.

- **Develop DoD Implementation Plans**
  DoD Components, supported by OUSD(R&E), will develop digital engineering implementation plans that show desired outcomes to achieve the goals in the Digital Engineering Strategy.

- **Implement Pilot Programs**
  DoD Components will implement a number of digital engineering pilot programs to identify barriers and evaluate tools, processes, and cost before full-scale implementation of digital engineering in major programs. The goal of the digital engineering pilots is to learn, measure, and optimize digital approaches for engineering efficiency and effectiveness.

- **Sustain Digital Engineering Transformation**
  DoD will implement policy, guidance, training, and continuous improvement initiatives to institutionalize digital engineering across government, industry, and academia.

REFERENCES

[1] Deputy Assistant Secretary of Defense for Systems Engineering, “Digital Engineering Strategy,” Department of Defense, Washington, DC, 2018.

[2] Zimmerman, P., Gilbert, T., & Salvatore, F. (2017). Digital engineering transformation across the Department of Defense. The Journal of Defense Modeling and Simulation.

[3] Office of the Secretary of Defense, “National Defense Strategy,” Department of Defense, Washington, DC, 2018.

[4] Deputy Assistant Secretary of Defense for Systems Engineering, “Digital Engineering,” Department of Defense, [Online]. Available: http://www.acq.osd.mil/se/initiatives/init_de.html. [Accessed March 1 2019].

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Securing, Authenticating, and Visualizing Data-Links for Manufacturing Enterprises

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ABSTRACT

Managing digital resources generated from product design, manufacturing, and sustainment activities has become a significant burden for enterprises. In response, we introduce a prototype implementation of the Securing and Authenticating Data-Links (SADL) Interface, which interacts with a manufacturing handle registry to facilitate traceability of digital resources for engineering projects. This paper outlines the intended use of SADL and the handle registry by laying out hypothetical questions from potential users. Additionally, we map the core concepts of key standard data representations in manufacturing to a popular data type taxonomy. Future work will include the design and testing of data visualizations based on our mapping protocols.

INTRODUCTION

Manufacturing operations produce an immense amount of data, estimated at two exabytes of data annually in 2013 [1]. Considering the emergence of more complex electro-mechanical devices to the market, e.g., fully electric automobiles, the amount of code and manufacturing data is expected to grow significantly [2]. As a result, managing the associated digital resources has become, and will continue to become, a burden. An efficient and robust approach for labeling, categorizing, and curating diverse data is an essential first step for visualizing trends and deriving actions. In this paper, we present a prototype implementation of the manufacturing handle system, aimed at recording appropriate meta-data ("data about data") for digital resources related to the product lifecycle. Additionally, we present initial guidelines for developing data visualizations for the handle system to facilitate data exploration.

Each phase of the product's lifecycle incorporates its own data representations, organizational functions, and business processes. Each of these functions and processes uses tools and methods (e.g., computer-aided design (CAD) applications and requirement formalization). Though there have been efforts in improving information exchange across the various lifecycle phases (e.g., design and manufacturing) [3], there has not yet been a conclusive and robust demonstration at scale to achieve the so-called "digital thread" [4]. The metaphor "digital thread" conveys the seamless exchange and flow of data between engineering, manufacturing, business process and across supply chains [5].

However, in practice, the dearth of interoperability has led to gaps in information flow across manufacturing enterprises contributing to a number of challenges, including communicating across multi-tiered supply chains, reacting to engineering changes, and responding to customer requirements. For small-to-medium sized

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enterprises, these challenges are even more difficult to overcome, since most solutions targeted at the Digital Thread are expensive, expert-driven one-off prototypes. In response to these challenges, we present the following research contributions: (1) a prototype interface, coined the Securing and Authenticating of Data-Links (SADL) Interface that allows users to register digital resources, add meta-data, and query the registry, (2) a classification scheme of lifecycle data from manufacturing phases, e.g., as-designed, as-planned, as-executed, and as-inspected, based on data nature and type [6], and (3) requirements on the further improvement of the SADL interface. It is our hope that this work facilitates a better digital resource certification management in a product's lifecycle for end-users, including plant managers, design teams, and supply chain managers.

Our efforts aim to facilitate the realization of a Model-Based Enterprise (MBE) that can quickly respond to product lifecycle disruptions, e.g., engineering change requests, weather events affecting suppliers, and machine degradation. From this perspective, we focus on the design, manufacturing, and inspection phases that incorporate a standard data representations, which have been primary focuses of the MBE journey. Managing these representations as digital resources, and changes to them, poses a significant challenge.

THE SADL INTERFACE AND THE MANUFACTURING HANDLE REGISTRY

SADL (Securing and Authenticating of Data-Links) is an application serving as a middleware between digital objects hosted on a Handle.Net registry and its end-users. Its goal is to offer a customizable overview of a product's lifecycle digital objects, the product data, by providing additional meta-data (e.g. lifecycle phase or product category) from which users can query, rank, order, classify, and construct links between objects.

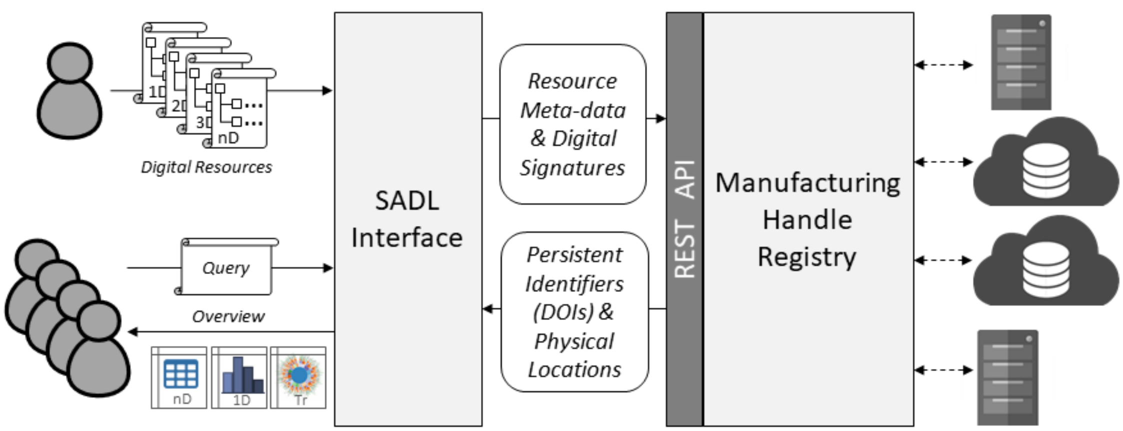

Figure 1: Vision of the SADL Interface and its interactions with users and the Handle Registry.

Figure 1 introduces the vision of the work presented in this paper. Initially, users label meta-data for digital objects by interacting with the SADL Interface. The SADL interface then leverages the Representational State Transfer (REST) Application Program Interface (API) of the Handle.Net registry to assign digital signatures and meta-data to the objects. The pipeline leverages existing technology that creates persistent identifiers (Digital Object Identifiers or DOIs [7]) to manage the physical locations of the resources. Other users can then submit queries through the SADL Interface to access report summaries of a collection of digital resources relevant to a manufacturing-oriented use case.

The pipeline presented above relies on the concept of the Handle System. Released by the Corporation for National Research Initiatives (CNRI) in 1994, the Handle System offers a means to locate, track, and manage data even in the face of constant modification [8]. In particular, manufacturing represents a domain that faces constant data modification and improvement. For instance, given engineering needs, it is very common that a product's design goes through several iterations before being approved for manufacturing, which leads to the creation of multiple design files. It is critical to construct a digital footprint outlining the complete history of each digital resource for various scenarios, e.g., liability investigations and engineering change requests. By providing a unique identifier for each digital object, the Handle System Registry acts as a DOI Repository providing a unique access point to all the digital resources inside an enterprise. Each "handle" (i.e., the name given to each of the DOIs) contains a set of meta-data about a specific digital object and allows for modifications to incur on the source file without compromising the validity and integrity of the handle.

By using the digital repository provided by the Handle System as a gateway to a broader view of all the different data objects inside the product's lifecycle, users can visualize the digital objects and link them together. This broader view describes the concept of a digital map encompassing critical digital resources given a particular use case. The Handle System provides digital record-keeping with a way to also offer efficient feedback to end-users and to facilitate better understanding of complex interactions with a product's lifecycle. Additionally, it is important that the current view in the registry reflects the current status in the real world. A proof-of-concept for a "System Lifecycle Handler" [9] confirmed the utility of these idea. In our pipeline, we include a means to store digital signatures to certify the validity of the stored data.

Throughout the rest of this paper, we explore potential means for visualizing a large collection of digital resources through the SADL Interface. We examine the expected range of data nature and type assuming that the registry is well-seeded with manufacturing-oriented data. This includes mapping expected business functions, from well accepted data representations to possible visualization schemes. We then conclude by addressing hypothetical, explorative questions from envisioned users to demonstrate the impact of the SADL Interface.

TOWARDS VISUALIZING A LARGE COLLECTION OF DIGITAL RESOURCES

In practice, the collection of digital resources for a given handle system would be quite large and a challenge to navigate. In response, we perform a data type mapping between the business processes and information embedded in standard data representations, namely STEP AP242 [10], STEP AP238 [11], MTConnect V1.4 [12], and QIF 3 [13]. STEP AP 242 provides an exchange format for design data including fully characterized Product and Manufacturing Information (PMI). STEP AP238 is a descriptive data representation for machine instructions, providing an additional layer of semantic descriptions compared to traditional G-code. MTConnect is a read-only communication protocol for capturing execution data from machine tool controllers. QIF is a semantically rich data format for representing, exchanging, and storing inspection plans, rules, and results. We applied the seven data type taxonomy used in Shneiderman's task-by-type taxonomy [6] keeping in mind that future work will involve designing and implementing data visualizations to respond to user queries to the SADL Interface. Nomenclature and a brief description of all seven data types are below.

***1-dimensional* (1D):** linear data types that are organized in a sequential manner, e.g., textual documents that only contain alphabetically ordered strings. From the perspective of engineering design, 1D data types can relate to the rules and requirements needed to apply STEP AP242. Considering the rules and requirements elements, a Mural visualization in the background of the scrollbar [14] might be appropriate. This visualization would highlight different parts of the text that are related to a particular requirement.

***2-dimensional* (2D)**: planar or map data including maps, floorplans, or newspaper layouts. Manufacturing-oriented examples could include entire factory layouts or plans for individual cell layouts. In a robotic factory, a production cell layout could highlight the distance between the robotic arm and other assets. A higher-level instance of 2D data could represent the entire plant factory decomposed into multiple cellular maps each relating to one another.

***3-dimensional* (3D)**: real-world objects or representations that represent volumetric data, such as solid models or computer-aided design (CAD) files. From a visualization perspective, the challenge is to find a balance between the view of the real-life object and the information within it. The aspect of the object must correlated with the data in a way that the user understands its spatial positioning in a larger context, e.g., a complex assembly.

***Multi-dimensional* (nD):** relational and statistical databases manipulated as multidimensional data in which items with *n* attributes become points in a *n*-dimensional space. QIF inspection results, including probe information are an example. One visualization technique to represent a database table is a cube visualization [15]. Each face of the cube is composed of one attribute of the table and layers of each face correspond to a possible value of the face attribute. The intersection of two adjacent faces represents a data point.

Temporal* (Ts)*: time series data, such as historical presentations or future projections. The difference between 1D and temporal data is rather nuanced. Both can be simple text documents, but the main difference is that Ts data is anchored through a timeline. Process plans in STEP AP238 and sample type data in MTConnect streams are examples of Ts data types.

Tree* (Tr)*: hierarchies with each item having a link to one parent item except the root. For example, an MTConnect Device model is organized based on the design of devices. Using a tree visualization, like a Tree-map [16], could provide a snapshot of capabilities and characteristics of available devices.

Network* (Nk)*: items linked to an arbitrary number of other items not following rules of trees. For example, the STEP AP242 Assembly structure contains parts and subassemblies as items, and multiple type of links can exist between these items. Some links might have numerical values or represent specific actions or modifications. A matrix diagram [17] is a way to expose different items and their associated links. The matrix can be color coded so that the user has a better understanding of the differences in type and meaning of the links.

			Data Types						
Representation	**Business Function**	**Concept Description**	**1D**	**2D**	**3D**	**nD**	**Ts**	**Tr**	**Nk**
STEP 242 (as-designed)	Specification, Breakdown & Configuration	Assembly Structure						●	●
		Transformations, Geometry, & Coordinate System		●	●				
	... ...								
STEP 238 (as-planned)	Model-Based Manufacturing Process	Generic Toolpaths		●	●				
		Parameters (feeds, speeds, etc.)	●						
	... ...								
MTConnect (as-executed)	Historical Machine Operations	Samples					●		
		Conditions	●						
	... ...								
QIF (as-inspected)	Model-Based Definition	Computer-aided design (CAD) data			●			●	
		Product manufacturing information (PMI) data				●			
	... ...								

Figure 2: Classification of data type per business function and concept description within each studied data representation. The complete table[1] can be accessed here: https://goo.gl/Zbkqmb.

[1] An initial draft of the mapping. We expect it to evolve as we dive deeper into each data representation.

Figure 2 illustrates the structure of the data type classification completed for each business function of studied standard representations. We conducted this classification to identify design opportunities for custom visualizations for the SADL Interface. Besides individual visualizations per business function, we also envision potential for effective overview visualizations. In other words, given that an organization registered a large amount of digital resources within the handle system, we can present, for example, a hierarchical representation based on a prominent concept description, e.g., the assembly structure of a product. In the future, we plan to implement and test the effectiveness of sunburst plots, cartesian node-link diagrams, and matrix views [18] using accepted information visualization principles [19].

FROM DATA SETS TO VISUAL INDICATORS

In the previous section, we introduced a mechanism to uniquely identify, locate, authenticate, and navigate through a product's lifecycle digital objects using the Handle.Net and our SADL interface. We also described different data visualization types. In this section, we will discuss some steps towards generating and visualizing insight and performance metrics from trusted product data. While our area of focus is limited to as-designed, as-planned, as-executed, and as-inspected lifecycle data, the ideas and methods introduced here can be applied to other data.

The first step consists of identifying and categorizing the different product data generated and available to the organization. During this step, one must ensure that (1) the data is complete and fits under one of the four lifecycle stages previously mentioned, (2) the data is available in an open-standard format to reduce the cost of processing and enable interoperability, and (3) the data concepts are properly identified (as in the third column in Fig. 2).

The second step consists of identifying metrics or indicators based on key organizational characteristics and derived from the data concepts previously identified. These metrics and indicators should provide answers to questions related to organizational resources, activities, and performance. In this project, we have focused our questions on basic organizational components, namely processes, products and people (or the 3Ps). The following is a set of hypothetical questions illustrating some basic metrics and indicators that can easily be computed and/or inferred from the data sources/standards we use:

1. **Process**:
   1.1. How long did it take to execute process X during the past 10 days?
   1.2. How many parts a day are handled during process X?
   1.3. Was there a quality improvement between V2 and V1 of process X?
2. **Product**:
   2.1. What was the assembly structure of Product Y?
   2.2. How many parts were affected after changing feature X on product Y?
   2.3. Was the new design of Product X actually ready to move to production on November 2, 2018?
3. **People**:
   3.1. Who inspected the version of part Z that was built on November 2, 2018?
   3.2. What was the chain-of-command for Product X through its lifecycle?

The third and last step maps the different questions from the second step to the right source of data, data concepts, and visual data types to address each question. The output should be similar to Table 1 and be used as a guideline for the solution implementer(s). Our recommended output is a Table with the following columns:

1. **Question**: the question whose answer is a metric or indicator regarding a key organizational component
2. **Representation** or data source: the format of the data that will be used to compute the metric or indicator in response to the question
3. **Key concepts**: a list of the data elements that need to be extracted from the data source to compute the metric or indicator
4. **Shneiderman's Data Type**: the data type used to visualize the metric or indicator based on the list of types identified in the previous section

In this section, we presented a three-step process to guide a user from identifying the type of data sources available, derive performance metrics and indicators, and map them to a visual data type using the Shneiderman's classification. This process would facilitate the design and development of a visualization dashboard providing insight to engineering teams through open data representations.

Table 1: Recommended output to describe requirements for presenting relevant data through the SADL Interface based on an enterprise-driven question.

Question	Representation(s)	Key concept(s)	Shneiderman's Data Type
1.1	MTConnect	Events	Ts
1.2	MTConnect	Part Count, Samples	1D
1.3	MTConnect, QIF	Events, Measurements data	1D
2.1	AP242	Assembly structure	Tr
2.2	AP242	Assembly structure	Tree/1D
2.3	AP242	Meta-data entered at SADL*	Tr
3.1	AP242, QIF	General Mgmt. Information	1D
3.2	AP242	Meta-data entered at SADL*	Ts/Tr

*Not part of the standard representation itself. The digital signatures would be appended to the digital resource once the user enters the information in the SADL Interface.

CONCLUSIONS

We presented progress towards the SADL, an interface designed to secure and authenticate data-links within a standardized handle system. In doing so, we stressed the importance of implementing effective and interactive visualizations that aid users in querying a large collection of digital resources. We demonstrate this process across four leading standards for the model-based enterprise: STEP AP242, STEP AP238, MTConnect, and QIF. We expect that others can follow the same process for other standards as well. Relating the underlying domain-specific data to a taxonomy of domain-agnostic data types eases the integration of state-of-the-art visualizations. Such visualizations are expected to be integrated within the SADL interface. Future work will consider the feasibility of generalized visualizations so that a variety of digital resources can be represented to enhance organizational decision-making.

DISCLAIMER

No endorsement of any commercial product by NIST is intended. Commercial materials are identified in this report to facilitate better understanding. Such identification does not imply endorsement by NIST nor does it imply the materials identified are necessarily the best available for the purpose.

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REFERENCES

[1] Auschitzky, E., Hammer, M., & Rajagopaul, A. (2014). How big data can improve manufacturing. *McKinsey & Company*, *822*.

[2] Yin, S., & Kaynak, O. (2015). Big data for modern industry: challenges and trends [point of view]. *Proceedings of the IEEE*, *103*(2), 143-146.

[3] Panetto, H., & Molina, A. (2008). Enterprise integration and interoperability in manufacturing systems: Trends and issues. *Computers in industry*, *59*(7), 641-646.

[4] West, T. D., & Blackburn, M. (2017). Is Digital Thread/Digital Twin Affordable? A Systemic Assessment of the Cost of DoD's Latest Manhattan Project. *Procedia Computer Science*, *114*, 47-56.

[5] Hedberg, T., Lubell, J., Fischer, L., Maggiano, L., & Feeney, A. B. (2016). Testing the digital thread in support of model-based manufacturing and inspection. *Journal of computing and information science in engineering*, *16*(2), 021001.

[6] Shneiderman, Ben. "The eyes have it: A task by data type taxonomy for information visualizations." *Visual Languages, 1996. Proceedings., IEEE Symposium on*. IEEE, 1996.

[7] Paskin, N. (2010). Digital object identifier (DOI®) system. *Encyclopedia of library and information sciences*, *3*, 1586-1592.

[8] Kahn, Robert, & Wilensky, Robert, "A framework for distributed digital object services," May 13, 1995. URL: http://www.cnri.reston.va.us/home/cstr/arch/k-w.html. Accessed December 1, 2018.

[9] Bajaj, Manas, and Thomas Hedberg Jr. "System Lifecycle Handler—Spinning a Digital Thread for Manufacturing." *INCOSE International Symposium*. Vol. 28. No. 1. 2018.

[10] ISO (2014). 10303-242: 2014, Industrial automation systems and integration—product data representation and exchange—Part 242: Application protocol: Managed model based 3d engineering. *Geneva (Switzerland): International Organization for Standardization (ISO)*.

[11] ISO (2007). 10303-238: 2007, Industrial automation systems and integration—product data representation and exchange—Part 238: Application protocol: Application interpreted model for computerized numerical controllers. *Geneva: International Organization for Standardization (ISO)*.

[12] Sobel, W. (2015). MTConnect standard. Part 1—overview and protocol. *Standard—MTConnect.* URL: http://www. mtconnect. org/standard. Accessed December 1, 2018. .

[13] Dimensional Metrology Standards Consortium. (2018). Part 1: Overview and Fundamental Principles in Quality Information Framework (QIF)—An Integrated Model for Manufacturing Quality Information. *Dimensional Metrology Standards Consortium*. URL: http://qifstandards.org/. Accessed Dec 1, 2018.

[14] Jerding, Dean F., and John T. Stasko. "The information mural: A technique for displaying and navigating large information spaces." *IEEE Transactions on Visualization and Computer Graphics* 4, no. 3 (1998): 257-271.

[15] Stolte, Chris, Diane Tang, and Pat Hanrahan. "Multiscale visualization using data cubes." *IEEE Transactions on Visualization and Computer Graphics* 9.2 (2003): 176-187.

[16] Shneiderman, Ben. "Tree visualization with tree-maps: 2-d space-filling approach." *ACM Transactions on graphics (TOG)*11.1 (1992): 92-99.

[17] Van Ham, Frank. "Using multilevel call matrices in large software projects." *Information Visualization, 2003. INFOVIS 2003. IEEE Symposium on*. IEEE, 2003.

[18] Heer, J., Bostock, M., & Ogievetsky, V. (2010). A tour through the visualization zoo. *Commun. Acm*, *53*(6), 59-67.

[19] Carpendale, M. S. T. (2003). Considering visual variables as a basis for information visualisation.

Why QIF Matters – A Roadmap for Digital Manufacturing

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ABSTRACT

This paper discusses how the ANSI/DMSC Quality Information Framework (QIF) standard provides benefit to the model-based enterprise (MBE) in two important ways: (1) automation of cyber-physical processes, allowing faster realization of higher quality products at lower cost, and (2) by providing traceability of massive quantities of measurement-related data to the authority product definition model. Over the last decade, efforts have been made to develop digital interoperability standards that address the connection points for information transfer through the product lifecycle. Through early work in the Automotive Industry Action Group (AIAG) and the Digital Metrology Standards Consortium (DMSC), new data models have emerged and achieved significant maturity levels.

The benefits of automation and business process systemization are made possible with meaningful, semantic data packaged in the QIF format. With Model Based Definition (MBD) data (i.e., PMI, FT&A, etc.) becoming more commonplace, QIF is becoming an attractive complete and unambiguous MBD delivery mechanism for industrial end users. In addition to automation benefits, QIF helps to provide data traceability in this age of Big Data, where traceability is sorely needed. MBE provides a paradigm for organizing this data by mapping it all to a meaningful product definition: the master model-based definition enabled by a product data management system. QIF is designed to instantiate this MBE approach to data management.

This paper will explain the background for why QIF is needed, and the features built into QIF which will ensure that it is equipped to handle the needs of modern industry.

BACKGROUND

Today's manufacturing enterprise is plagued with the problem of disconnected, disorganized, and duplicated data. Furthermore, recent advances have seen an exponential increase in the volume of industrial data being generated, particularly data related to computer-controlled systems of all types. Terms like "Industrial Internet of Things" (IIoT) and "Industrie 4.0" describe this revolution in big data. However, fundamental issues exist that need resolution. First, the majority of data is only minimally accessible and is unable to be mapped to data from other domains of a manufacturing enterprise. For example, how does raw data collected from a sensor embedded in a jet engine gets mapped to the machine tool operation which machined the blades or the shaft of the engine? A mapping of this type would require a human-in-the-loop to carry out the association based on a tedious study of the part serial number, then a review of the records for the manufacturing process, then the machine tool reporting logs, and finally then a hand-generated mapping to the machining of the feature in question. Reliance on a human-in-the-loop presents the following issues: it is a tedious process of high cognitive

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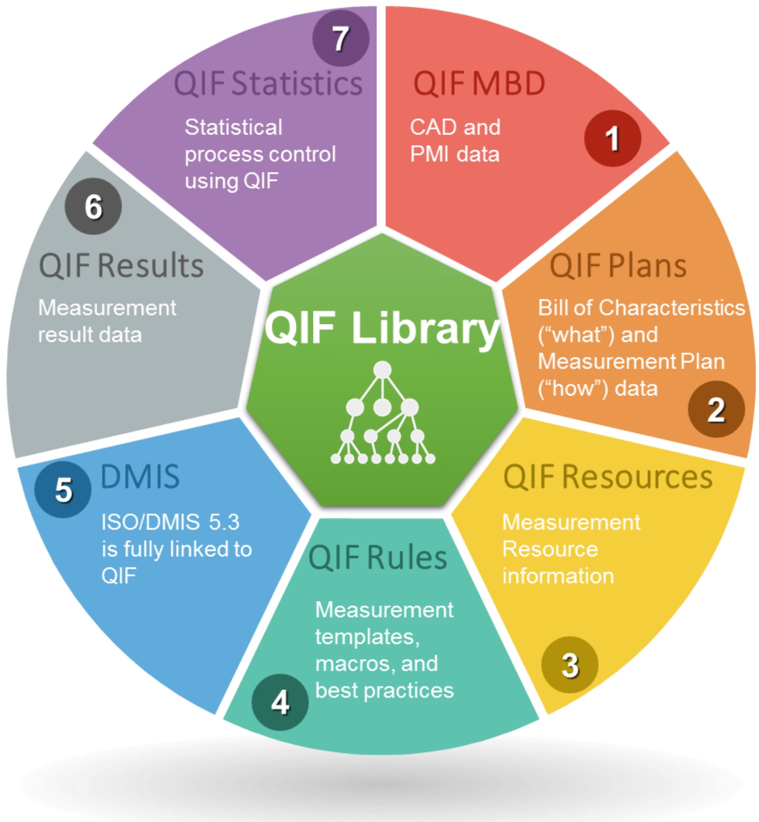
load which introduces errors, it is costly, it is not an efficient use of engineer's time, and it prevents software algorithms for automatically mining the data for meaningful patterns and anomalies. A second fundamental problem faced in the field of industrial big data is the inaccessibility of the different data formats encountered. Data is stored in a variety of file formats (e.g., PDF, TXT, TIF, CSV, XLS, STEP, JT, IGES, PRT, QIF, XML, etc.). Some of these formats are proprietary, and require costly software tools to access the data. Other formats are common for archival, but are of minimal utility for software data mining (e.g., a coordinate measuring machine (CMM) inspection report stored in PDF format). Therefore, the issue of non-robust data formats prevents industry from easily connecting troves of data to the digital thread.

THE QUALITY INFORMATION FRAMEWORK (QIF)

The Quality Information Framework (QIF) was created by a group of manufacturers, software and hardware vendors, and metrology experts within the Digital Metrology Standards Consortium (DMSC) as a response to this dilemma. QIF is a feature-based ontology of manufacturing metadata, built on XML technology, with the foundational requirement of maintaining traceability of all metadata to the "single source of truth" – the product and all its components as defined in CAD/MBD. It is an open, ANSI standard which includes support for a complete semantic derivative Model Based Definition (MBD) model, measurement planning information, and measurement results information. This characterization allows users to establish a Digital Twin by capturing the duality of aspects of manufacturing data: the as-designed product, and the as-manufactured product – including the mappings between the two aspects.



The full listing of the application areas of QIF are as follows:

QIF MBD	Derivative model with support for robust, semantic PMI, metrology features, and mappings back to the native model
QIF Plans	Typically considered to be the "Bill of Characteristics" (that which will be measured) and the Measurement Plan (how it will be measured – at a high level)
QIF Resources	Specification of available measurement resources (e.g., CMMs, calipers, scanners, gages)
QIF Rules	Measurement "templates", macros, organizational best practices for measurement, etc.
(DMIS)	DMIS is *not* a part of the QIF standard, and addresses a much lower level of technology. However, harmonization between DMIS and QIF has been built into the latest DMIS release to allow for full traceability to the authority CAD model from a DMIS program – enabled by QIF data traceability
QIF Results	Measurement result data
QIF Statistics	Statistical process control methods and outcomes

The primary benefits of QIF can be thought of relative to the direction of data flow to and from the “single source of truth” (CAD): downstream benefits from CAD (particularly the manufacturing and quality validation processes), and upstream benefits back to CAD.

DOWNSTREAM BENEFITS OF QIF

Modern manufacturing is heavily reliant on *process*. A large manufacturing enterprise is made up of thousands of engineers, each with their own field of expertise. In addition, it is common for *well more than 80%* of manufacturing to take place externally to an OEM as a first-tier supplier, second-tier supplier, or even farther up the supply chain. For a system of such complexity to function efficiently, a strict and rigorous process must define interactions and workflows. Therefore, an OEM’s capability to produce both a high-quality product at a minimum cost and their ability to measure key performance indicators, is directly tied to the structured process for their manufacturing operations.

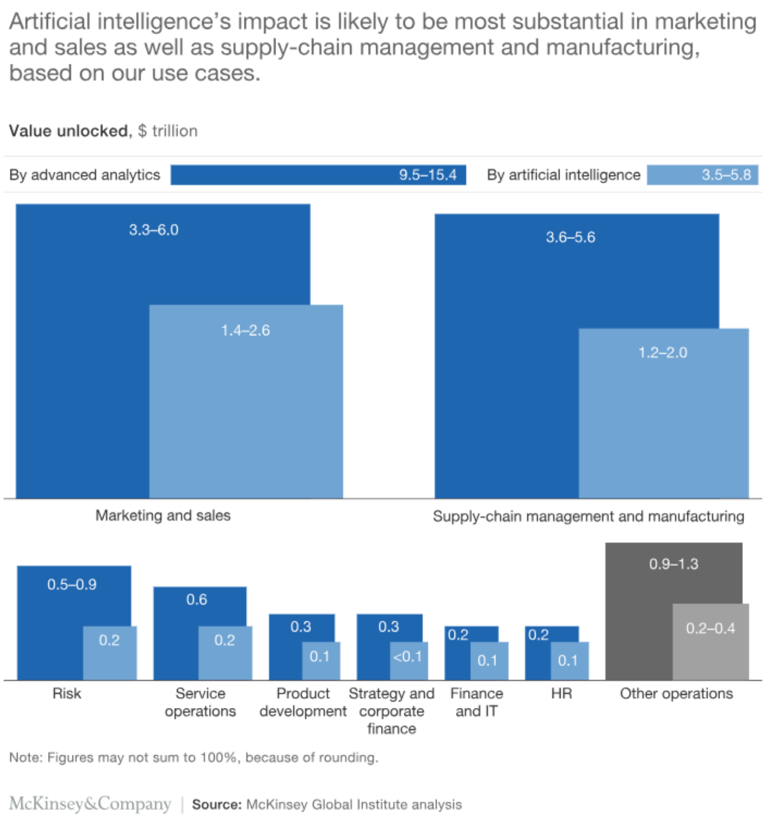
Current processes in the metrology domain are heavily reliant on a human-in-the-loop, which runs counter to the idea of automated process-driven manufacturing. To the extent that an engineer is needed for translation, interpretation, or re-entry of data, the knowledge and practices of that individual will play a large role in the result, leading to arbitrary outcomes and the likelihood for introduction of errors arising from a lack of standardization. (In addition to this, these are hardly tasks which require the types of innovation for which an engineer is best suited, making it a waste of time). An example of this type of inefficiency in metrology is the predominance of the 2D static drawing. The typical process for creating a CMM program, for example, is to load a *shape-only* derivative model with *unknown pedigree* into the CMM software, and then *manually* confirm that the model matches the 2D drawing and then *manually* enter the GD&T information from the 2D drawing into the CMM software. This is time consuming, error prone, and leaves space for interpretation by the operator. This is why the ability to transmit this GD&T data directly and semantically from the CAD model’s PMI is such a crucial feature of QIF: it ensures that data stays intact throughout downstream systems, helping to add structure to a manufacturing process.

In addition to the basic value of adding structure to a process, this XML-based approach can be leveraged to drive automation of software and cyber-physical systems. In a pilot study carried out at Raytheon, a comparison of an MBD-based process, powered by QIF, was compared to a traditional 2D drawing based workflow. In this study, it was determined that a QIF approach reduced the amount of time needed to create CMM programs by more than 80%. Another benchmark study conducted by Rockwell Collins and NIST found nearly 90%-time savings. We expect to see more software automation along these lines as the industry becomes more and more accustomed to MBD.

UPSTREAM BENEFITS OF QIF

The “upstream” benefits of QIF are derived from the quality of the data for analysis. That’s why a critical design objective of QIF is that the data should be *structured*. QIF is a highly organized grammar and vocabulary for software systems to communicate manufacturing data structures. With software interoperability as the goal, and vendors and end-users available to verify (through both pilot studies and production-system deployments), QIF was put under the ultimate stress-test that the data is truly *semantic*. Another important design objective is data traceability to the authority product definition model. Each piece of metadata in a QIF dataset is mapped to the owning GD&T, feature, and model surface in the authority CAD model. This high-resolution mapping to the “single source of truth” ensures that any other data derived from the model can be traced through a graph to the mass of QIF data. This is why QIF matters beyond just metrology: it provides the mapping to metrology data for the entire Model Based Enterprise.

Ultimately, data must be structured and connected to other key data (i.e., the authority model) in order to make it ideal for advanced analytics, artificial intelligence (AI), and data mining. Imagine, as an exercise, a terabyte of ".DAT" files with raw data dumps from a machine tool or CMM. While there is certainly a large amount of data present, there is little *context* to the data, so it is of relatively little value.



The value added to industry from the growing fields of AI and advanced analytics are expected to rise sharply over the next few years. According to a McKinsey Global Institute study: "*We estimate that the AI techniques we cite in this briefing together have the potential to create between $3.5 trillion and $5.8 trillion in value annually across nine business functions in 19 industries. This constitutes about 40 percent of the overall $9.5 trillion to $15.4 trillion annual impact that could potentially be enabled by all analytical techniques*". Of all the sectors examined by this study, supply-chain management and manufacturing sector received the second most benefit – for a total estimated value of somewhere between $4.8 and $7.6 trillion.

The prerequisite to realize this value is structured and mapped data. QIF's robust semantic nature, and its strong mappings to the authority model make it a rich target for this type of advanced analytics and feedback to design.

QIF ROADMAP FOR SUCCESS

The DMSC has adopted a depth-first approach to ensuring the continued viability and further success of the QIF standard. Below are some of the pillars of the DMSC's approach to the propagation of the QIF standard.

Continued development of QIF schemas

The software vocabulary and grammar of QIF is defined by the QIF XML Schema Definition Language (XSDL) schemas. These schemas are at the core of what define QIF. The quality of the schemas is of the highest importance to the DMSC. The QIF Working Group is actively attended by influential members of large industrial end user organizations, software and hardware vendors, and prominent academics. Their constant input and effort are what ensures that QIF is capable of transmitting data from real-world manufacturing workflows, and that QIF meets the needs of industry. QIF is currently deployed in production systems and pilot projects in a wide range of manufacturing sectors, and this real-world feedback has been instrumental to ensuring that QIF has the capabilities required by industry. In addition, QIF has opened up research opportunities within the digital thread that will allow for more innovative transformation of the manufacturing space in the future. These priorities will remain at the forefront of the DMSC's priorities.

Data integrity

In this age of data, the questions of data trustworthiness and provenance are paramount. In order for QIF to reasonably fit into the larger picture of Model Based Enterprise, the DMSC has put a large amount of effort into addressing these questions. At a high level, there are three primary pillars to QIF's approach to these data quality: XSD validation, XSLT integrity checks, and digital signatures.

XML Schema Definition (XSD) validation is a test where a QIF instance file is checked for validity to the QIF digital "language" defined in the QIF schemas. This test ensures the interoperability of QIF data from one software system to another. This basic validation gate is the most basic and fundamental check to ensure connectivity of QIF data to MBE at large. Future plans for DMSC propagation of this validation testing includes the release of a free, publicly accessible tool that will make QIF instance file validation extremely easy to end users.

Extensible Stylesheet Language Transformations (XSLT) is a Turing-complete language for processing XML files. Included with QIF is a set of XSLT scripts which are capable of carrying out integrity checks on QIF instance files that are not possible with a simple XSD validation test. A few types of checks currently exist. There are checks to ensure the validity of the structure of the data itself (e.g., making sure that links to external IDs in other documents truly exist, or ensuring that the number of elements contained in a set is correct). There are checks to verify the quality of the data contained in a QIF files (e.g., the quality of a NURBs surface contained in the file). And finally, there are checks to examine the semantics of the data contained in a QIF file (e.g., that a Feature Nominal should have a geometric definition). These checks help to ensure the integrity of the data and assure its usefulness and reliability within the enterprise at large.

Finally, QIF has the ability to control the provenance of the data via digital signatures. This infrastructure helps to ensure that QIF instance files can be imbued with the trust necessary to use it throughout the product lifecycle. NIST has developed an open source toolkit which is capable of creating digital signatures for manufacturing data, and future DMSC efforts will propagate the use of digital signature on QIF instance files by providing sample workflows and how-to documentation on adding digital signatures to QIF instance files.

Integration with current and emerging digital standards

Several of the manufacturing processes are defining digital information appropriate to the semantic and flow requirements of each process. For example, efforts are underway to integrate QIF with the MTConnect specification (mtconnect.org) for certain manufacturing systems, including machine tools and in-process verifications. Furthermore, robotic systems are being increasingly used in manufacturing operations for inspection operations, and certain digital standards (e.g. ROS-Industrial (rosindustrial.org)), will need to be integrated with QIF.

Facilitate software development for QIF

For the propagation of QIF data throughout a manufacturing enterprise to be successful, it is crucial that key software systems be able to "speak the language" of QIF. This is a problem that is faced by any emerging standard data format. Software and custom scripting are becoming more and more common every day, and most recent college engineering graduates have some form of experience with software programming. For this reason, the DMSC has made implementation of support for reading and writing QIF files easy with source code bindings for C++, C#, and Python. These are freely available and open source. Within a matter of a few hours, a developer can be quickly transferring software data structures to and from QIF instance files. With this capability, it opens up the door to an array of opportunities: software vendors can quickly prototype a QIF implementation to understand its capabilities, software vendors can build formal support for QIF with minimal effort, and even end users can write their own code to carry out data mining of a QIF data lake in a high-level scripting language like Python. These source code bindings have helped ensure that QIF is fully immersed in the economy of software tools being used throughout the digital thread for manufacturing. In the future, expect more robust software bindings, examples files, and tutorials from the DMSC.

Free open source tools for QIF

The DMSC plans to help the QIF user community by providing free and open source tools for creating and editing QIF Resources and QIF Rules instance files. These particular types of instance files stand apart from QIF MBD, Plans, Results, or Statistics files in that they are a bit more static in nature than data pertaining to a specific model, serial number, or batch of parts. Generally speaking, Resources and Rules instance files would be created by an organization to be consumed by QIF-enabled software, and would not be heavily modified or updated. For this reason, in the future we will see open source tools for authoring and editing QIF Resources and Rules instance files made available to QIF users and software implementers.

QIF community

The active QIF community has been a pillar of the continued success of QIF. Organized through the DMSC, the QIF community is led by the foremost experts in digital metrology in industry. This community is passionate about digital metrology and QIF, and has banded together to advance the digital exchange of data throughout enterprise via QIF. Members of the QIF community come together to cross-pollinate with QIF implementation and workflow ideas, with mutual support for Model Based Enterprise journeys, future QIF implementation and direction, and general community. This community is active on the internet, in bi-weekly DMSC meetings, and in in-person working group and social events. This community passion, coupled with DMSC outreach efforts on behalf of QIF, are what has helped to catapult QIF's success.

CONCLUSION

The tapestry of software systems, hardware, data formats, and people that make up a Model Based Enterprise is a massive and complex ecosystem. Metrology – the domain of a manufacturing enterprise which by its very nature gathers the most high-quality data related to a manufactured good – is a key part of this tapestry. This is why QIF is essential. The roadmap for QIF is to ensure that it fits into the Model Based Enterprise at large. This requires that is has both a goal to address the vertical requirements (a semantic ontology of metrology data which truly reflects industry real industry workflows), and a goal to address the horizontal requirements (connectivity and trustworthiness of QIF data within the larger context of a Model Based Enterprise). With these goals in mind, expect to see QIF fill a crucial role in the product lifecycle management regimes of a Model Based Enterprise.

BIBLIOGRAPHY

Herron, J.; Brown, C.; Campbell, D. (2018). QIF: Quality Information Framework. What is ANSI QIF? An Overview. Dimensional Metrology Standards Consortium (DMSC). NIST MBE Summit 2018.

Frost Perspectives. (2017, January 19). Big Data in Manufacturing. In Frost & Sullivan. Retrieved 21:10, January 2, 2019, from https://ww2.frost.com/frost-perspectives/big-data-manufacturing/

Bergsma, B.; Campbell, D.; Nielsen, M. (2018) CMM Automation from MBD: A case study of optimized Model Based Inspection. NIST MBE Summit 2018.

Chui, M. et al. (April 2018). Notes from the AI frontier: Applications and value of deep learning. In McKinsey Insights. Retrieved 16:00, Dec 21, 2018, from https://www.mckinsey.com/featured-insights/artificial-intelligence/notes-from-the-ai-frontier-applications-and-value-of-deep-learning

Hedberg, T. *Enabling Connections in the Product Lifecycle using the Digital Thread* PhD diss., Virginia Polytechnic Institute and State University, 2018. Web. November 2018.

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A Need for Digital Enterprise Workforce Development

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ABSTRACT
As model-based definition (MBD) becomes prevalent throughout the enterprise, the need to educate both new hires entering the workforce and those who author and consume traditional product definition is critical. A tactical education and training plan is essential to the success of MBD adoption. Workforce development for MBD adoption within an enterprise requires three phases: 1) Establishing literacy 2) Building practitioners 3) Establishing mastery. As an organization moves its people through these phases of awareness, competency, and mastery, not only are training programs required but a strong communication ramp-up is also needed to bolster the enterprise knowledge. Challenges in current practice will be highlighted as they relate to establishing a successful MBE workforce.

A Future State of Digital Manufacturing

According to numerous studies [1, 2, 3] somewhere around 2025, the typical U.S. worker will have around 20% of the information they need to do their job created and delivered to them by a machine, likely some type of computer with some form of artificial intelligence (AI). Near that same time period, the world will experience over 35 billion things connected to the Internet. Living in such a connected world will no doubt have an influence on how people work, as well as how they are prepared for such work. A very good example of this playing out before our eyes today is in the U.S. manufacturing sector.

According to many of those same studies, the U.S. will have likely experienced the creation of roughly 3 million manufacturing jobs that do not exist today by 2025, and will still have roughly 2 million unfilled jobs that have been digitally transformed to require a new skill set. This scenario will create even more strain on an already burdened labor market in manufacturing [4,5]. When the strain on the existing workforce is coupled with new models of working, such as a borderless workforce and non-hierarchical organizations, and the design and manufacture of wearable products and continuously connected, intelligent devices, and one can see that an entirely new ecosystem of work is developing. One for which our current education systems and methods have but minimal preparation. Current life expectancies in developed countries point to a person born today living to be nearly one hundred years old. How do we educate a person born today to exist in a world where they not only change jobs multiple times, but potentially change *careers* multiple times as technology advances? Demand for skills of the head (cognitive), have dominated those of the hands (technical) and to a lesser extent, those of the heart (social) over the past 300 years. In the future, those skills shifts are about to go into reverse. During the first three Industrial Revolutions, the skills workers needed to keep ahead of the machines were largely cognitive. Machines were doing manual tasks and cognitive tasks were the exclusive domain of humans. However, with the rise of social networks, AI, and the digitalization of information, Industry 4.0 threatens to change the balance of power in what had been exclusively the human's cognitive domain.

By most accounts these days, the manufacturing sector in the U.S. is doing well, even with the recent downturn in the automotive vertical. However, it is difficult to pick up a newspaper without reading something in it about

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the challenge companies are facing when trying to fill their open jobs in manufacturing [6]. According to numerous recent studies by the likes of Gartner, Deloitte, McKinsey and others, the current manufacturing output is high, but the future looks a bit bleak. Not necessarily due to competition with low-labor cost countries or due to some governmental policy per se, but to a lack of a skilled workforce coupled with rapid technological change. When reading the contemporary literature about these phenomena, most authors peg the shortage between three million and six million manufacturing workers by 2027. Regardless of the cause, even if it is "fixed", it will not likely address a more fundamental trend in the U.S. that has been ongoing for many years – people choosing other career fields over manufacturing. But before diving into a discussion about education and workforce development, let's look briefly at the technological transformation at the heart of this predicament in which we find ourselves.

Most of us grew up learning about *the* Industrial Revolution – the *mechanization* of work to ease the load on human beings and to increase their efficiency. However, what many people may not be aware of is we have had several industrial revolutions over the last two hundred years. Industry 1.0 began with the mechanization of work, which led to the *electrification* of work during Industry 2.0 in the late 1800s and early 1900s. In the early 1960s, electrification of work gave way to the *automation* of work with the rise of personal and industrial computing to create Industry 3.0. And as those technologies became commonplace and we saw the use of data begin to increase, we have arrived in the 2010s to Industry 4.0 – the *digitalization* of information to support the intelligent automation, and computing backbones that have been built. Not only are we on our fourth industrial revolution, but the elapsed time between the revolutions has been substantially decreasing, somewhat analogous to Moore's Law and the clock speed of computing over the years. It gets faster and faster in shorter periods of time.

In parallel to the technological gains in efficiency, accuracy, and sustainability that the manufacturing sector finds itself experiencing today, it is struggling to transform its workforce. For every industrial revolution the world has seen, there has been an accompanying educational revolution. In the U.S. and Europe, those transformations came in the movement away from the master/apprentice model (Education 1.0) to the movement around Manual Arts and Industrial Arts (Education 2.0), which focused on basic job skills for the growing mass production economy. Over the 20th century, we saw the move towards Technology Education, with its focus on domain-specific content areas and a systemic view of technology as a discipline in and of itself (Education 3.0). The current education transformation relative to manufacturing is now focused on design thinking and a 'system of systems' view (Education 4.0) of developing and implementing technology, and using digital data to assess, diagnose, and implement solutions to problems.

Yet, if we have had parallel revolutions between industry and education, why does the manufacturing sector find itself with such a shortage of skilled workers, and how might we begin to address this shortage? The remainder of this article will focus on those questions, and while there are certainly issues such as politics, global economics, family and social dynamics, and personal preferences at play here, those are not specifically within the scope of the current discussion at hand. The current discussion will primarily be focused on how we can adapt our Education 4.0 revolution to better address the needs of the manufacturing sector of our economy.

The dawning of technologies such as AI means that humans will no longer have the cognitive playing field completely to themselves. Machines will be able to process more quickly, more cheaply and with fewer errors than their human counterpart, at least in some activities. While this could lead to the hollowing-out of human tasks, now cognitive as well as manual, at a far greater rate than ever before, it could also present future opportunity for jobs that relate to the designing, developing, and maintaining of intelligent systems [7]. So what do humans have left? What should we prepare our students and evolving workforce for? Students must be exposed to and become proficient in multiple modes of problem solving; cognitive tasks requiring creativity and intuition to solve tasks or problems whose solutions require great logical leaps of imagination. There will remain a demand for skills to program, test and oversee machines. Personalized design and manufacturing will become more common as the information needed to customize products for individuals is more readily available. A student's ability to use their social skills to execute, and when necessary, lead tasks that require emotional intelligence rather than cognitive alone. Preparing graduates solely for cognitive skills will not be enough for the 4th Industrial Revolution.

Educating the Workforce

We must build upon the traditional literacies of reading, writing and mathematics [8,9]. Students must still be able to take in information, assimilate it with what they already know, and form a conclusion. They must still be able to understand the physical and temporal phenomena expressed by modern mathematics and science. However, we must move them past simply assimilating and synthesizing information and towards interpretation and systematic decision making based on that information synthesis. New types of literacy might include:

- **Data literacy**: the ability to read, analyze and apply information. Advanced data gathering and analytics tools will seek to act on the user's behalf when presenting highly visual information. It will be incumbent on our students to know how to *apply* that information to their problem.
- **Technological literacy:** coding and engineering principles. Technologies have been created and used since the beginning of human kind, which is arguably one of the things that separates humans from their ancestors. Yet the new incarnation of technological literacy will be one that sees our students able to incorporate intelligence into their physical tools and objects they design and build.
- **Human literacy**: humanities, communication and design. Our ability and willingness to connect to fellow human beings through, and in spite of, our technologies will become increasingly important. Solving complex problems will not only need the rational theorems and postulates of our mathematical techniques, but the empathy that comes from being human, as we have yet to develop a computing technology with the human capacity to assimilate, interpret, and *feel*.

Not only do we need to develop in our students these higher-order literacies based on digital tools and information and higher-order *mindsets* and ways of thinking about and viewing the world, we must also do that within the incumbent (existing) workforce. We must encourage them to embrace systems thinking; not necessarily the abstract mathematical representations of it, but the Gestaltist [11] view that yields the ability to view an enterprise, machine or subject *holistically*, making connections between different functions in an integrative way. The manufacturing sector will not have the luxury of displacing or replacing all of its existing employees. Manufacturing employees must also become culturally agile, as physical and geographic borders become increasingly irrelevant in an age of global commerce and the economic viability of singular customers, and supply networks become increasingly complex. To accommodate such a transformation in the manufacturing paradigm, a product and process information set must be sufficiently sophisticated, encompassing not only explicit definition and meaning, but implicit and semantic details as well. Doing this will require the creation of digital product and process definitions that are built on sound fundamentals of geometry creation, materials and process definition and capture, and coherent Product Manufacturing Information (PMI) schemas that eliminate ambiguity. The following sections of this paper outline specific details for accomplishing sound MBD creation.

Current Practice Challenges

Today CAD training is just that, pick and click CAD training. It is missing the data and human aspects of Model-Based Definition (MBD) that can be leverage throughout a Model-Based Enterprise (MBE). It is essential that not only do we teach how to use the tools, but that we also teach the most efficient methods to not only author, but to also understand and consume these MBE technologies to increase communication.

Humans and MBE technology intersect at comprehension of:

- The Fundamentals of MBE
- CAD Re-use and Interoperability
- Unambiguous Product Definition

The Fundamentals of MBE

Engineers entering the workforce have typically not experienced how engineering data is connected through the digital thread to the rest of the enterprise and the effect that engineering data may have on seemingly unrelated areas of operation. Realistically, today, this knowledge is gained through personal experience, on-the-job training, and mentorship over the first two to four years of employment.

Each education level then builds on MBE awareness topics and transition into building literacy through exposure to details in process, standards and tools. Certificate programs can cover concepts as well as tool knowledge around CAD systems and other product data authoring systems, while more general training can focus on CAD agnostic standards and processes. This approach builds a bridge between general literacy and domain-specific competency. At a competency level, workers can dive into the specific CAD systems, MBD applications, and common digital data consumptions tools, to engage with the problems specific to their own functional area. Mastery comes when students not only apply tools and methods to their specific area, but when they combine their deep domain competency with broad organizational knowledge to implement solutions to both specific and broad problems. Figure 1 illustrates a sample model of how MBE understanding can be built with stackable credentials.

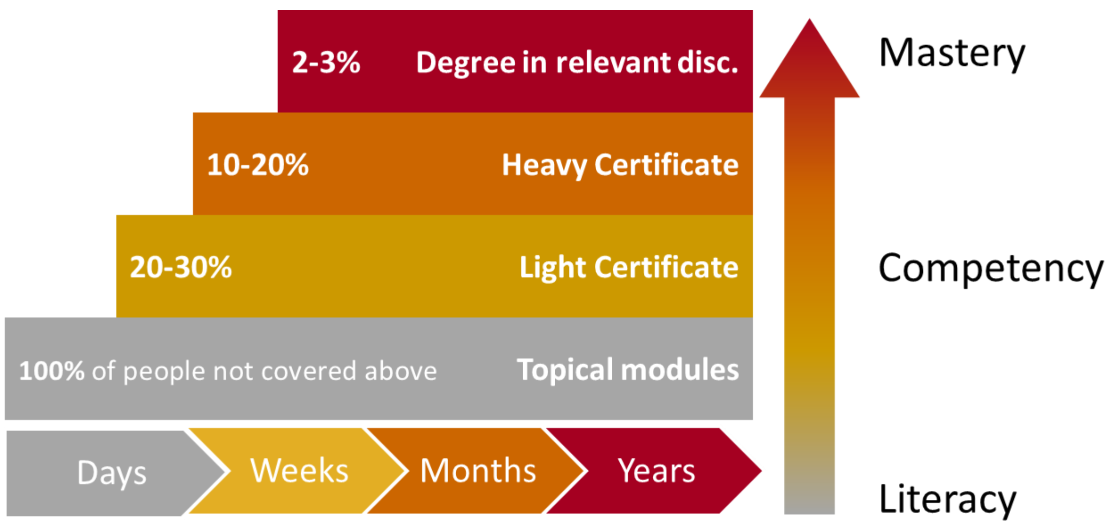

Figure 1: Sample education structure for MBE training and development

A more general structure of job-specific training credentials is shown in Figure 2. Macro credentials are options such a traditional degree or courses. Micro credentials could be traditional courses, but they are most commonly industry-specific training courses. Nano credentials are often focused on specific topics, such as MBD, PLM, or other topics. They are often done in a continuing education approach, with appropriate credits or badges awarded. Pico credentials are also typically dedicated to a specific topic, but in a more detailed way, such as surface modeling for airfoils or applying tolerancing to injection-molded plastic parts. As shown in Figure 2, one of the most obvious differences between these levels is the time scale, with Macro credentials often measured in days or weeks and Pico credentials often measured in singular hours.

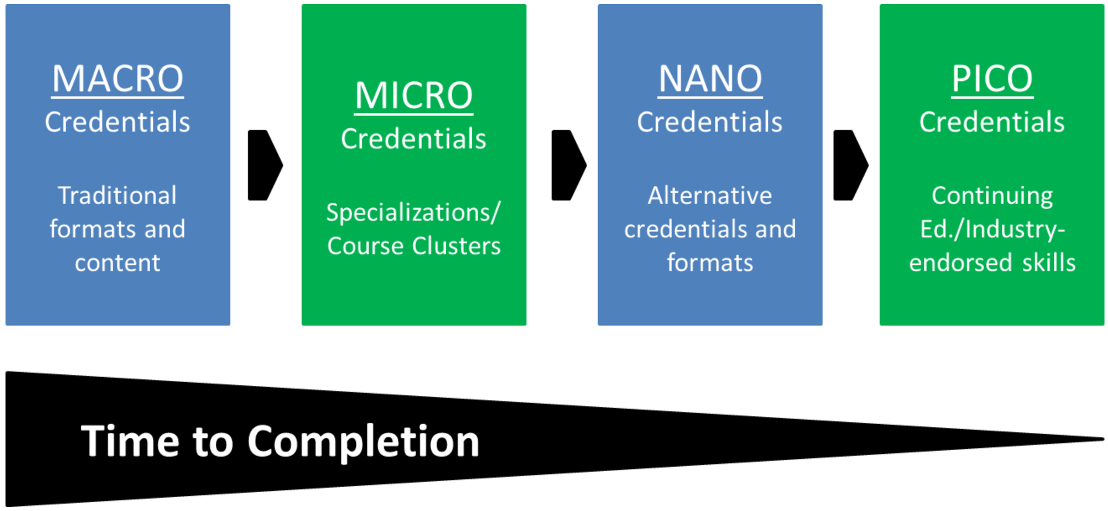

Figure 2: General model for stackable skills

CAD Data Reuse and Interoperability

Many engineers and designers rightly understand CAD data as a communication tool for design intent. However, the nuances of the consumption of CAD data in other areas of the enterprise including manufacturing, inspection, and quality functions to name just a few are often left unexplored. Well defined CAD models are required to gain the full benefit of CAD data reuse as it is woven into the digital thread of information. Good quality models (includes geometry, annotations and attributes will prevent data failures and tooling clashes as data is translated into various formats required for suppliers to utilize its data. This knowledge is gained through experience, usually at the expense of scrapped parts, CAD rework, and project over-runs which all require valuable time resulting in increased product costs which negatively impact the bottom line.

Unambiguous Product Definition

The traditional methodologies of capturing product information through manual application of GD&T on a 2D drawing, intended for human interpretation and human consumption only drives ambiguity into the product definition. Misinterpretation of the information and manual programming of the information to devices that automate the manufacture and inspection of the products is an opportunity to avoid human mistakes. Understanding how to disambiguate design intent through a more modern GD&T scheme that is sematic, enables shared input of engineering data by all involved parties in the product's life-cycle from the beginning, allowing for concurrent engineering and efficient reuse of the design, therefore reducing non-conformances which results in lower cost. CNC, Additive Manufacturing, and other computer-based machines able to directly consume 3D geometry consume the PMI directly from the solid model eliminating the need for visual annotation.

Conclusion

Having a well-educated workforce, able to take advantage of the rich information in a Model-Based Enterprise, will make U.S. manufacturers a more competitive and desirable option to compete with growing overseas companies. Educating through the MBD and MBE knowledge gap will increase the data, technology and human literacy available within the workforce, and provide experienced levels in industry that are innovative and efficient. The manufacturing sector, and the education system that supports it, cannot hide from these technological changes. It would be like trying to away from a tsunami; we will eventually be overtaken. The educational community must embrace these changes, engage with the manufacturing sector, and adapt our respective curricula to meet the needs of a future and a transitioning workforce. The manufacturing sector must be willing to engage with academia and provide its challenges, use cases, and desired outcomes in a compelling manner. By doing so, we can provide the manufacturing sector with the workforce it needs, and we can provide the manufacturing workforce pipeline some sense of stability in an otherwise rapidly advancing future.

References

1. Giffi, C.A., Rodriguez, M.D., Gangula, B., Michalik, J., de la Rubia, T.D., Carbeck, J., and Cotteleer, M.J., 2015). *Advanced technologies initiative: Manufacturing & innovation.* Retrieved from https://www2.deloitte.com/content/dam/Deloitte/us/Documents/manufacturing/us-indprod-deloitte-and-council-on-competitiveness-advanced-tech-report.pdf
2. Pajula, S., Wellener, P. and Dollar, B. (2018). *2018 manufacturing skills gap study.* Retrieved from https://www2.deloitte.com/us/en/pages/manufacturing/articles/future-of-manufacturing-skills-gap-study.html
3. Bhens, S., Lau, L., and Sarrazin, H. (2016). *The new tech talent you need to succeed in digital.* Retrieved from https://www.mckinsey.com/business-functions/digital-mckinsey/our-insights/the-new-tech-talent-you-need-to-succeed-in-digital
4. Ezell, S.J. (2018, April). *Why manufacturing digitalization matters and how countries are supporting it.* Information Technology & Innovation Foundation.
5. Ezell, S.J., Atkinson, R.D., Kim, I., and Cho, J. (2018, August). *Manufacturing digitalization: Extent of adoptions and recommendations for increasing penetration in Korea and the U.S*. Information Technology & Innovation Foundation.
6. Hendrickson, C., Muro, M., and Galston, W.A. (2018, November). *Countering the geography of discontent: Strategies for left-behind places.* The Brookings Institution. Retrieved from https://www.brookings.edu/research/countering-the-geography-of-discontent-strategies-for-left-behind-places/
7. Husain, A. (2017). The sentient machine: The coming age of artificial intelligence. Scribner: New York. ISBN: 978-1-5011-4467-7
8. National Academies of Sciences, Engineering, and Medicine. 2017. *Building America's Skilled Technical Workforce*. Washington, DC: The National Academies Press. doi: https://doi.org/10.17226/23472.
9. Giffi, C.A., Dollar, B., Gangula, B., and Rodriguez, M.D. (2015). *Help wanted: American manufacturing competitiveness and looming skills gap.* Deloitte Review issue 16. www.deloittereview.com.
10. Wikipedia https://en.wikipedia.org/wiki/Gestalt_psychology
11. ASME Y14.41-2013

GEOMETRIC APPROACH FOR EVALUATING MANUFACTURABILITY OF PARTS PRODUCED WITH INJECTION MOLDING AND DIE CASTING

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ABSTRACT
Cost and time reduction of mold and die production is a critical issue for any manufacturing company. Machine part designers are not always manufacturing experts; therefore, they often design parts with various problems for manufacturing using injection molding and die casting. These problems are usually detected by manufacturing engineers in later production stages. Problems are reported to the part designer, and they are resolved by modifying the part shape. The reduction of such reworks would aid the efficient production of the mold and die and, consequently, efficient part production. In this work, a software system, named "manufacturability assistant", that reduces the number of reworks is explained. This system detects the shape elements of a part with potential manufacturability problems by applying various shape extraction procedures to the computer-aided design model of the part. By using this system, designers can evaluate the quality of apart from the perspective of manufacturability. They can reflect the evaluation result in the part design to obtain a part with higher manufacturability.

INTRODUCTION

Most component parts of a mechanical product are fabricated using injection molding and die casting. In the automobile industry, six months are generally required to prepare all necessary molds and dies for producing the parts. Cost and time reduction of mold and die production is a critical issue for any manufacturing company. Figure 1 illustrates a typical production flow for the mold and die. In the design department, shape information and other engineering information regarding a part is defined as a computer-aided design (CAD) model. Model data are transferred to the tooling department where molds and dies for mass production of the part are fabricated.

Part designers are not always manufacturing experts, and their knowledge of machining, injection molding, and die casting may be limited. Therefore, they often design a part with manufacturability problems. A typical problem is to design a part for which it is difficult to fabricate molds for producing them — for example, a part with many undercut shapes or a part with deep slots. Another problem is designing a part with potential defects in the molding result, such as sink marks or short shots of the plastic part.

These problems are usually detected by manufacturing engineers in the process planning, computer-aided manufacturing (CAM), or trial production stages. Some of them are resolved in the tooling department by modifying the mold and die CAD models. Serious problems are reported to the part designer and resolved by modifying the part shape. These reworks require a lot of time and have a high cost. Reduction of the reworks is important for realizing efficient production of the mold and die and, consequently, efficient machine part production.

MANUFACTURABILITY ASSISTANT

In this work, a software system that reduces the number of reworks, named "manufacturability assistant, is explained. Figure 2 illustrates the concept and functions of the manufacturability assistant. This system is developed as a supporting tool for the interactive shape-defining process by a machine part designer. At any moment in the design process, the designer can invoke the assistant to check the part shape for potential manufacturability problems. The designer can improve the part shape according to the detection result.

Some manufacturability problems can be detected by using numerical simulation systems. For example, mold flow simulation is helpful for detecting potential molding defects, such as short shots. Some machining difficulties can be detected by using numerical control (NC) milling simulation software. These simulation systems are, however, not useful as supporting tools in the interactive design process because of the long computation time. To use the systems, it is necessary to input various parameters concerning the simulation conditions appropriately. Such a setting task becomes a burden to a busy designer with limited manufacturing knowledge.

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To be a user-friendly system for the machine part designer, the manufacturability assistant must process at a high speed, and it must be free from troublesome parameter setting.

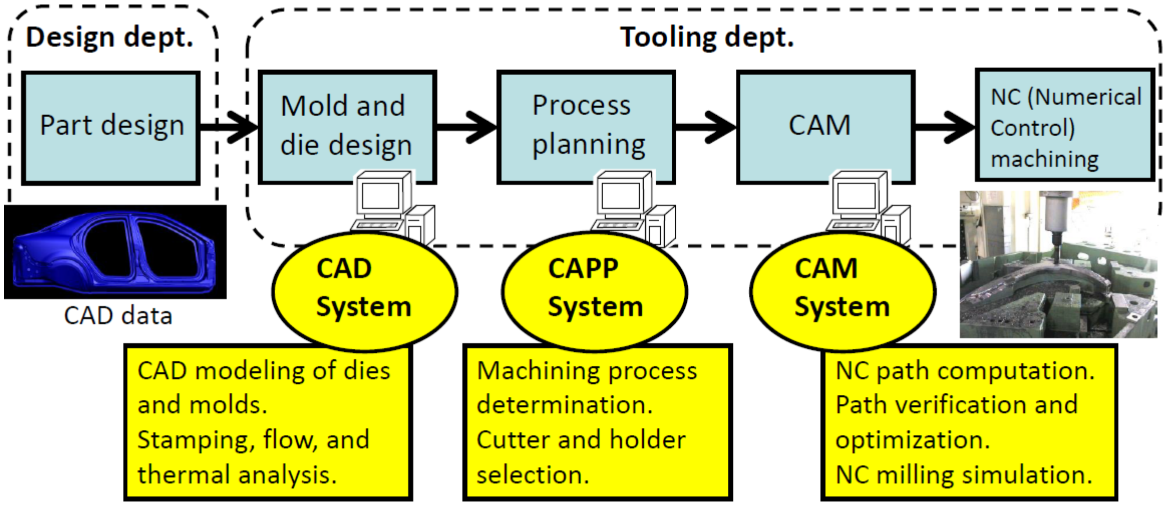

Fig. 1. Typical manufacturing process of molds and dies

Through field studies of many manufacturing companies in Japan, it is found that machine part CAD models designed by experienced designers generally need fewer reworks. Because experienced designers have more empirical knowledge of the shape elements and their arrangements that tend to cause manufacturing problems, they carefully avoid defining such problematic shapes in the design. Based on this consideration, software systems have been developed for detecting shape portions that will cause manufacturing problems. The manufacturability assistant is not a monolithic software, but it is a package of software subsystems for detecting various problematic shapes in a part, as shown in Figure 2. By using the systems, designers can evaluate the quality of a part from various manufacturability viewpoints. They can reflect the evaluation result in the part design to obtain a part with higher manufacturability.

Subsystems for manufacturability evaluation are constructed on a common geometric modeling system, which is a hybrid system of a boundary representation modeling system and a dexel-based modeling system [1]. This system provides the display functions, file input/output functions, and some geometric processing functions, such as offsetting, Boolean operations, cutting operations, and object's thickness evaluation. Most functions of the geometric modeling systems utilize the parallel-processing capability of a graphics processing unit (GPU) for accelerating the computation. The manufacturability assistant detects shape elements with potential manufacturability problems by applying various shape extraction procedures to the geometric model of the part. These procedures are implemented by using the functions provided by the geometric modeling system.

The development project for the manufacturability assistant software started in 2008. The first function of the assistant was a cutter accessibility analysis of the mold part for detecting cutting-difficult shapes in the part. Since then, more than ten functions have been developed for extracting various form features with potential manufacturability problems. In a prior work [2], the overview of the manufacturability assistant software and three functions of the system was explained. In the present work, two new functions of the system are described: an undercut detection function and a visualization function of the sink marks of a plastic part.

RELATED STUDIES

The manufacturability evaluation of the mechanical part was actively studied in 1990s [3]. Application of the knowledge engineering method, some scoring methods of the machining easiness of features based on the template knowledge, evaluation of the machining cost based on the removal volume of the workpiece and cutter path length, and a manufacturability evaluation by diverting the assemblability evaluation technique are known. The target part of the prior works was a simple prismatic part with slots, steps, and pockets. Manufacturability relating to the molding or casting were not studied. Detection of problematic shapes can be recognized as a type of form feature extraction. Form feature extraction has been a classic topic in the CAD of the mechanical product.

Some approaches are known for extracting the form feature from the 3D CAD model, including a grammatical approach for parsing the solid model of a part, a graph-matching-based approach, a convex-hull-decomposition-based approach, and an artificial-intelligence-based approach employing expert systems. These methods generally extract the features by applying a predefined rule to the surface or volumetric elements of the CAD

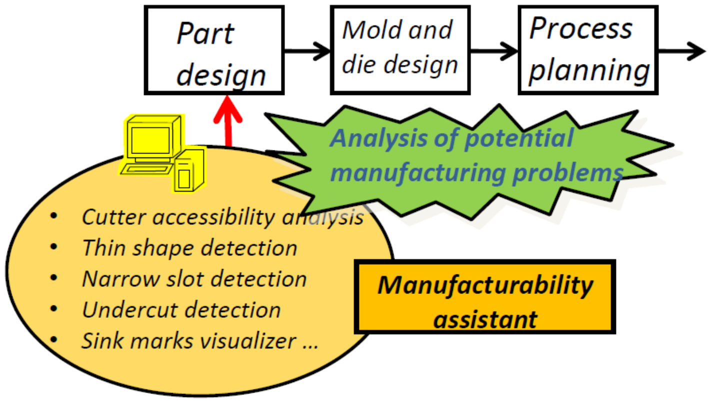

Fig. 2. Concept of the manufacturability assistant

model. Conditions relating to the manufacturability of a part are usually very complex, and they are difficult to describe in a simple rule style. In the manufacturability assistant, most feature extraction functions are realized in a procedural style with various geometric computations.

IMPLEMENTATION METHOD

The manufacturability assistant is a package of various subsystems for extracting shape elements relating to potential manufacturability problems. Each subsystem detects problematic shape elements by using geometric computation with part CAD models. Through the development of many subsystems, the following common strategy was found for implementing a manufacturability evaluation software.

Step 1: *Interview with the expert designer.* Development of a system starts with the interview of the expert machine part designer. In the interview, the designer's experience of the reworks caused by the manufacturability troubles, the reasons for the troubles, and the method for modifying the part shape to resolve the troubles are studied. This is the most critical step in the development. Through the interview, important conditions of the manufacturability evaluation are collected.

Step 2: *Interpretation as geometric constraints.* In this step, the basic strategy of the manufacturability evaluation is determined. In the manufacturability analysis in the product design process, a fast response is crucial; otherwise, the thinking process of the designer is much disturbed. Based on this consideration, we transform the manufacturability condition collected in the prior step to equivalent (and hopefully simple) geometric constraints that can be evaluated using a CAD model of the part.

Step 3: *Implementation of extraction procedures.* Shape elements and their arrangements with potential manufacturability problems are extracted from the part CAD model based on the geometric constraints. In the systems used, most of the extraction process is realized by applying geometric computation procedures to the surface elements in the CAD model. Some extraction procedures utilize discrete volumetric representation of the 3D shape such as Z-maps, voxels, and dexels. The extraction procedures are implemented using the functions provided by the hybrid geometric modeling system. Because these functions can utilize the powerful parallel-processing capability of GPU, most extraction procedures can return the result in less than a minute.

Step 4: *Field test in the manufacturing environment.* The systems developed are provided to the manufacturing companies cooperating with the laboratory to test the practical applicability of the system in the problematic shape extraction. The computation speed and extraction accuracy of the problematic shapes are checked by the company. If the test results do not meet the requirements, steps 2–4 are repeated to refine the system.

EXAMPLES OF MANUFACTURABILITY EVALUATION

Since the manufacturability assistant project began, various functions have been developed for extracting shapes with potential manufacturability problems. Examples of the functions are detection of cutting-difficult shapes [4], detection of too thin shapes [5], detection of too narrow slots [6], and so on. In this section, two new functions of the manufacturability assistant, which are an undercut detection function and a sink mark visualization function, are explained.

Undercut Detection

Most plastic parts are produced by injection molding. In this method, the molded part must be removed from the mold core in a single ejecting direction. To realize the smooth removal, the part should be designed not to have any "undercuts" in the ejecting direction; otherwise, expensive sliding core mechanisms are necessary. A system was developed for automatically determining the optimal ejecting direction of the part with the minimum number, minimum volume, or minimum area of the undercuts [7]. Because plastic parts are generally very thin, many rib features are placed in the inner side of the part to give sufficient structural strength to the part. Each rib feature strictly constrains the possible ejecting direction. Our system extracts rib features from the CAD model of the part and derives the candidate ejecting directions based on the geometric properties of the extracted features. It then selects the optimal direction with the minimum undercuts.

The system uses a discrete representation of the Gauss map for recording the candidate ejecting directions. In the Gauss map, each direction corresponds to a point on a unit sphere. The point distribution method for the discrete Gauss map is based on the architectural geodesic dome concept. This method can locate points on the unit sphere in a constant density. A hierarchical structure is also introduced in the point distribution, a higher-level "rough" Gauss map with sparse point distribution and another lower-level "fine" Gauss map with a much denser point distribution. The algorithm selects the optimal ejecting direction using the hierarchical structure of the Gauss map. In the first step, the rough Gauss map with sparse point distribution is used for selecting allowable ejecting directions. Then, the fine Gauss map with dense point distribution is used for accurately determining the optimal direction around the initial solution.

The system needs less than 10 s for determining the optimal ejecting direction of a CAD model with more than 1 million polygons. One example of the optimal ejecting direction determined by the system is illustrated in Figure 3. This model has 51,928 polygons. The system derives that the ejecting direction parallel to *Y*-axis direction is the optimal direction with the minimum number of undercuts. This direction is illustrated as a bold line in the figure. For determining the optimal ejecting direction for this case, 2.34 s is necessary. In the figure, shapes causing the undercut are painted in red.

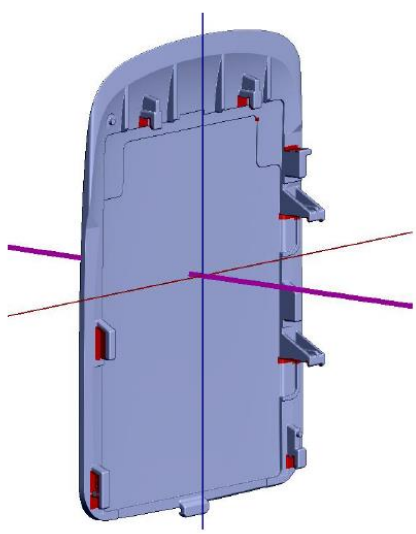

Fig. 3. Detected undercuts in the optimal ejecting direction [7]

Sink Mark Visualization

Because injection molding is a complex technology with many potential production problems, part designers must be concerned with not only the function and aesthetic property of the product, but also various physical conditions of the molding process; otherwise, molding defects cause the part quality to deteriorate. Sink marks appearing on the part surface are one of such molding defects. The plastic material shrinks in the hardening process of the injection molding. Because the thicker portion of the part shrinks more than the thinner portion, the surface of the thicker shape surrounded by thinner shapes often has a localized depression because of a difference of the shrinkage amount. Such sink marks in the exterior impair the aesthetic quality of the product. Costly redesigning becomes necessary when they are detected in the trial production stage.

A novel method was proposed by the authors for generating a solid model with sink marks in the surface. For part designers with less experience, it is difficult to understand the effect of the thickness change to the sink marks. By using the proposed method, solid models with local depressions are quickly obtained based on the thickness analysis in the part surface. The aesthetic quality of the part can be evaluated by visualizing the solid model with shallow depressions using the computer graphics technology. The system requires a polyhedral CAD model of a plastic part as an input. The surface polygons of the input model are finely tessellated in almost the same size. For each polygon of the model, the system computes the thickness at its center of gravity. The amount of shrinkage at the center point is then computed based on the thickness analysis result. In the next step of the algorithm, the position of the vertices of the model is modified. For each vertex, the polygons surrounding the vertex are checked. Shrinkage values of the surrounding polygons are summed, and their average value is adopted as the shrinkage value at the vertex. The normal vectors of the surrounding polygons are also averaged. The inverted direction of the averaged normal vectors is used as the direction of the shrinkage at the vertex.

Figure 4(a) illustrates a simple plastic part model with 888,366 small polygons. Figure 4(b) shows the thickness analysis result of the part. In the image, red is assigned to zero thickness and blue is assigned to the maximum thickness of the model. Figure 4(c) is a photo of an actual plastic part of the same shape. Some sink marks are visible in the surface. Figure 4(d) illustrates the sink mark visualization result. In this case, glossy black is used as the color of the part. In the visualization, the ray-casting method provided by commercial computer graphics software [8] is used. In this example, 142.38 s is necessary for the thickness computation and an additional 16.94 s is necessary for generating a solid model with local depressions (sink marks). After the model has been generated, sink mark visualization can be done at an interactive rate. Sink marks are clearly visible in the surface regions. The visualization software gives a very similar result to the sink marks appearing in the actual part.

Sink marks are generally not very noticeable in a part with a bright color. Figure 4(e) illustrates the visualization result of the same model in white. In this case, the sink marks are not visible in the part's surface. By using the system, the designer can check the effect of the color on the visibility of the sink mark. He/she can check the visibility of the sink marks in the part with different surface finish (for example, a glossy finish or mat finish) also.

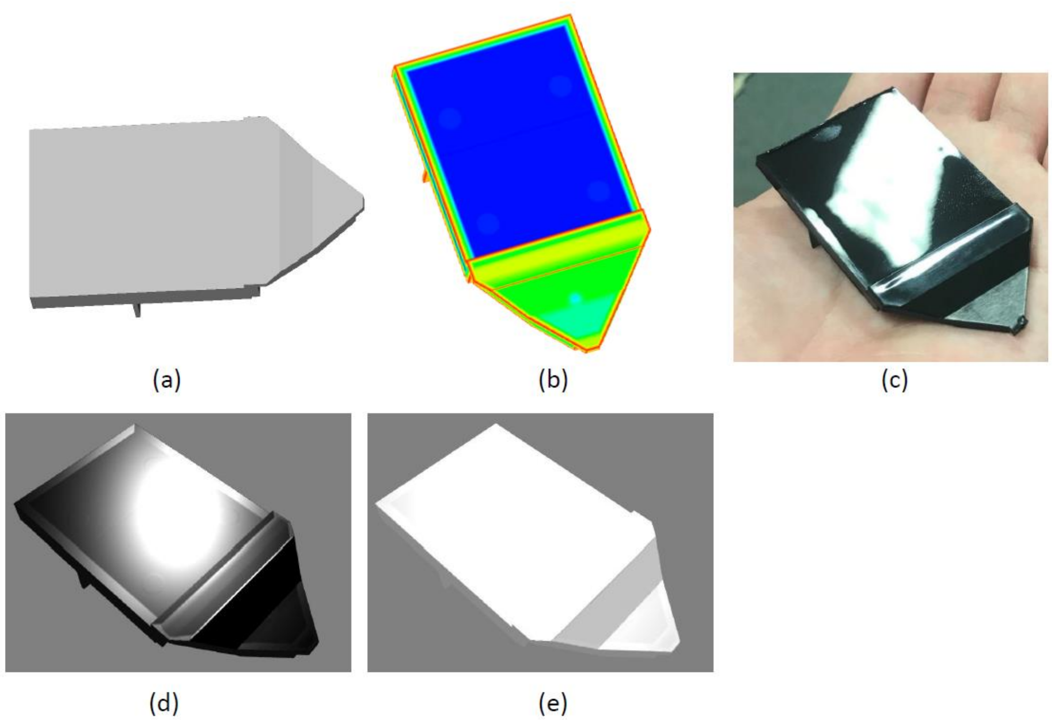

Fig. 4. Visualization result of sink marks in the plastic part surface

REUSE OF MANUFACTURABILITY EVALUATION RESULTS

In the part-designing process, the following information is usually defined by using 3D CAD systems.

- Shape data of the part — position of vertices, geometric information of curves and surfaces
- Form features, such as holes, slots, steps, and pockets — they are usually defined as a set of surface elements of the part: some features are defined as volumetric elements
- Annotation information, such as dimensions and tolerances — they are specified to the form features

These data are transferred to the following manufacturing process and used in the process planning, machining, assembling, and inspection information generation. For example, the NC machining commands are generated by using the geometric information of the part surface. Form features with dimension and tolerance specifications are crucial for determining the machining method. Specification of the datum system is useful in the automatic process planning, especially in the determination of the machining order of the features.

The main advantage of using the 3D CAD system is the cost reduction by utilizing the CAD model (shape, features, and annotation data) defined in the part design process many times in the succeeding production processes. Before the introduction of the 3D CAD system, users of the NC machining systems had to manually redefine the shape data of a part to generate commands for the machining of the part. A similar task was necessary for other engineers using robot programming systems for the automatic assembling and programing systems for the coordinate-measuring machine for automatic inspection. By using the CAD models, the cost for such redefining of the product data in the manufacturing stages can be eliminated.

The authors think that the manufacturability evaluation result obtained in the designing process is helpful not only for the designers but also for manufacturing engineers concerning the mold and die fabrication in the tooling department. For example:

- The detection result of the undercut shapes in a part is useful for designing the sliding core mechanism in a mold for producing the part.
- The cutting-difficult shape extracted by the manufacturability assistant usually corresponds to the shape to which the electrical-discharge machining method is applied.
- To mold the thin shape of a part, it is necessary to devise various contrivances when designing the mold. The extraction result of the thin shape in the manufacturability evaluation is thus valuable for the mold designer.

In current practice, most engineering information generated in the part design process is used only in the design activities. After the reference, most of them are discarded, and the shape, form features, and annotation information are only transferred to the succeeding manufacturing stages. Research is planned to develop a new framework for transferring any engineering information generated in the design process to the following manufacturing processes. The manufacturability evaluation result is a potential candidate for the information to transfer.

CONCLUSIONS

Because machine designers are not manufacturing experts, they often design parts with various manufacturability problems. These problems are usually detected in the later manufacturing stages. They are reported to the part designer and resolved by modifying the part design. Such reworks generally require substantial time and cost. Reduction of the rework is important for realizing the efficient production of the mold and die. In this work, a software system to reduce the number of reworks was explained. This system detects shape features of a part with potential manufacturability problems by applying various shape extraction procedures to the CAD model of the part. Some application results of the system are also illustrated: undercut detection and the sink mark visualization. These systems are constructed using the functions provided in the original geometric modeling system.

The manufacturability assistant is still in an experimental stage. Future works will improve the functions based on the comments and requests from a designer in a field test. The extension of the functions of the manufacturability assistant is also a future research subject. One potential extension is to provide a function to transfer the manufacturability evaluation result to the following process planning, machining, assembling, and inspection stages to eliminate the cost for regenerating the manufacturing information that has already been obtained in the manufacturability evaluation.

REFERENCES

[1] Van Hook, T., “Real-Time Shaded Milling Display,” Computer Graphics (Proc. of ACM Siggraph 86) vol. 20, no. 4 (1986), pp. 15-20.

[2] Inui, M., and Umezu, N., “Reduction of Reworks by Detecting Possible Manufacturing Problems of Plastic and Diecasting Parts in Early Design Stage,” Proc. 2016 Asia Design Engineering Workshop (A-DEWS 2016), December 12-13 (2016), Osaka University, Japan.

[3] Gupta, S.K., Regli, W.C., Das, D., and Nau, D.S., “Automated manufacturability analysis: A survey,” Research in Engineering Design, vol. 9, no. 3 (1997), pp. 168-190.

[4] Inui, M., Maida, K., and Hasegawa, Y., “Cutter Accessibility Analysis of a Part with Geometric Uncertainties,” Proc. IEEE International Symposium on Assembly and Manufacturing (ISAM 2009), November 17-20 (2009), Suwon, Korea, pp.2258-2265.

[5] Inui, M., Iwanami, T., and Umezu, N., “Extraction of Thin Shape of Part Using Distance Field,” Proc. of 16th International Conference on Precision Engineering, ICPE 2016, November 14-16 (2016), Hamamatsu, Shizuoka, Japan

[6] Inui, M., Imai, T., and Umezu, N., “Recognition of Narrow and Deep Slot Features of a Part Using External Distance Field,” Proc. of ISAM 2016, IEEE International Symposium on Assembly and Manufacturing, August 21 (2016), Fort Worth, Texas, U.S.A.

[7] Inui, M., Umezu, N., and Kamei, H., “Automatic detection of the optimal ejecting direction based on a discrete Gauss map,” Journal of Computational Design and Engineering, vol. 1, no. 1 (2014), pp. 48-54.

[8] Shade 3D https://shade3d.jp/en/

Digital Problem Resolution (DPR) Utilizing 3D Scan Data for In-Service Aircraft Carriers (ISCVN)

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Introduction

In recent years, the emergence of improved three-dimensional scanning products and software has begun to disrupt various processes at Newport News Shipbuilding (NNS). The technology is evolving at a very rapid pace and we are continuing to develop new uses for it resulting in benefits for nearly all areas of our business. More importantly, we are recognizing it as a major component in our digital transformation and it is impacting how we understand the digital thread. Figure 1 below shows NNS' quintessential digital thread with areas where laser scanning is impacting the business.

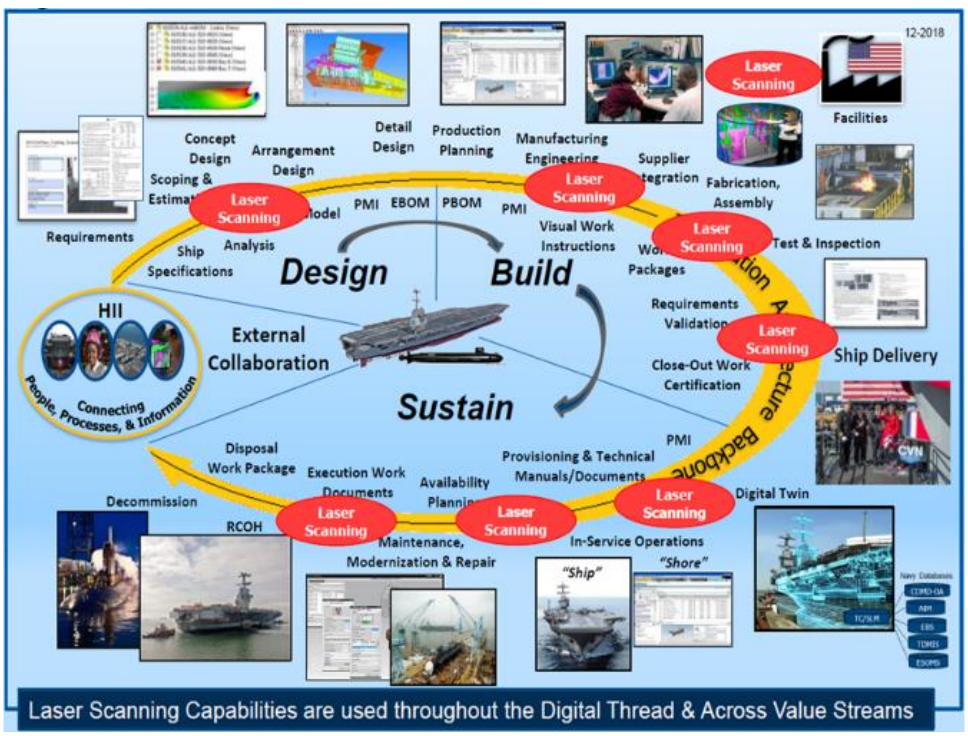

Figure 1. NNS' digital thread and the usage of laser scanning technologies

This paper is broken into two sections. The first section, titled *Technology Summary*, contains an overview of laser scanning technology, how it works, and its current applications. The second section, titled *Digital Problem Resolution (DPR) Project Overview*, describes our most recent project involving laser scanning technology.

Technology Summary

What is Laser Scanning?

Laser Scanning is the controlled steering of LASER beams followed by a distance measurement at every pointing direction. This method, often called 3D object scanning, 3D LASER scanning, or LIDAR, is used to rapidly and accurately capture shapes of objects, buildings and landscapes. A variety of sensors exist in the yard with tolerances ranging from .002"–0.125" and ranges from 12' –100's of meters.

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3D Scanning is the process of capturing digital information about the shape of an object with equipment that uses a laser or light to measure the distance between the scanner and the object. The "digital information" that is captured by a 3D scanner is called a point cloud. Each point represents one measurement in space. Lines are used to connect all the points together into a polygon model. The lines all connect to form triangles. Surfaces can be constructed on the polygon model or its shape can be used to help define 3D solid shapes for creating a solid model.

SLAM (simultaneous localization and mapping) – registration algorithm that allows scanning units to approximate real-time position using common features (corners, pipes, colors, etc.) combined with Inertial Measurement Unit (IMU) data. Registrations using this technology generally see accuracy between 2 –5 cm. Sensors that use this technology trade efficiency for accuracy. The technology can be used indoors or outdoors.

GPS (global positioning system) – GPS is generally used as a constraining network (referred to as “control”) that helps 1) Reduce error stack up on large site surveys, 2) locate data into a common reference system. It is for outdoor use only. Some terrestrial sensors have GPS functionality, but it is generally used for a “rough” location only. GPS control points are generally created by a secondary sensor.

How does it work?
Laser scanning, in a broad sense, is a sensor that collects spatial and sometimes color information on an object and converts it into a format that can be used in a 3D design environment. This format is most often a “point cloud” (a collection of discrete points that have X, Y, and Z coordinates). A variety of other data can be attributed to each point as well, such as color, intensity, normal vectors, etc.).

Data that is originally scanned as a point cloud is often later converted to a polygonal mesh or a CAD model. The sensors pick up scan data from a variety of methods, but most of them revolve around the same principle: A laser is sent out from the sensor, bounces off the object of significance and returns to the sensor with the required information. If color data is required, a picture of the object is taken as well and overlaid with the generated point cloud.

Various Applications
There are a range of scanning applications spanning across multiple areas of the value stream. A selection of those applications are:

- As-built condition assessment and ship check
- Clash detection and analysis
- Accurate 3D Modeling
- Virtual product measurement
- Execution of damage investigation
- Critical alignment
- Improved quality review
- Collection of data in normally inaccessible areas
- Asset documentation
- Laser projection
- Job briefings and animations
- Digital problem resolution (DPR)

There is not enough time to elaborate on all of the above use cases and therefore the focus of the paper will be on the most recent area of exploration: Digital Problem Resolution (DPR).

DPR Project Overview

The *Digital Problem Resolution* project is funded through the Navy Manufacturing Technology Program (MANTECH) under the Office of Naval Research (ONR). Supporting the project are multiple Navy entities including Naval Shipbuilding and Advanced Manufacturing (NSAM), In-Service Aircraft Carrier Program Office (PMS 312), CVN 79/80 Program Office (PMS 312) and the VIRGINIA Class Program Office (PMS 450).

The project will develop a process for capturing and retaining growth work items using digital information capture technologies and create a Knowledge Base to store these identified resolutions for each growth work item. Processes will be developed to exploit the development of laser scanning solutions to increase fidelity of applicable growth work resolutions. Additionally, other forms of digital capture technologies will be evaluated during the project to provide engineers and planners the capability to identify an appropriate level of fidelity required for specific resolutions.

Newport News Shipbuilding (NNS) currently uses digital technologies to capture information in support of shipcheck operations. Laser scanning technology on a small scale (i.e. hand scanners) is a growing field and one that can be leveraged to improve the accuracy and efficiency of identifying and resolving engineering issues during the shipboard maintenance process. While digital capture technology meets the needs of this project, a secure Knowledge Base that can easily be shared has not been explored. This project will provide the bridge between the scanning technology and the customized data storage repository and create the concept that will ultimately result in a more collaborative environment.

The objective of this project is to roll out methods that will digitally capture growth work items for use and evaluation by problem resolution teams across aircraft carrier contracts. Individual teams will complete their evaluations looking at cost, schedule, and quality performance differences between current processes and processes utilizing various methods of data capture. This project will be executed in two phases described below:

Phase 1

- Define technical requirements for Knowledge Base, digital capture technology and data security
    - Survey end users (Trades, Engineering, and Planning) to determine which inputs and outputs will best support the Problem Resolution Data Base
    - Eliminate aspects of the problem resolution that do not apply to growth work
    - Automating the approval workflow
- Establish a Knowledge Base for processing and storing digital information used to resolve engineering resolutions
    - Allows efficient management of digitally captured information
    - Upload shipboard information for use by liaison engineering
    - Digital work instructions transmitted to trades craftsmen
    - Serves as a repository for growth work items that leads to best practice solutions for any future growth work items
    - Promotes better planning by factoring known growth into the future availabilities

Phase 2

- Define the new problem resolution process
    - Evaluate the process and prototype Knowledge Base in active contracts
    - Pave the path for successful implementation following project completion
- Develop the process for resolving and capturing growth (unplanned) work using digital technologies
    - Leverage the development of laser scanning solution from CVN Reality Capture ManTech project (Shipcheck)
    - Increase fidelity of applicable growth work resolutions
    - Evaluate other forms of digital capture technologies (digital photos and digital videos, etc.)

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Machine-readable physics for space-time-dependent simulations in MBE

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ABSTRACT

Space-time dependent simulations (STS) aid decision-making across the product lifecycle, such as verifying behavior of virtual products against requirements during design. These simulations are described by partial differential equations (PDEs) and supported by 1) domain-specific tools that usually provide pre-defined behavior models (library models) that can be parametrized and by 2) domain-independent tools that enable specification of behavior and making numerical choices (e.g., finite elements), but are too abstract for immediate application. Using domain-dependent software is facilitated by parametrizing pre-defined templates, but simulation is limited to capabilities in predefined library models. Furthermore, documentation of pre-defined models might describe the same behavior in a variety of ways within and across tools, making them difficult to compare. On the other hand, domain-independent tools enable formulation of behavior models, including numerical choices (e.g., finite elements) to solve PDEs, but lack integration with physics needed in engineering. We propose a human- and machine-readable physics that graphically represents physical laws as computation instead of equations. The objective is to enable engineers to create their own domain-dependent library models and link them to numerical solvers. STSs expressed in this way are more flexible and much more accessible to engineers, because physical laws and their application to engineering problems are explicitly represented in human- and machine-readable models.

1. ROLE OF STS ACROSS THE PRODUCT LIFECYCLE

Computer aided design (CAD) and computer aided engineering (CAE) over the last 50 years virtualized product development in increasing detail, transitioning from 2D to 3D in the 1990s to virtual reality in the 2010s, made possible by advances of computer hardware and software. Virtual products are mathematical representations of product geometries created or represented in CAD tools. Behaviors of such virtual products are specified by partial differential equations (PDEs) of physics, which connect configuration variables (physical quantities measured at points in space) to loads applied to products during their operation. Software tools for behavior simulation, such as finite element analysis (FEA), finite volume method (FV), finite difference (FD), computational fluid dynamics (CFD), multibody dynamics (MBD) are examples of computer aided engineering software (CAE). Space-time simulations (STS) are used in engineering to verify whether simulated behavior of a geometry in a specific use case meets requirements. Testing requirements with virtual prototypes is a cost- efficient alternative to physical prototype testing. STSs are increasingly used in other stages of the product lifecycle, e.g., in manufacturing to evaluate impact of designs on processes, and in product service to predict life-times from sensor data.

Three approaches to designing virtual products are waterfall, iterative, and generative. Waterfall approaches test virtual products at the end of design, before handing off to production. Iterative approaches continuously test virtual products as designs are refined, identifying flaws earlier, accommodating requirements that change over time, and guiding designers towards better solutions (simulation driven design). For example, STS early in design can identify locations of maximum stresses on a virtual product, which can be assessed against safety margin requirements, and digitally corrected using CAD software if needed. Parametric CAD and better integration of CAD and CAE have been instrumental to success of iterative approaches. Generative design reformulates STS models with additional constraints, so-called material distribution methods, to generate designs. Additive manufacturing is often needed to manufacturing complex shapes resulting from these generated virtual products,

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as they are usually too complex to produce with traditional processes. Examples of generative design can be found in [1].

In manufacturing, STS helps optimize manufacturing processes and evaluate the impact of manufacturing chains and designs on each other. Process optimization is concerned with improvement of manufacturing tool designs. For example, in [2], potential optimizations of 3D printer hardware and software are evaluated using thermal simulation. Another application is assessing impact of chained manufacturing processes, where each unit process (casting, forging, heat treatment, etc.) transforms geometries, starting with simple raw material geometries, and ending with part geometries of virtual products. Each STS evaluates residual stresses from a unit process. The combined stress from simulating a chain of these processes can be checked against requirements, providing more accurate results by accounting for the effects of manufacturing.

For products in service, STS helps verify whether product behavior meets requirements, and predict product life-times using virtual representations of products in service (digital twins), coupled with real-time sensor data for boundary conditions of pre-defined behavior models. For example, real time pressure sensor feeds of a landing gear capture repeatedly applied loads, producing stress fields that can be evaluated with STSs against requirements (e.g., safety margin) and predict its lifetime using stress-cycle curves.

Workflows to create STSs are the same for design, manufacturing, and service. They start with algorithms that generate linear representations (tessellations) of a virtual product, also called mesh. The next step is simulation preparation, consisting of selecting pre-defined behavior models from libraries of simulation tools, associating boundary conditions types to mesh regions, and entering parameters values into simulation templates associated to these pre-defined behavior models. The final step is running the simulation, which generates results that can be post- processed if necessary.

In this paper, we will first introduce the two kinds of tools in current STS tool chains, and describe the benefits and limitations of both. In the second part, we propose a human- and machine-readable physics that graphically represents physical laws as computation instead of equations, with the objective of combining the benefits of both tool chains to address their limitations.

2. THE CURRENT STS TOOL CHAIN: TWO KINDS OF TOOLS

There are two kinds of STS tools, one that focuses on physical domains, another that focuses mathematical relationships, each having different inputs:

1) *Physics-dependent* tools are usually commercial off the shelf solutions (COTS), providing pre-defined behavior models (library models) and support for STS workflow. Pre-defined behaviors are conveniently parametrized using simulation templates. Integration of these tools with CAD helps create meshes from CAD geometry and also to graphically select mesh regions for simulation set-up (e.g., boundary conditions). Post-processing of results, which computes secondary physical quantities (e.g., stress) is automatically executable by user selection. These tools help use pre-defined behaviors, either in textual form represented in so-called input decks, or graphically by setting parameters values in input templates. They also visualize results of STSs by projecting them onto meshes.

2) *Physics-independent* tools are usually open-source, such as [3][4] for FEA, giving engineers flexibility to create new behaviors by specifying PDEs or PDE weak forms, as well as numerical choices (e.g., which finite elements to use). The mathematical orientation of these tools enables behavior definitions to be reused in multiple physical domains. However, it also means the connection to engineering is only in the mind of the user or captured separately in documentation, rather than represented in software, as in physics-dependent tools. Behavior definition is flexible, but not specific to engineering applications.

Physics-dependent tools are easier to use, but are less transparent and flexibile. Numerical details and physics models are explained in tool documentation with varying details, rather than represented directly in the tools. Finding the correct behavior models for an application can be time-consuming due to the large number of variants of the same behavior. In order to replicate an STS, pre-defined behavior models are usually identified by proprietary reference codes. When a pre-defined behavior is not available, engineers have three options: acquire additional tool licenses, write custom code for the tool, or buy another tool. The first option is limited by availability of pre-defined behavior models in the software library and their cost, the second requires software development and maintenance support of a tool-specific environment, and the third involves either migrating simulations to the new tool or using multiple, incompatible tools. Migrating simulations between tools is only reliable when they are interoperable, including syntactically through shared file formats, and semantically through shared concepts. The Standard for the Exchange of Product model data (STEP) [5], has an application protocol (AP) for multi-disciplinary analysis, STEP AP 209 [7], defining standardized schemas and concepts to capture analysis (all APs use EXPRESS as an exchange format [7]). Product analysis in AP209 is specified by STEP P1387 [8], which uses STEP P104 [9] to specifically describe FEA concepts, which are currently limited to structural and fluid mechanics. A tool that interoperates with AP209 for FEA of mechanical structures use P104 to declare its pre-defined behaviors, each identified by a proprietary reference code. This enables them to store analysis results in STEP format, but not run STSs with other tools unless a third party maintains translators between STEP files that reconcile model references between tools. Model reconciliation with STEP AP209 (evaluating if two models are equivalent) is difficult because tool vendors have varying descriptions of their pre-defined behaviors. STEP AP209 is not a computational model. This is problematic for solution migration when companies decide to change tools, for supplier collaboration when two companies use different software, and for long-term archiving if the software is not supported in the future. A problem with physics-dependent COTS currently is lack of transparency and flexibility, which hinders interoperability and increases vendor lock-in.

Physics-independent tools are transparent and flexible, but they are more difficult to use. Their simulation descriptions are purely mathematical, making association to physical quantities and engineering difficult. Defining behavior models using PDEs or PDE weak formulations is uncommon among engineers. In addition, the mathematical classifications of PDEs often does not correspond to classifications of physics or engineering problems. For example, thermal conduction uses parabolic PDEs, while steady state thermal conduction uses elliptic [10]. Another behavior model that describes thermal conduction with temperature-dependent thermal conductivity uses hyperbolic PDEs [11]. The relationship between mathematical classification and engineering becomes even more difficult in coupled physical domains, which are described by systems of PDEs. PDE classification is useful for solver classification and mathematical analysis, but inefficient for connecting and classifying physics in a consistent and systematic manner for application to engineering. Another problem in using PDEs for behavior description is they only show relations between unknown variables and some of the loads. For physical problems, some boundary conditions refer to physical quantities that are not part of the PDEs (e.g., heat rate in thermal conduction). In addition, without documentation showing derivation from multiple physical laws, PDEs give only a partial view of the complete model, limiting STS post-processing for other secondary model variables (e.g., stress). It requires knowledge of physical laws as well as numerical models of physical quantities to derive post-processed variables. Physics-independent tools are difficult to use due to a lack of systematic connection to physics and limited integration with product model geometry.

The benefits of the two kinds of tools above are complementary: the benefits of one are the limitations of the other. Physics-dependent tools provide pre-defined behaviors for reuse, while physics-independent tools support definition and reuse of these for multiple physics. Physics-dependent tools are easier to use, but are opaque and inflexible, while physics-independent are more difficult to use, but flexible. Engineers use physics-dependent tools by selecting pre-defined behaviors and setting parameters to run STSs limited to behaviors available in tool libraries. In contrast, engineers using physics-independent tools define behaviors with PDEs and make numerical choices (e.g., finite element) to run STSs that are purely mathematical. Combining flexibility with usability requires a new, machine-readable model input that is understandable by most engineers.

3. MACHINE-READABLE PHYSICS

We propose to combine the beneficial aspects of physics-dependent and -independent simulation tools using only mathematical equations, but treating their application in physics and engineering as computations, and tieing them to physical and engineering problems. With equations, many possible rearrangements are possible, each one intended to isolate computation of a particular variable on one side of the equation. The proposal is to make these computations explicit, with machine-readable directed relations indicating how computations proceed, and eventually connect to other computations. By computation we mean finding an output for a given input, giving answers to specific questions. In physics, physical laws are expressed as equations with many rearrangements, which we propose to represent as multiple computational models.

Physical laws are equations that relate one physical quantity to others, such as constitutive laws (e.g., strain to stress via the elasticity tensor in Hooke's law), differential laws (e.g., momentum to force), integral laws (e.g., force to impulse), energy laws that relate energy to conjugate quantities by multiplication, conservation laws that connect many physical quantities to a single one by addition. Examples of the first three are:

- Linear constitutive laws have two formulations written as inverse equations. For example Hooke's law can be represented in the stiffness form that relates strain to stress via the elasticity tensor or represented in the compliance form that relates strain to stress via the compliance tensor. Another example would be Ohm's law using resistance or conductance as parameters for two formulations as equations. There are two equations for the same physical phenomenon because the equations are used as computations, putting the result on the left hand side of the equation and how to compute it on the right.

- Univariate differential (ODEs) and integral laws, usually representing time-only dependent physical laws, also have two formulations, but they are not simple inverses as above, because inversion in these laws introduces a new physical quantity. For example, time-only dependent force is defined as the time-derivative of momentum, but inverting derivatives by integration adds boundary conditions to the integral. Integrating force produces impulse, rather than momentum, but adding initial momentum to impulse produces momentum. Writing differential laws and their inverse integral laws as computations enables them to be combined to capture the relationship between them.

- Some nonlinear material laws have no inverse, and differential laws involving multivariate physical quantities (apart from gradient operation) have no inverse integration process. For example, the inverse of the conservation law relating a heat source and heat flux density (a pseudo-scalar function and a vector function with a divergence operator), is underdetermined. We can only compute an indirect measure of the heat flux density (the heat rate on the boundary of a volume) by integrating the heat source over the volume. This is the so-called divergence theorem, which is a special case of Stoke's theorem that applies also to gradient and curl.

These examples illustrate that equations for physical laws are used implicitly for computations. Representing physical laws as computations makes this explicit.

Defining STSs using PDEs (space and time variables) in engineering applications requires knowing how PDEs are derived from physical laws to apply to specific engineering problems. Currently, PDE derivation is captured in documents that refer to physical laws from textbooks. Cross-referencing and document-based search is time-consuming when equations and physical laws are mixed together and presented with varying descriptions as mentioned in the previous paragraph (e.g., different symbols, differential or integral representations, etc.). With a computational model of physics, physical laws are explicit, connected, and machine-readable.

The three building blocks of the proposed computational model are:

- Physical quantities specified by functions, which we call *math objects*, that usually take time and/or space coordinates as input and give physical quantities as output
- Operators applied to maths objects (e.g., differential operator, unary operators, such as multiplication and addition, etc.) that specify how math objects are computed from others.
- Physical laws expressed as computational programs, with operators applied to math objects as instructions.

Representing physical laws as triples (inputs, operator, output) provides a basis for storing computation in a graph data structure, specifically a directed graph composed of two alternating kinds of nodes (bi-partite graph), one for physical quantities and another for operations linking two physical quantities, as shown on the right in Figure 1. The figure describes math objects in three layers (horizontally from left to right), which:

1) Specify the type of each math object. In physics, the types are tensor fields, which are arrays of functions, each function taking space or time coordinates or none as inputs, each coordinate represented by a symbol and associated to real numbers, and each function yielding real numbers as output. The shape of the tensor field is specified by the array dimension.
2) Give symbolic representations of functions, with expression trees that can be serialized in many formats, such as MathML [12] or Latex [13], as well as output data, which can be represented by a graph or plot. These associate real number intervals to coordinates.
3) Build graphs showing math objects as inputs and outputs of operations. Connecting physical laws is achieved using the same physical quantity in two laws, corresponding to the manual process of cross-referencing physical laws on paper.

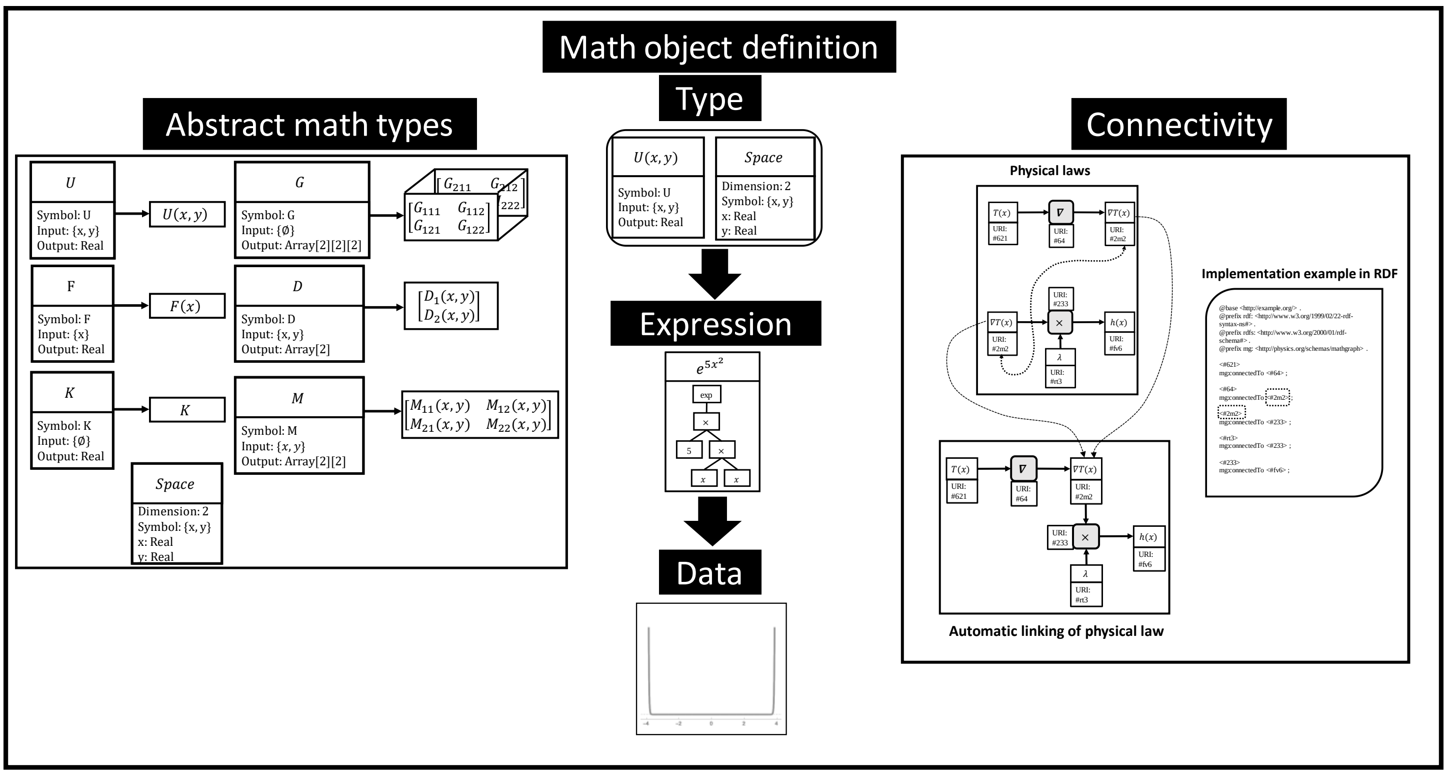

Figure 1: Layers of math objects

Each physical quantity in a graph can be uniquely identified, e.g., by a unique resource identifier (URI) or web address, as shown on the far right in Figure 1. The Resource Description Framework (RDF) [14], the web data model, has an explicit representation of relationships between two resources (subject and object) using another resource (the predicate) as the relationship, in the same way natural language constructs simple phrases. This is also a graph model, but has the advantage of being a web standard and serialized into many formats (XML [15], JSON [16], etc.). Another benefit of RDF is that each resource can be enriched with attributes through additional statements, such as units, and dereferenced by retrieving the representation of the resource (e.g., HTML [17]).

By computing physical quantities with respect to each other, these three machine-readable layers capture processes normally done on paper: selecting physical laws, typing mathematical objects, defining functions by mathematical expressions, applying mathematical operators to function expressions following operator rules, all in preparation for numerical evaluation. These machine-readable representations can be managed with existing technologies and give solver-independent descriptions that are understandable by engineers. The result is a computational graph of physics that can be supported by an open standard. Graph representations can be stored in databases, making them searchable for discovery and reuse. Graphs for multiple physical laws can be connected into a larger graph for multi-physics problems. The connection between mathematics and physics in these graphs is represented by associating math objects to physical objects.

A physics problem is defined by selecting pairs of physical quantities at the edges of a graph that are connected by one or more paths of computations through it. These subgraphs can be extracted and selected to define a behavior model. *Functional programs* are defined by the mathematical relations between start and end nodes of a path through the graph from one edge to another. Operators used along these paths are the instructions for functional programs. Currently, symbolic tools provide command lines where operators can be applied to expressions, providing symbolic results. A sequence of such expressions and operator applications is usually stored in proprietary scripts. Instead of storing scripts, a graph of physics provides options to select and generate functional programs according to modeling decisions. Functional programs are uniquely identified by their instructions and can be used to generate scripts.

We have three kinds of functional programs resulting from the above process, depending on whether start nodes of paths are known or unknown quantities, leading to two kinds of graphs:

1) *Direct functional program*: When start nodes are known, relations from known start nodes to unknown end nodes are computable. These are *physics evaluation graphs* (PEG);
2) *Inverse functional program*: When start nodes are unknown and the path uses only linear relations or one-dimensional derivatives, inverse paths can be generated to define inverse PEGs;
3) *Constrained functional program*: When start nodes are unknown and the path that cannot be inverted, functional programs are constrained by the known end node. These are *physics solver graphs* (PSG).

Each relation in a PSG (two physical quantities connected by an operator) is a representation of a physical law equation as a computation. Functional programs defined by PSGs include boundary conditions. Boundary conditions are needed whenever differential operators are used in functional programs. The general Stokes law enables systematic associations between boundary condition types and differential operators. PSGs specify PDEs: functional programs of PSGs take unknown start nodes as input (physical quantities only defined by an abstract math object type with a symbol) and apply operators to transform an expression dependent on the start node. Because this transformed expression must be equal to the known end node, we have an equation to solve: finding the best approximation for the unknown start node specified by the expression constraining the functional program. PDE solvers (programs computing such approximations) could be systematically associated to PSGs via functional programs. PGSs are documentation for solvers as well as computational models of them. PSGs can also be used to post-process secondary physical quantities. Another benefit of PSGs is that two programs are behaviorally equivalent when they compute the same function at the end node. With PSGs, we can classify physics problems by the behavioral equivalence of their functional programs.

Some numerical methods require additional information for solver definition. For example, in FEA, unknown and known quantities are specified by finite elements. In [18], we created a finite element specification that defines a computational model for finite elements with a syntax that is understandable by most engineers. By combining PSGs with finite element information, numerical graphs can be created to design and generate domain-specific behaviors in a transparent and flexible manner, and associate them to domain-independent solvers. This is enough information to derive weak form expressions and construct linear algebraic systems of equations that can be solved by linear algebraic solvers. Simulation templates (input forms of model parameters and boundary conditions) can automatically be extracted from PSGs and represented in many forms such as SysML [19]. With machine-readable physics and physical laws represented as computations, domain-specific behavior models represented by PSGs can be defined and associated to physics-independent tools to run STSs. The relationship between input and output node of a PSG is a functional program constrained at its output, which defines a PDE. This provides behavior descriptions that are accessible to engineers and interpretable by solvers.

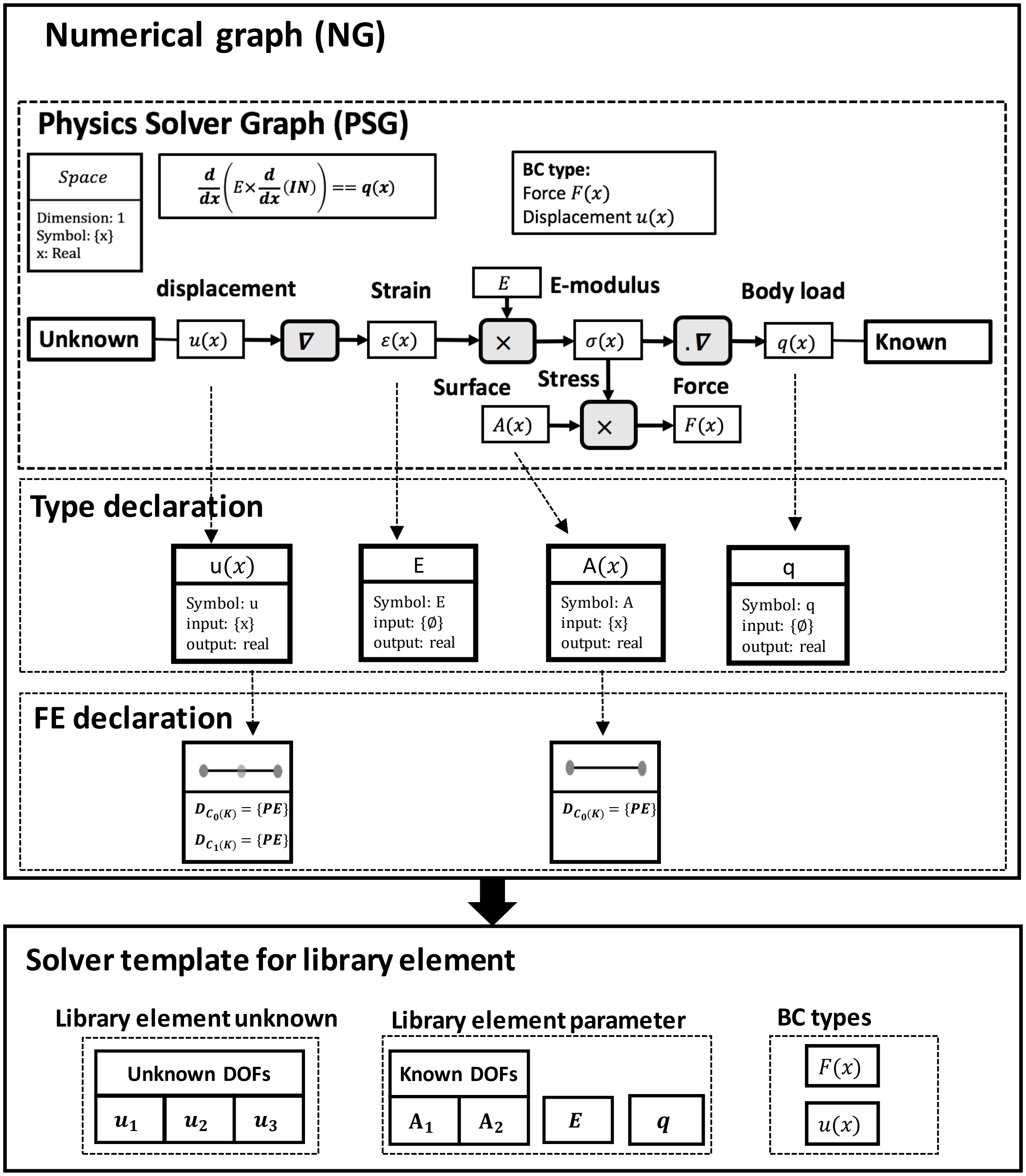

Figure 2: Example numerical graph for a bar element

4. CONCLUSION

STS are used throughout the product lifecycle to characterize behavior of virtual products. This paper dicusses two kinds of STS tools: physics-dependent ones that focus on physical domains, and physics-independent ones that focus mathematical relationships, each having different inputs. Engineers using physics-dependent tools give parameters for pre-defined behaviors to run STSs, while those using physics-independent generate behavior models by specifying PDEs and numerical choices (e.g., finite elements) that can be reused for multiple physical domains. Physics-dependent tools only provide parametrizations of pre-defined behaviors, making them opaque and inflexible, and standardization difficult. On the other hand, physics-independent tools lack systematic association between mathematical and physics-dependent information, making them less accessible to engineers.

We propose to achieve the benefits of these two kinds of simulation tools through human- and machine-readable physics that treats physical laws as computation instead of equations. Physical quantities are represented by math objects. These are manipulated by operators defined as expression trees, and numerically evaluated. Directed graphs of these math objects and operators on them provide a computational representation of physical laws, storable and querable in databases. Behavior models are defined by extracting subgraphs that connect configuration variables to loads. Operators and mathematical objects used on these subgraphs define functional programs that specify PDEs when constrained at their outputs, specifications that can be associated to domain-independent tools. These subgraphs provide physics- dependent metadata to solvers by detailing relationships between physical quantities as well as defining domain- dependent boundary conditions. The models are more understandable by engineers because physical laws are an explicit part of a graphical model. Another benefit is domain-specific behavior can be created and reused, instead of just parametrized. We created many example graphs of physics and integrated pieces of code to test traceability between physical concepts. Representing physics as human- and machine-readable computational graphs could also benefit education and simulation data management, as well as potentially lead to a new tool ecosystem addressing design and simulation challenges facing manufacturing and other engineering domains.

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6. REFERENCES

[1] Autodesk research, (2018). project dreamcatcher, https://autodeskresearch.com/projects/dreamcatcher

[2] Jerez-Mesa, R. & Travieso-Rodriguez, J.A & Corbella, X.& Busqué, R. & Gomez-Gras, G. (2016). Finite element analysis of the thermal behavior of a RepRap 3D printer liquefier, mechatronics. Elsevier.

[3] Alnaes, M.S. & Blechta, J. & Hake, J. & Johansson, A. & Kehlet, B. & Logg, C., Richardson J. & Ring, J.& Rognes, M. E.& Well, G.N. (2015): The FEniCS Project Version 1.5: Archive of Numerical Software. vol. 3.

[4] Hecht, F., (2012). New development in FreeFem++. Journal of numerical mathematics, 20(3-4), 251-266.

[5] ISO 10303 (2019). Standard for the Exchange of Product Model Data: ISO – International Organization for Standardization.

[6] ISO 10303 STEP AP 209 ed2 (2013). Composite and metallic structural analysis and related design: ISO – International Organization for Standardization.

[7] ISO 10303-11:2004. Description Methods: The EXPRESS Language Reference Manual: ISO – International Organization for Standardization.

[8] ISO 10303-1387:2014 - Application module: Product analysis: ISO – International Organization for Standardization.

[9] ISO 10303-104:2000 - Integrated application resource: Finite element analysis: ISO – International Organization for Standardization.

[10] Cebeci, T. & Shao, J. P. & Kafyeke, F. & Laurendeau, E., (2005). Numerical Methods for Model Parabolic and Elliptic Equations in Computational Fluid Dynamics for Engineers. Springer.

[11] Glass, D. E. & Özişik, M. N. & D. S. McRae, (1986). Hyperbolic heat conduction with temperature-dependent thermal conductivity, Journal of Applied Physics 59, 1861.

[12] W3C (2014) Mathematical Markup Language (MathML) version3.0 2nd edition https://www.w3.org/TR/MathML3/

[13] Latex project (2019) Latex – a document preparation system - https://www.latex-project.org/about/

[14] W3C (2014) Resource Description Framework (RDF) 1.1 https://www.w3.org/RDF/

[15] W3C (September 2006) Extensible Markup Language (XML) 1.1 (Second Edition).

[16] W3C (December 2017) The JSON Data Interchange Syntax: http://www.ecma-international.org/publications/files/ECMA-ST/ECMA-404.pdf

[17] HTML 5.2 W3C Recommendation (December 2017), https://www.w3.org/TR/html52/

[18] Szarazi, J. & Bock, C., (2017). Integrating Finite Element Analysis with Systems Engineering Models, NAFEMS World Conference, NAFEMS.

[19] Object Management Group (September 2017). OMG Systems Modeling Language™, version 1.5. http://www.omg.org/spec/SysML/1.5

Bringing Legacy Small and Medium Enterprise Manufacturers into Digital Manufacturing and Towards a Distributive Manufacturing Network

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ABSTRACT

While large scale manufacturers are able to continually invest in the equipment and infrastructure of their manufacturing systems, small and medium size manufacturers are more financially constrained. These smaller organizations are slower to invest in new systems with digital capabilities. Small and Medium Manufacturers (SMMs) commonly have different generations of CNC machines with varying levels of digital capability. Many SMMs still own and operate fully manual legacy machines. This research investigates how to provide digital manufacturing capabilities to manual legacy machines. Three different price points of sensor suites are investigated to monitor legacy manual machines for quality, operator training, and predictive maintenance. This project creates the foundation for the development of a distributive manufacturing network at Auburn University.

INTRODUCTION

Small and medium sized manufacturers (SMMs) rely on numerical control (NC) and legacy machines as a critical component of their operational capacity. Unlike large enterprises, SMMs typically cannot afford to replace their machines with each technological advancement. This results in a mix of machine capabilities spanning a number of generations in their shops. SMMs are also slow to adopt and change their processes or service offerings. In a UK study, 36% of SMMs had introduced a new or significantly improved service while 37% had introduced a new or significantly improved process [1].

Academic institutions are uniquely positioned to aid industry in identifying cost effective technologies to augment legacy machining infrastructure with digital capabilities. At Auburn University the Mechanical Engineering department has a required machining course for all undergraduate students. This class has a typical enrollment of 150 students per semester. The students learn to machine and assemble a simple part with tight tolerances. The part geometry includes a square aluminum plate and a press fit aluminum cylinder created using manual mills and lathes. With so many student operators creating the same part with the same features, this provides a unique opportunity to collect a rich data set across a variety of operator skill levels. This data can be used to both improve educational training efforts and provide guidance on the digitalization of legacy equipment for SMMs.

Many SMMs do not possess the financial capital to update their equipment with each technological advancement, and need a strong business case with achievable return on investments (ROIs) for capital investments [2, 3]. A goal of this project is to provide process monitoring sensor templates at varying price points to allow SMMs to choose the level of capability necessary for their needs. Additionally, the ROI for each sensor template will be evaluated by quantifying the savings associated with avoiding unplanned outages by monitoring machine statistics and increased part quality by monitoring tool wear of the cutting process.

Installing a single sensor on a machine provides a single channel of information. A significant part of this project aims to develop students that understand the intricacies of machining, increase the teaching efficacy of machining principles in the lab, and improve the quality of the student outputs; thus a single measurement about quality is not sufficient for these goals. Providing student operators with relevant information during the process will allow for real-time corrections of their work. The team intends to collect data that allows the student to monitor the material removal rate and the effects of their actions in real time. To do this data will be collected to monitor motor current draw, spindle speed, tool position, feed rate, acoustics emissions [4], and vibration [5]. While the cutting acoustics could provide data on tool wear alone, coupling this with measurements of the motor current allows us to have two factors of confirmation and compare the accuracy of the two methods [6, 7]. Additionally, monitoring the position, feed rate, and spindle speed can be another method for tool wear monitoring [8]. To

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track which student is using the machine, the time spent on each part of the project, and which tool is installed in the machine, a passive RFID system will be used [9]. Each student's badge will be equipped with an RFID tag that identifies the operator. Each tooling package will be equipped with RFID tags to identify the size and type of tool used by the operator. This functionality will also be used to track the history of the tool over the course of multiple student operators. These data points will provide another layer of information to enable additional analytics possibilities to understand the dynamics of the entire lab.

The goals of this project are to retrofit legacy machines to increase the teaching value they provide, identify quality metrics from multiple sensor sources, create sensor templates that can be implemented with other legacy equipment, and provide a node for a distributed manufacturing network. The project will investigate three different price points of sensor templates to determine if there is any difference in data processing, accuracy, and reliability at each investment level. The result will document capability of each configuration versus costs to implement, allowing SMMs choice for performance based upon their budget. Each setup will have sensors collecting data, transferring the data to an acquisition unit and a user interface, and then route the data to a server. The project will employ the MTConnect standard for data collection from the machines. Once data is collected, individual sensor data will be reviewed for quality, training, and maintenance points of interest while aggregate data will be generated to find trends and similarities between different users, quality, and shop wide process flow. This work will develop a plan to bring legacy equipment into a digital network to monitor condition and quality while maintaining reasonable price points. The sensor templates will be generalized for different types of machining processes allowing for flexibility on different machines by different manufacturers. This work will provide a basis for transforming legacy analog machines into digitally capable machines providing data to users and managers. The outcomes of this project will help in determining tool quality, operation status, machine state, maintenance tracking, predictive maintenance, and operator training for manual legacy machining processes.

Project plan discusses the project design, sensor selection, machine choices, the proof of concept design, data channels, and planned analysis. The plan forward describes the implementation and data comparison strategies for quality, monitoring, and visualizations. Conclusions provides remarks that draw the paper to its conclusion and potential future work is identified.

PROJECT PLAN

In the following sections the components of the project plan are discussed. Specifically, consideration of the data types that need to be monitored, the sensors types used to collect those data channels, the base machine we will initially focus our efforts, an example of a sensor array template, our next step with a proof of concept, and how data will be collected.

Data Needs

When considering the process, literature was reviewed on current research in tool wear and process monitoring, and the professor and graduate students who operate the lab were consulted [10]. Acoustic emissions are a method for monitoring the tool and work piece condition, tool wear, and the machining process [6, 11, 12, 13]. Vibration has been used to monitor the bearing status, chatter of the tool and work piece, and tool condition [5, 14, 15]. Monitoring the current draw of the motor can be used for tool wear monitoring and operation status of machines [10, 16, 17]. From the experience in the lab, position and tool speed can be monitored for depth of cut, feed rate, and the process used. Reviewing the specifications of the mills in the lab and literature, Table 1 was created to show the specifications of each data type.

Sensor Selection

Once the type of data to be collected was determined the type of sensors to provide that data were considered. In reviewing previous research on types of sensors and monitoring equipment, indirect monitoring was determined to be the best non-intrusive method for data collection [10]. Non-intrusive was a system requirement because the project space is a functioning and active teaching laboratory. Sensors were needed to monitor motor current, spindle speed, work piece and tool position, cutting vibration, and cutting acoustic emissions. Sensors were selected in each category at different price points. For example, for work piece and tool position, Digital Readout (DRO) sensors were considered. There is a wide selection of DRO sensors available, and a $150 option, a $800 option, and a $1,500 option are under consideration. Each of the sensor options have different capabilities in terms of accuracy allowing for robust comparison.

Machines

The first phase of the project is focused on the vertical mills used in the lab. The lab uses Grizzly model G0463 mills that have 3/4 HP motors and max spindle speed of 2000 RPM. They are hand wheel driven and allow the students to use dial indicators and the markings on the hand wheels for measurement.

Table 1. Data requirements of sensors

Data	Specifications
Spindle Speed	0-3725 RPM
Motor Current Draw	0-7 A full load 15 A circuit size
X-axis Travel	15-7/8 inches
Y-axis Travel	5-3/4 inches
Z-axis Travel	14-7/8 inches
Acoustic Emissions	70-155 kHz
Vibration	Still being determined

An example of one sensor set up will be a Grizzly mill with a Johnson Controls current transducer on the power cable monitoring motor current draw, a Monarch sensor monitoring spindle speed, and a Mitutoyo absolute magnetic digital readout scale attached to the table (x- and y-axis) and head (z-axis) for work piece and tool position. Those sensors will allow for the basics of motor current, spindle speed, and position of the work piece and tool position for operator feedback and process monitoring. An Omega three axis accelerometer attached to the table vise will monitor for vibration of the part in the vise and for tool chatter, while a Physical Acoustics acoustic emission sensor mounted on the z-axis will be oriented at the tool and work piece junction monitoring the tools acoustic emissions. This will allow for more quality feedback by monitoring close to the area where the work is taking place. Last, a RFID scanner, and an operator interface will be mounted to the mill as well. The RFID scanner will allow the tool description to be entered into the system and the operator identified, and the operator interface will give feedback from the system of sensors. The operator will then proceed with manufacturing and the system will provide speed and position indications on the operator interface. All the sensors will have the data collected by a Mazak Smartbox, which will connect to the campus network and send the data to the servers in our proof of concept lab for aggregation and post processing.

Proof of Concept

Since the teaching lab is continuously running classes, the plan is to build a prototype shop with the same equipment to test the sensor system configurations, gather initial data flows, build a user interface, and develop acoustic filters. The lab space for the proof of concept is identified and designated. This will let allow for the tuning of the sensors setups in a controlled environment. The proof of concept lab should be especially useful for working out the requirements for placement and use of the acoustic emissions sensors to isolate from the neighboring machine.

Data Collection

The data will be collected from each individual sensor and compiled at the data acquisition unit. It will then be shared with the user interface at the machine so the operator can see spindle speed, position, and acoustic emissions. The data acquisition unit will also send the data to the servers via the routing system. From the servers, data can be accessed by system control center computers to be processed and analyzed. The data will be used in multiple ways to investigate aspects of the machining process. Correlating data from different sensors will allow categorization of the machine condition during different aspects of the process. Correlating the data in post processing will allow for simulation of the steps of the process and the range of responses from the individual sensors. For example, correlating the feed rate, depth of cut, and spindle speed with the acoustic emissions of the tool and the number of service hours the tool has been in use can predict surface finish quality of the pass.

THE PLAN FORWARD

Lab Wide Implementation

After the proof of concept is complete, the sensor setups will be installed in the teaching lab between semesters. The volume of data collected will increase significantly from the proof of concept, and the initial hypothesis from the proof of concept will be tested against results from the lab. The lab will have six of the sixteen mills and six of the sixteen lathes equipped with sensors, and of those six machines, two setups of each budget point will be installed. Student usage is randomized on a first come, first served basis. As shown in Figure 1, the system will feed all of the machine data up to the routing system, to the server, and then the data is able to be accessed from the system control center. Processing will occur at the system control center level. The data collected from the lab will be analyzed to determine emerging patterns. These patterns will provide quality markers to monitor lab performance and student progress.

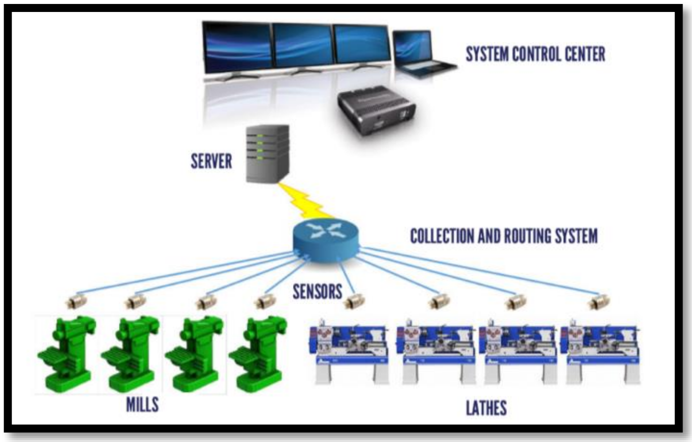

Figure 1. Design and manufacturing lab connectivity

Shop Floor Flow and Project Status

One aspect that the implementation of RFID tracking allows for the lab is the monitoring of student activity, time spent on each process, and movement in the shop. For example in the lab, the ability to see the correlation between the amount of time spent sanding to attain the required surface finish and depth of cut on the last pass, or the ability to see amount of time spent in the metrology area and hole location accuracy, allows for increased teaching focuses for the lab but can also allow for real time job status monitoring.

Another aspect of having data flows from the machines and tracking of students/operators is the ability to monitor machines status for the entire shop and usage statistics. With the RFID scanners, routine maintenance could have an assigned card, and when performed, the card is scanned. This can update the machine status and health to help monitor and track maintenance routines per machine. The RFID system will also allow the lab supervisor to more easily monitor attendance and active machining time per student in the lab. It also allows for tracking students in and out for priority of machines since the lab is run on first come first served basis.

Campus Dashboard and Distributive Manufacturing

The data flows will be consolidated into a campus dashboard to show the status, health, and hours of all the machines. This can be useful for manufacturers who need the ability to make quick status updates of operations without having to go to the machine location. The campus dashboard will be expanded to include NCs, additive machines, and other production capabilities on Auburn University’s campus. This implementation will provide an initial node in a future distributive manufacturing network.

CONCLUSIONS

This project strives to prove that using a combination of data from real-time sensing and providing this information to the student/operator will increase the quality of the product produced. A second goal is to show that the quality of education increases by having feedback on the acoustics of the cutting process to help train the ear of a student/operator. Third, the project will provide data collection and analysis options for SMMs to choose from at different price points and different levels of capability to aid in the adoption of digital competencies.

Being able to make decisions based on data is key for businesses. This project will take and present data from multiple machines for easy decision making from an overall lab view. The ability to track the quality of projects, time spent in each process, and time spent covering the material can help determine areas of needed focus for the teaching aspect of the class. For a company, being able to view the process from an overall system perspective can help identify the bottle necks, where defects occur, project status, estimated time till completion, and schedule adherence.

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REFERENCES

[1] Saridakis, G., Idris, B., Hansen, J. M., and Dana, L. P., 2019, “SMEs’ Internationalisation: When Does Innovation Matter?,” J. Bus. Res., 96, pp. 250–263.

[2] Ausloos, M., Cerqueti, R., Bartolacci, F., and Castellano, N. G., 2018, “SME Investment Best Strategies. Outliers for Assessing How to Optimize Performance,” Phys. Stat. Mech. Its Appl., 509, pp. 754–765.

[3] Filippi, S., Motyl, B., and Ciappina, F. M., 2011, “Classifying TRIZ Methods to Speed up Their Adoption and the ROI for SMEs,” Procedia Eng., 9, pp. 172–182.

[4] Maia, L. H. A., Abrao, A. M., Vasconcelos, W. L., Sales, W. F., and Machado, A. R., 2015, “A New Approach for Detection of Wear Mechanisms and Determination of Tool Life in Turning Using Acoustic Emission,” Tribol. Int., 92, pp. 519–532.

[5] Oleaga, I., Pardo, C., Zulaika, J. J., and Bustillo, A., 2018, “A Machine-Learning Based Solution for Chatter Prediction in Heavy-Duty Milling Machines,” Measurement, 128, pp. 34–44.

[6] Ravindra, H. V., Srinivasa, Y. G., and Krishnamurthy, R., 1997, “Acoustic Emission for Tool Condition Monitoring in Metal Cutting,” Wear, 212(1), pp. 78–84.

[7] Zhang, J., Qin, W., Wu, L. H., and Zhai, W. B., 2014, “Fuzzy Neural Network-Based Rescheduling Decision Mechanism for Semiconductor Manufacturing,” Comput. Ind., 65(8), pp. 1115–1125.

[8] Shaffer, D., Lorson, P., Plunkett, Z., Ragai, I., Danesh-Yazdi, A., and Ashour, O., 2018, “Development of Experiment-Based Mathematical Models of Acoustic Signals for Machine Condition Monitoring,” Procedia CIRP, 72, pp. 1316–1320.

[9] Zhong, R. Y., Dai, Q. Y., Qu, T., Hu, G. J., and Huang, G. Q., 2013, “RFID-Enabled Real-Time Manufacturing Execution System for Mass-Customization Production,” Robot. Comput.-Integr. Manuf., 29(2), pp. 283–292.

[10] Teti, R., Jemielniak, K., O’Donnell, G., and Dornfeld, D., 2010, “Advanced Monitoring of Machining Operations,” CIRP Ann., 59(2), pp. 717–739.

[11] Liu, M., and Liang, S. Y., 1991, “Analytical Modeling of Acoustic Emission for Monitoring of Peripheral Milling Process,” Int. J. Mach. Tools Manuf., 31(4), pp. 589–606.

[12] Jose, B., Nikita, K., Patil, T., Hemakumar, S., and Kuppan, P., 2018, “Online Monitoring of Tool Wear and Surface Roughness by Using Acoustic and Force Sensors,” Mater. Today Proc., 5(2, Part 2), pp. 8299–8306.

[13] Ferrari, G., and Gómez, M. P., 2015, “Correlation Between Acoustic Emission, Thrust and Tool Wear in Drilling,” Procedia Mater. Sci., 8, pp. 693–701.

[14] Barreiro, J., Fernández-Abia, A. I., González-Laguna, A., and Pereira, O., 2017, “TCM System in Contour Milling of Very Thick-Very Large Steel Plates Based on Vibration and AE Signals,” J. Mater. Process. Technol., 246, pp. 144–157.

[15] Yue, C., Gao, H., Liu, X., Liang, S. Y., and Wang, L., 2019, “A Review of Chatter Vibration Research in Milling,” Chin. J. Aeronaut.

[16] Maeda, M., Sakurai, Y., Tamaki, T., and Nonaka, Y., 2017, “Method for Automatically Recognizing Various Operation Statuses of Legacy Machines,” Procedia CIRP, 63, pp. 418–423.

[17] Li, X., and Tso, S. K., 1999, “Drill Wear Monitoring Based on Current Signals,” Wear, 231(2), pp. 172–178.

Utilization of a Manufacturability Assessment Methodology and Metric: A Case Study Application

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ABSTRACT

The exact amount of a product's cost that is committed during the design phase is commonly debated, however based on the literature it is generally agreed that 70-85% of the costs are committed during the design phase. This information combined with the Department of Defense (DoD) focus on engineered resilient systems (ERS) has led to the research and development of a Manufacturability Assessment Knowledge based Evaluation (MAKE) methodology. This research is focused on the development of a manufacturability methodology to evaluate and assess alternative product designs in the early life cycle stages. McCall et al outlines the research efforts focused on the creation of the methodology and development and testing of a corresponding software tool. The research has continued forward with enhancements to the MAKE methodology and tool based on case study findings, which is the basis for this paper.

One particular case study involved assessment of an early life cycle design by Speedbox, LLC. Speedbox, founded and owned by a Special Forces veteran, was developed in response to the arduous task of loading and unloading gear for the U.S. Army Special Forces military community. The first generation container, the Voyager-70, stacks and interlocks securely on a 463-L pallet. After receiving customer feedback, the need and specifications for a second generation container, referred to as Endurance, was defined. The initial requirements for the Endurance-40 included a smaller, more compact size envelope, ideal for first responders and outdoorsmen but with similar cargo capacity as the first generation product.

The research team developing the MAKE methodology partnered with the owner of Speedbox and his design team in development of the second generation product. With the goal of moving manufacturability "to the left", i.e. as early in the design phase as possible, involvement with Speedbox was both timely and beneficial in the development of the assessment methodology. By working with Speedbox, the team was able to focus more concentrated efforts on providing manufacturability input into development of a product that was still in the conceptual/early design phase.

As a result, the Speedbox case study provided valuable insight into the research and development activities needed to improve the methodology to better fit with an early lifecycle development phase. Subsequently, a software tool redesign effort took place to improve the outputs available to the user and to streamline the methodology process. This paper will discuss the improvements for the design of the updated version of the MAKE tool and how it can be used for future assessments of DoD products for benefit to the warfighter.

Research Background and Initial Methodology

Design for manufacturability (DfM) typically revolves around the need to design products with the manufacturing environment in mind, resulting in products with low manufacturing cost, high quality, and that meet the customer demands. To this end, there is an abundance of DfM information available to design engineers in the form of guidelines, checklists, data sheets, software programs, etc. (Bralla, 1996; Anderson, 2014; Boothroyd & Dewhurst, 1994). This information is focused on providing design engineers with the best practices, or rules-of-thumb, necessary to design parts and assemblies with a focus on manufacturing. Rather than design engineers basing their decisions on traditional form, fit and function, DfM adds another layer of complexity for trade off analyses associated with the design.

Most of the information available in the DfM community is focused on the analysis of individual parts and assemblies by identifying characteristics of the parts or assemblies that may cause issues during the intended manufacturing process (i.e. machining, casting, welding, assembly, etc.). Typically, other functional areas of manufacturing that may impact cost are not included in the DfM analysis. For example, the labor required for training with new or specialized processes or environmental, health and safety (EHS) concerns that may drive the need for special equipment or training (McCall, et al., 2018).

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Prior research has led to the development of a Manufacturability Assessment Knowledge-based Evaluation (MAKE) which is a methodology developed to assess the manufacturability of a product at various stages of a product's life cycle. MAKE serves to identify areas within multiple manufacturing areas (Quality, EHS, Supply Chain, etc.) that are impacted by characteristics of the design. The concerns identified in the assessment drive the determination of a manufacturability metric than can be used to compare alternatives of a design at any level from the individual components up to the final assembly (McCall, et al., 2018).

Research by McCall et al., (2017) defined the Manufacturability Interaction Matrix (MIM) as "a taxonomy-based system used to classify the key criteria of manufacturability" that "serves as the basis for the assessment and is used to provide a structured process for evaluating parts and assemblies within a given design." This matrix allows the Subject Matter Expert (SME) to ask the question, "What is the impact of a particular aspect of design on a particular aspect of manufacturing?" Over the course of several case studies and taxonomy improvement iterations, the current version of the MIM, V3.0, was developed (Figure 1). This MIM was used to perform the Speedbox assessment, detailed in the following sections.

Figure 1. Version 3.0 MIM

Aspects of Design → / Aspects of Mfg ↓	Material	Product and Manufacturing Information (PMI)	Design Geometry
Process	X	X	X
Quality	X	X	X
Supply Chain	X	X	X
Capital Equipment & Tooling	X	X	X
Labor	X	X	X
EHS & Ergonomics	X	X	X
Capacity and Scalability	X	X	X

Speedbox Case Study: Overview and Background

The Speedbox product is a ruggedized container system developed for the transportation of military gear during rapid deployment of the war fighter. The design involves a robust container that is portable and stackable with the ability to be clustered to fit standard military pallets. Speedbox was designed and developed by a former military special operator who is also the sole owner/manager of Speedbox LLC.

The MAKE research team began working with the Speedbox owner during a critical redesign effort. The first generation unit, the Voyager-70 was designed to fit and interlock securely on a 463-L military pallet. Since its inception, Speedbox has expanded its customer base to include Emergency Response, Fire & Rescue, and the Outdoors Community (hunter/fisherman). As a result of the feedback from existing customers and added requirements from potential customers, the product line underwent development of a 2nd generation product referred to as the Endurance-40. This next generation production is 2/3 the scale of the first, but still has the stackable option and ruggedness to withstand being strapped to pallets and shipped to the forward bases.

A goal of the research team has been to deploy the MAKE methodology as early in the product lifecycle as possible. The timing of the Speedbox redesign effort (between Milestones A and B) allowed the team to get involved early in the development phase of the lifecycle. Additionally, this early involvement provided the details needed for the research team to conduct a meaningful manufacturability assessment prior to finalization of the design and purchase of costly mold tooling.

As previously mentioned, version 3.0 of the MIM was used to perform the Speedbox case study. This case study served several purposes: illustrate that a flexible, reduced MIM is still effective in manufacturability assessments, allow the methodology to be applied to an early lifecycle product, and provide feedback for an assessment software tool redesign effort. In addition to the MIM, best practice templates and SMEs were utilized during the assessment. The Endurance-40 design is based off the previously developed Voyager-70 design, which allowed the research team to perform an assessment on the existing product and apply the recommendations to the design efforts for the new product.

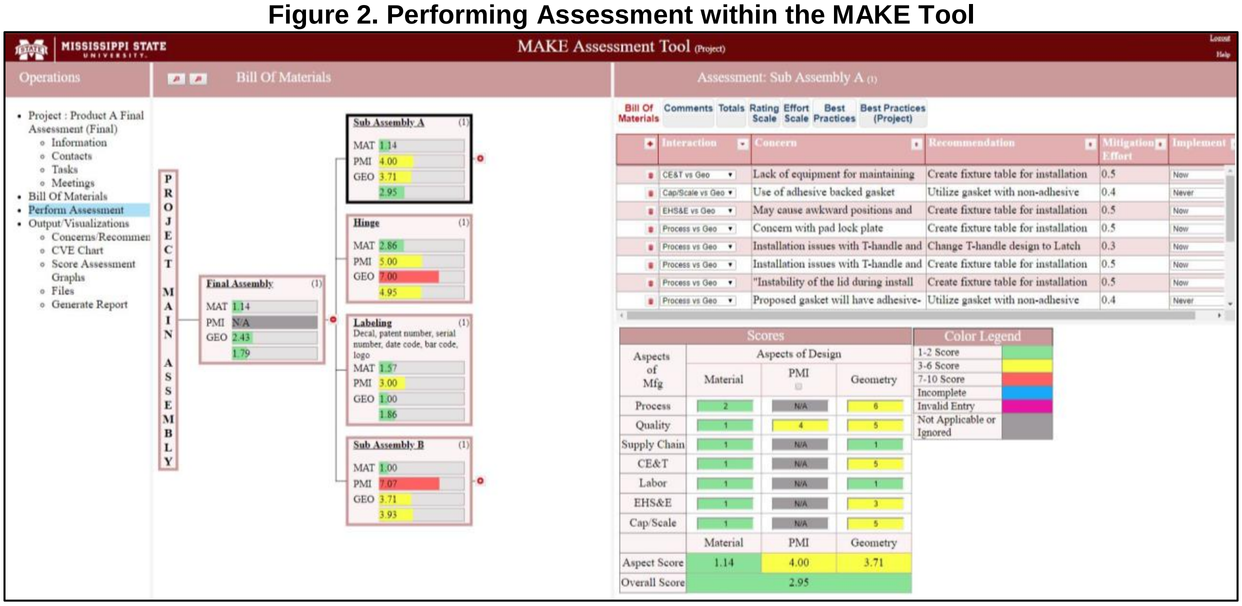
Application of MAKE Software Tool

Wall, Fuller et al. (2018) states that the MAKE software tool is a web-based application with the server-side software written in Python, using the Django framework. It is an organizational tool that allows the SME to evaluate each part, score the interactions from the MIM in Figure 1, and document the concerns and recommendations related to the interaction score. Wall also outlines the initial tool design through screenshots and a detailed walkthrough of the tool's capabilities. One such capability is the ability to build and export an indented Bill of Materials. In previous case studies, the research team has noted that many small to medium manufacturers don't always have a BOM available. If a BOM does exist, the user can import that directly into the tool to begin the assessment process.

Improvements were deemed necessary after utilizing the initial tool in a case study. These improvements included allowing the user to ignore areas not considered applicable, inclusion of scoring guidelines (interaction and mitigation effort) and best practices, the ability to store files within the tool, and enhanced reporting capabilities. Improving the tool in this manner allows for a more effective, organized assessment.

Figure 2 shows the portion of the tool that allows the SME to perform the assessment. Concerns and recommendations are documented in the upper right side. Scores for the interaction, based on the concerns, are entered in the matrix below. As the scores are entered, the bill of materials hierarchy structure in the center is updated with scores for each of the aspects of design and the total score for that particular part. During the Speedbox case study, the Endurance-40 product was still in the design and development stages during the assessment. As such, many of the interactions related to Part and Manufacturing Information (PMI) were not rated due to lack of information. This is typical for a product in early design phases. The methodology and MAKE tool accounts for this by not scoring an interaction that is rated N/A. Furthermore, the software tool allows the SME to ignore all of the interactions related to PMI for an early life cycle product.

Figure 2. Performing Assessment within the MAKE Tool



As the team worked through various case studies, it became apparent how much time was spent reviewing scores and understanding what the scores ultimately mean. In previous improvements to the assessment process, the scoring criteria was improved to be more clear and concise. This improved scoring criteria, along with general manufacturing best practices were included as part of the tool, rather than kept as a separate document. When the user selects either rating scale, effort scale, or best practices in the above figure, the corresponding table will open. This allows the user to have the criteria readily available during scoring discussions. The effort scale relates to the recommendations provided for each concern. The score indicates the effort required to implement that particular recommendation. The best practices are phrased as questions to help guide the discussions and SME thinking.

Typically pictures, data files, and other documents are used as part of the assessment process. The MAKE tool was updated to allow for these files to be uploaded and stored within the database. For organizational purposes, the files are stored within the record for each part. By selecting a particular part on the bill of material structure, the user will get an option for uploading a file. These files are also exportable and therefore shareable among other team members.

Assessment Results

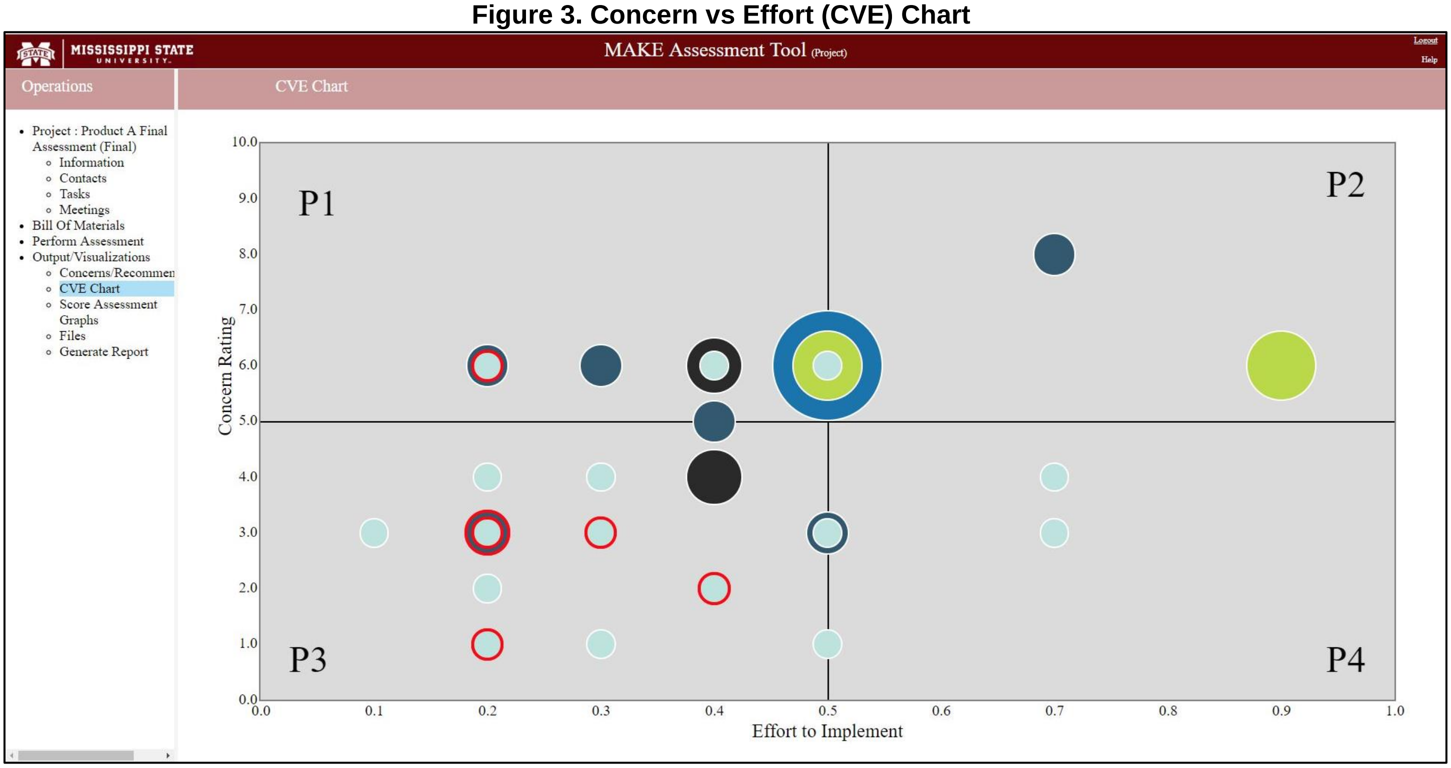
During an assessment, concerns are identified as well as recommendations, which allow the customer to develop their risk mitigation strategy. For the Speedbox assessment, a total of 56 concerns were identified, with 33 unique recommendations. This shows that a single recommendation can mitigate multiple concerns, which is typical in a manufacturing environment with interconnected systems. Within the visualization sections of the tool, a user can see the total number of concerns and recommendations for each part as well as for the entire project.

As previously mentioned, the identified concerns are rated from 1-10. The recommendations are also rated in terms of the effort required to implement said recommendation. The mitigation effort scale runs from 0.1 to 1, with 0.1 being minimal effort and 1 being the maximum effort required to implement the recommendation.

The concern and effort ratings were combined to create a concern vs effort (CVE) chart to provide indication of the benefit vs. effort relationship associated with recommendations. This chart is broken into 4 quadrants, from Priority 1 to 4. Priority 1 would be recommendations that solve high concern items with minimal effort. P2 items are high concern with higher effort. The majority of this case study's recommendations fell in P3, low concern and low effort to implement. Finally, P4 items are those with low concern but high effort to implement. Figure 3 shows the CVE chart for the Speedbox case study.

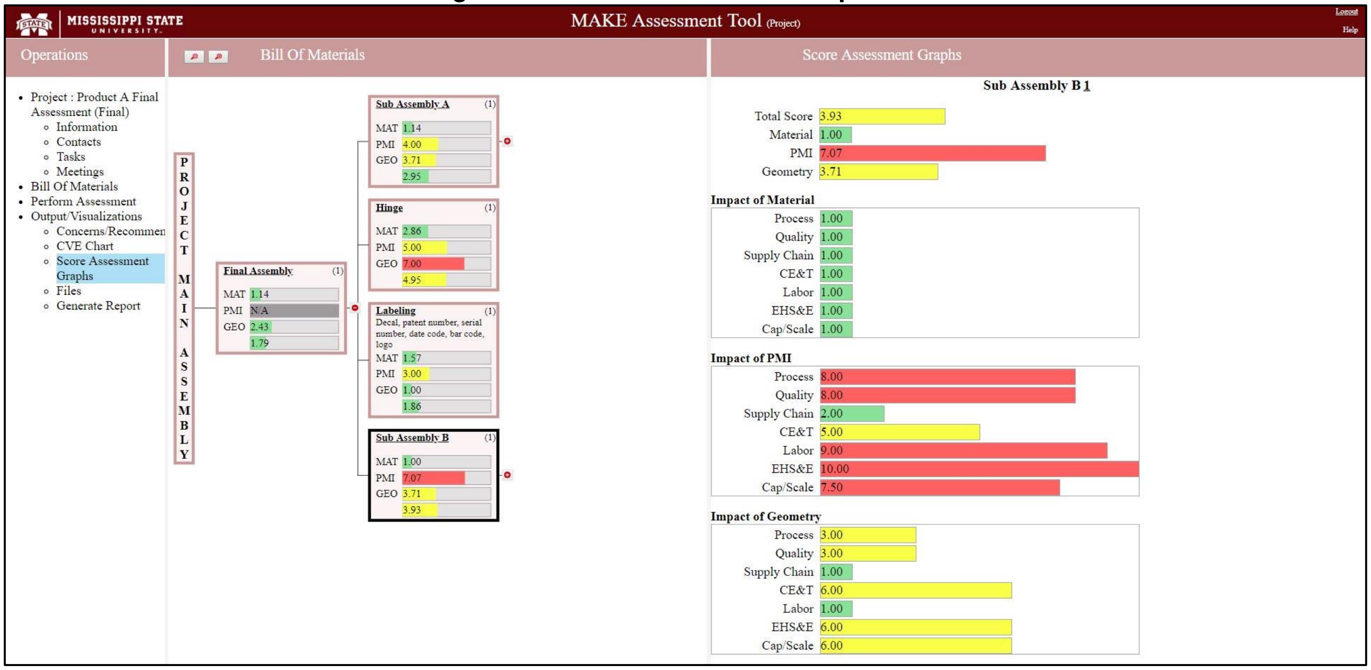
Since a single recommendation may mitigate multiple concerns, the CVE chart needed to indicate this impact. The tool allows the "bubbles" to grow larger as the number of concerns mitigated by that particular recommendation increases. Additionally, multiple concern/recommendation pairs can have the same concern and effort ratings. This is indicated by the red rings surrounding some of the bubbles.

Figure 3. Concern vs Effort (CVE) Chart



The MAKE methodology is based on the Evaluate, Diagnose, and Prescription (EDP) cycle (Walden, McCall 2016). As part of the diagnose phase, the SME may choose to dive deeper into what is causing the score for a particular part or assembly. Within the tool, the Score Assessment Graphs quickly allow a user to identify opportunities for improvement. For example, by analyzing the graphs in Figure 4, for subassembly B1, we can see that the PMI score of 7.07 is driving the score of overall 3.93. Diving further into the PMI area, we see that Environmental Health and Safety and Ergonomics (EHS&E) has the highest impact on PMI, followed by Labor. These would be potential areas where improvement efforts should be focused.

Figure 4. Score Assessment Graphs



The final step in the assessment process is to report the findings back to the customer. During previous assessments, significant amounts of time were spent creating reports for the customer. With the recent improvements made, a user can select from an executive summary style of report or customize the report based on the intended audience. These reports are exported in PDF format and can include any or all of the graphs, files, or charts created within the tool.

Future Work

Significant improvements have been made to the tool, allowing it to become an integral part of performing a manufacturability assessment. The tool ensures that all pertinent parts are assessed in a streamlined, organized manner. Future areas of improvement include the ability to perform analysis of alternatives within the tool, along with refinement of rollup scoring methods and ability to assign weights to certain parts or aspects.

Ultimately, the current methodology and resulting tool were developed with a focus on Milestone C activities. However, usage of the methodology for the Speedbox assessment has shown there is viable application of MAKE to Milestone B activities as well. Current efforts are underway on how to adapt this methodology to pre-Milestone A, where design fidelity is at a minimum. By doing so, the use of a yet to be defined version of MAKE to assess manufacturability of pre-Milestone A designs becomes more feasible and provides more of an impact in the life cycle costs.

References

Anderson, D.M. (2014). *Design for Manufacturability: How to Use Concurrent Engineering to Rapidly Develop Low-Cost, High-Quality Products for Lean Production*, Boca Raton, FL: CRC Press

Boothroyd, G., Dewhurst, P., & Knight, W. (1994). *Product Design for Manufacture and Assembly.* New York: Marcel Dekker Inc.

Bralla, J.G. (1996). *Design for Excellence*, McGraw-Hill, Inc., New York, NY.

McCall, T., Dalton, L., et al. (2018). "Developments of the Manufacturability Assessment Knowledge-based Evaluation (MAKE) and Application to Case Studies*,"* Technical Report for Engineer Research and Development Center, Vicksburg, MS.

McCall, T., Fuller, S., Dalton, L., Walden, C. (2017). "Manufacturability Assessment Knowledge-based Evaluation (MAKE) and a Pilot Case Study." Proceedings from the *2017 American Society for Engineering Management International Conference.* Huntsville, AL.

Wall, E., Fuller, S., Falls, T. (2018) "Design of the Manufacturability Assessment Knowledge-based Evaluation Tool." Proceedings from the *2018 American Society for Engineering Management International Conference.* Coeur d'Alene, ID.

Walden, C., McCall, T., Gedik, R. (2016) “Taxonomy Based Assessment Methodology: Improving the Manufacturability of a Product Design” Proceedings from the 2016 Industrial and Systems Engineering Research Conference. Orlando, FL.

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Assessment of Digital Twin Manufacturing Frameworks

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ABSTRACT

A manufacturing digital twin captures one or more aspects of a physical element for measurement. A framework for digital twining is a set of protocols and standards that assist in the synchronization of digital twins with their physical elements. This paper contains an assessment of ten digital twin manufacturing frameworks submitted to Working Group 15 of ISO TC184/SC4. The examples are being used to assist in the development of the ISO 23247 standard for digital twinning. The working group classified the examples into large, medium and small, and gave preliminary definitions to the concepts necessary to support the synchronization of digital twins with their physical elements. The definitions were subsequently tested on a small-scale framework, and measurements were made of the response times necessary to support real time digital twinning for manufacturing machining.

Introduction

On November 5th, 2018, ten examples of Digital Twin manufacturing frameworks were submitted to the digital manufacturing working group of ISO TC184/SC4. The examples included:

- Large scale frameworks showing current status to optimize operations
- Medium scale frameworks using precision measurement to prevent errors
- Small scale frameworks using adjustable models to achieve higher quality

The examples of large-scale frameworks included an airport and a dockyard. The examples of medium-scale frameworks included several production lines. The examples of small-scale frameworks included two five-axis milling machines. The examples included twins of machines and robots. At least one included twins of people.

The frameworks had the common theme of shortening development cycles by reusing information models. They enabled the sharing of lessons learned by visualizing results. They provided a common platform for software solutions. They enabled cross discipline understanding by using shared protocols to report manufacturing results. They integrated standards for plug and play. They hosted applications that enabled better traceability. They improved verification and validation of functionality. They enabled easier scheduling, better collision detection and closed loop manufacturing control.

This paper contains an assessment of the submitted digital twin manufacturing frameworks. The committee results are summarized in the next section. The author continued the analysis in Section 3, and performed some experiments on a small-scale framework given in Section 4. Some preliminary definitions for Digital Twin manufacturing frameworks are given in Section 5. The definitions are tested against real world data in Section 6, and future work is suggested in Section 7.

Classifications

Figure 1 shows examples taken from three of the frameworks. The first example is a large-scale framework showing the operation of a dockyard. The second example is a medium-scale framework showing the operation of a production line. The third example is a small- scale framework showing the operation of a machine tool. The committee used the examples to classify the frameworks as follows:

Level of Detail	**Physical Element**
- material/component level (production item) - process level (production line) - site level (many processes) - enterprise level (supply chain) - regulatory level (industry sector)	- Personnel - Equipment - Material - Process Definition - Product Definition
Communication styles	**Application Paradigm**
- closed loop adjustment - collision prevention - visualization - off line analysis	- real time control - off line analytics - preventative maintenance - health check

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The benefits of the frameworks were then assessed as follows:

- Owner/Operators
    - Want to know real time comprehensive status of their manufacturing/production
    - Want to drive optimization and production efficiency to maximize profit
- Production/Machinist/Operators
    - Want a more intuitive user interface
    - Want to prevent mistakes
- Engineers - design engineers / planning engineers / manufacturing engineers / quality engineers
    - Want more comprehensive view to understand the true value of their efforts
    - Want to eliminate non-value add tasks such as data re-entry
- Maintenance
    - Want insight to why equipment is failing
    - Want windows of opportunity to do preventative maintenance
- Subcontractors
    - Want access to information so they can bid more easily and accurately
    - Want ability to share manufacturing processes
- Equipment suppliers and builders
    - Want to make it easier to implement and integrate their products
    - Want to efficiently monitor equipment performance for improved performance
- IT developer / integrator
    - Want to be certain organizational security and access control protocols are being followed
    - Want system to robust, flexible, fault tolerant, accurate, scalable and wherever possible non-prescriptive
- Regulatory agencies
    - Want to prove that a process has been followed
    - Want a standardized interface into product information
- Software vendors - infrastructure, tool vendors, solution services
    - Want a consistent, reliable, affordable interface to external data, tools and systems
    - Want to make it easier to deploy their solutions
- Standards Development Organizations (SDO's)
    - Want to promote their standards
    - Want to enhance their value by becoming part of an eco-system

Analysis of the frameworks

The submitted frameworks showed three phases in their operation.

1. A build phase where physical elements are paired with digital twins.
2. A monitoring phase in which a manufacturing activity is mirrored in the digital twins.
3. An evaluation phase where measurements are taken to understand and optimize the activity.

The build phase populates one or more agents with hundreds or thousands of digital twins (see examples below). The monitoring phase uses a communication protocol to apply manufacturing results to the twins. The evaluation phase delivers feedback to a user or application.

The twins are defined using formal or informal information modeling standards. Examples of formal standards include STEP and IFC. They define interfaces to CAD systems and BIM systems. Data is exported from the system and imported into agents to populate digital twins. Not all the examples used a standards-based interface. Ad-hoc systems build their own interfaces to proprietary systems.

Example of communication protocols include MTConnect and Twitter. MTConnect can report the current state of a manufacturing process in great detail. Response rate in excess of 100Hz have been implemented. Twitter is less responsive but more descriptive which enables a richer but less detailed communication. Twitter also allows the listener to be more selective and only receive messages from subscribed resources.

Examples of reporting methods include WebGL and QIF. WebGL reports the current state to a web browser or phone. Such visualizations enable new levels of understanding about the system leading to new optimizations and new efficiencies. QIF reports the results of measurement to a data file. Off line applications can then analyze the data to assist production.

The agents run on a platform. The platform must have sufficient networking bandwidth to communicate with the physical elements in real time. The platform should be application and system agnostic. The platform should enable measurements of the physical elements so that applications can perform closed loop optimizations during the manufacturing.

Small-Scale Framework Example

Figure 2 shows a digital twin manufacturing framework that was applied to machining systems. The framework uses STEP to define its twins, MTConnect to stream its manufacturing changes, and QIF to report quality.

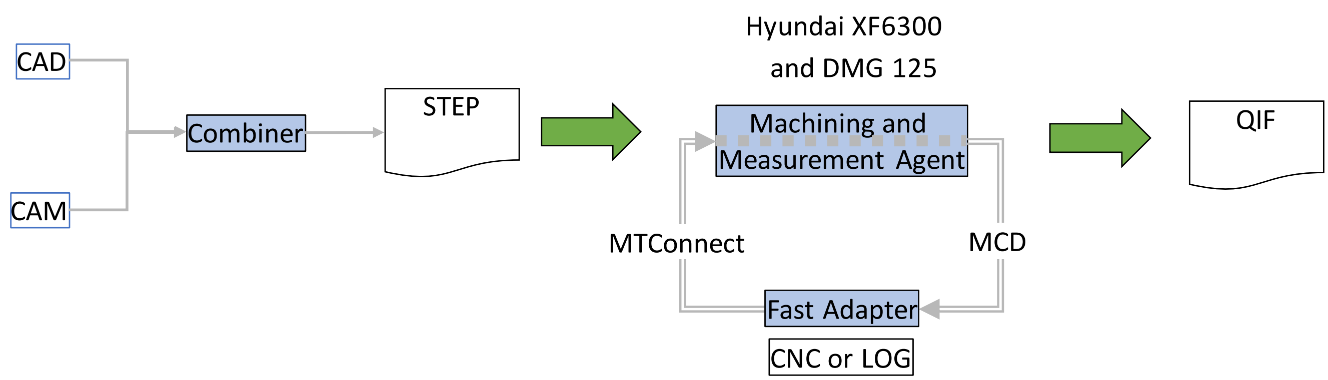


Figure 1 A Digital Twin framework for machining

The following types of physical elements were twinned: Equipment, Material, Product Definition and Process Definition. The equipment was two five axis machine tools. The material was aluminum 6061. The product definition was for a part called the fish head. This part had been designed by Airbus several years earlier in CATIA. Geometric dimensions and tolerances were added by Mitutoyo. Three process definitions were developed by Boeing, Hyundai and DMG [1]. The Boeing one was used for initial testing. The Hyundai and DMG ones were shown at IMTS 2018 in Chicago.

The twins were connected to the machine tools using a fast MTConnect adaptor. This adaptor plugged into the backbone of the machine tools to give a response rate in excess of 100Hz. The adaptor delivered data in the MTConnect SHDR format [2]. This data was read into a MTConnect agent for conversion to XML and passed into the agent for measurement.

The agent was responsible for simulating the machining results by removing digital material from a digital model. Keeping up with five-axis machining was challenging. The results were displayed to the user in a Web browser. At the IMTS demonstrations there was often a perceptible gap between the machining and the display.

The agent was also responsible for planning and evaluating touch probe measurements. It computed touch points using the digital model and used the difference between the as-planned value and the as touched value to determine if the part was in tolerance. For each touch point it sent MCD commands to the machine to make the measurement. The results were returned in the MTConnect data stream and evaluated by the agent. After evaluation, they were exported as QIF and displayed on the model by coloring the measured faces as red, green and yellow.

Two demonstrations were shown at IMTS 2018 in the Hyundai and DMG booths. The solution process was divided into four stages, with the first two stages completing the three-axis machining, and the last two stages completing the five-axis machining. The part was measured after Stages 2 and 4 using the touch probe. The stage 2 measurement was for in-process tolerances, and the stage 4 measurement was for the final tolerances.

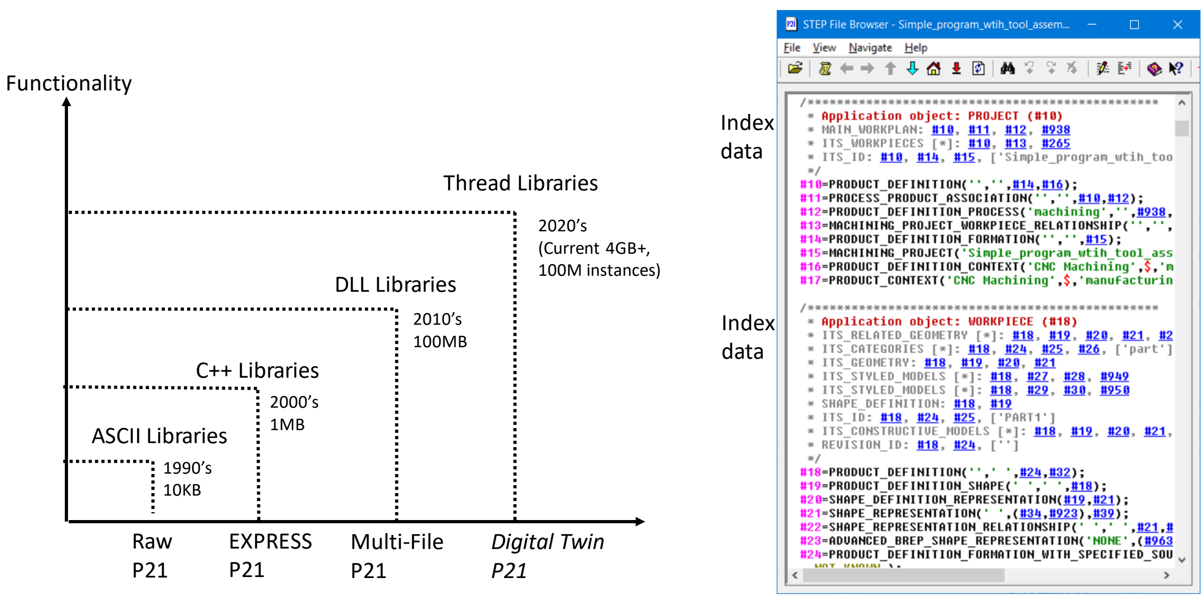
Several desirable elements were absent from the show. The part was not moved between the machines between the stages. This was blocked by the difficulty of moving a part around an active show and because the software was not yet ready to support such a transfer. The part was also supposed to be moved to a CMM machine for more detailed measurement. This was blocked by the same logistic difficulties, and by the absence of an agent for the CMM machine. Lastly it would have been desirable for the machine transfer to have been monitored by connecting robots or people to the framework, and this also could not be done in the time available.

Strawman Framework

The machining example suggests a Digital Twin manufacturing framework should include the following components

1. One or more information modeling protocols for defining the digital twins of physical elements (e.g. STEP or IFC)
2. One or more networking protocols for synchronizing twin models to physical elements (e.g. MTConnect or Twitter)
3. One or more reporting protocols to assess the current status of physical elements (e.g. QIF or OpenGL).
4. One or more platforms for hosting open and closed loop applications (e.g. Windows or Node.js)
5. A secure indexing method to find digital twins in the digital thread.

An indexing method is necessary because a production scenario will include thousands or millions of digital twins. For example, the twins of the cutting tools, the twins of the machining stages, and twins of the tolerances. A secure indexing method will make the framework safe by only delivering results when the user has the appropriate access control, by only executing on authorized platforms, and by only returning twins that have been validated with digital signatures [3].



(a) Evolution of Part 21

(b) Digital Twin P21 with index

Figure 2 Digital Twin Part 21with index data

A twin definition will be complex. The small-scale machining example related a STEP tolerance, to an MTConnect measurement, and a QIF report. In STEP there are multiple entities in a tolerance definition, in MTConnect there are multiple touch points on a surface, and in QIF there are multiple items in an evaluation report [4].

To relate the entities, the index defines groupings. Figure 4 illustrates the concept. Each grouping contains the entities that can be reached from a root. The root is the twin and it has the values and properties necessary and sufficient to represent its physical element. For example, the twin of a workpiece, the twin of a tolerance, or the twin of an airframe assembly.

In STEP, twins are defined by modules, and the properties of the twins are described by mappings. In the figure, the properties are shown as lines in the comments. The necessary entities are listed in order. Some of the entities are required to have specific values in some of their attributes. The entities are linked in their data by forward and backward references. The last entity in each line describes the value of the property. This value can be a simple text string, a complex representation such as an advanced boundary, or the root of another twin. If the value is another twin, then it will be described by its own set of comments elsewhere in the file.

Figure 3 show twin data for STEP and STEP-NC [1]. These two information models have been harmonized which means they can share their twin definitions. AP210 for printed circuit boards, and AP209 for composite ply's have also been harmonized so they can also define twins for this context.

Experimental Results

During manufacturing, changes to the physical elements are recorded in MTConnect or twitter and streamed over the digital thread. Agents that manage the twins then use the thread to update their twin representations.

Implicit changes occur as the result of controlled motions. For example, if the machine tool moves by 10 units, then the agent moves the cutting tool by 10 units and this may result in the removal of 10 units of material (depending on the current state of the workpiece).

The following table shows some statistics for the implicit changes made at IMTS. As previously stated, the machining was divided into four stages and performed on two machine tools. The table shows the speed of removal for each of those stages on each of the machine tools. They were each running different machining programs with different setups. The Hyundai setup was in the traditional flat posture while the DMG was placed on the fixture at a seventy-five-degree angle. (see Figure 1c).

The table shows an analysis of the movements made during the machining. Every time a sensor reading changes a new value is recorded in the MTConnect data. These are called twitches. Many of the twitches are rounding errors. For example, the least significant digit twitches from five to six and back again. This change represents a thousandth of a millimeter so the twin should not respond unless the twitch is the first in a series that delivers a meaningful value.

If the twitch is meaningful then the changes may be part of a continuing movement in the same linear direction. These can be aggregated to prevent a simulator from being swamped by many tiny movements. The table shows how far the changes can be aggregated before a new point becomes necessary. In practice new points are also delivered: (1) so that the simulator does not wait too long before giving feedback, and (2) because for five-axis machining the angle of tool cutting has changed. The latter are shown in the Angles column of the table. The positional values are in millimeters and the angular ones are in degrees.

									Time between Points		
	Twitches	Changes	Points	Angles	Change	Point %	Ang%		Avg	Short	Long
Stage12Hyundai	711451	639789	5303	344	90%	0.75%	0.05%		0.178	0.0009	49.38
Stage12Hyundai	711438	567313	3699	339	80%	0.52%	0.05%		0.226	0.0009	49.35
Stage12Hyundai	711439	542266	2628	237	76%	0.37%	0.03%		0.320	0.0009	49.66
Stage34Hyundai	1101531	1019597	5873	5090	93%	0.53%	0.46%		0.181	0.0009	34.48
Stage34Hyundai	1101529	948947	4411	3067	86%	0.40%	0.28%		0.260	0.0009	34.47
Stage34Hyundai	1101687	860632	3220	1443	78%	0.29%	0.13%		0.426	0.0009	30.24
Stage12DMG	597849	536257	4243	1022	90%	0.71%	0.17%		0.180	0.0019	46.173
Stage12DMG	596422	508317	1790	531	85%	0.30%	0.09%		0.390	0.0020	218.579
Stage12DMG	596452	500951	1044	248	84%	0.18%	0.04%		0.701	0.0029	218.607
Stage34DMG	797510	771306	3849	2069	97%	0.48%	0.26%		0.270	0.0009	262.23
Stage34DMG	797501	753930	2395	962	95%	0.30%	0.12%		0.450	0.0010	262.304
Stage34DMG	796388	735011	1456	379	92%	0.18%	0.05%		0.822	0.0020	262.33

The table shows a small data reduction between the Twitches and Changes and a dramatic reduction between the Changes and the Points. Each machining process was measured three times. For the first measurement the epsilons to determine Changes, Points and Angles were 1e-3, 1e-2 and 1e-1 respectively. For the second measurement the epsilons were 2e-3, 2e-2 and 2e-1, For the final measurement the epsilons were further widened to 5e-3, 5e-2 and 5e-1. The wider epsilons allowed for greater aggregation between changes. The growth is not linear because a sharp change in direction requires new points to be recorded regardless of the epsilon.

The last three columns of the table show the average, minimum and longest time between point changes in seconds. The longest values include wait times at the end of an operations and should be discounted.

The Hyundai thread contained 8,505 digital twins in 945,611 entities, and the DMG thread contained 7,207 digital twins in 700,190 entities. The Hyundai machining took 13 minutes 42 seconds for Stages 1 and 2, and 24 minutes 50 seconds for Stages 3 and 4. The DMG machining took 10 minutes 39 seconds for Stages 1 and 2, and 14 minutes 15 seconds for Stages 3 and 4.

The implicit changes were computationally challenging because of the necessary aggregation. The explicit changes less so. The explicit changes occurred when the MTConnect data contained records that identify a twin. For measurements each touch point was identified by the UUID of a feature. The agent was able to use this UUID to lookup the feature and apply the measured value to its digital twin.

The following listing shows a sample of this data. The first four lines contain implicit data. The last line contains an explicit record measuring a point on a feature with the UUID beginning “6a91fcca”. The expected distance is 8 and the measured distance is slightly more. This is one of five points measured on this feature. An algorithm in the measurement agent then uses these values to determine if the feature is in or out of tolerance, and the results are shown on the display screen as green for good, red for bad, and yellow for a mixture when a feature is meeting some, but not all, of its tolerances.

```
2018-09-12T16:16:53.865917|p1BlockNumber|57
2018-09-12T16:16:53.865917|p1block|N16 STOPRE
2018-09-12T16:16:53.873896|Yactm|19.29
2018-09-12T16:16:53.877885|Yactm|19.289
2018-09-12T16:16:53.886861|measure|feature: "6a91fcca-acb8-4815-b995-89a03680b7c3", order:1
count:5 id:"FACE327731" characteristic:"3DLocation" distance:8.02209585274248
```

Future Work

In the IMTS demonstration, the framework contained one agent that handled both the machining and measurement. The framework shown in Figure 4 has five agents: two for the CNC machine tools, one for a robot, one for a Coordinate Measurement Machine, and one for a manager to coordinate the manufacturing cell.

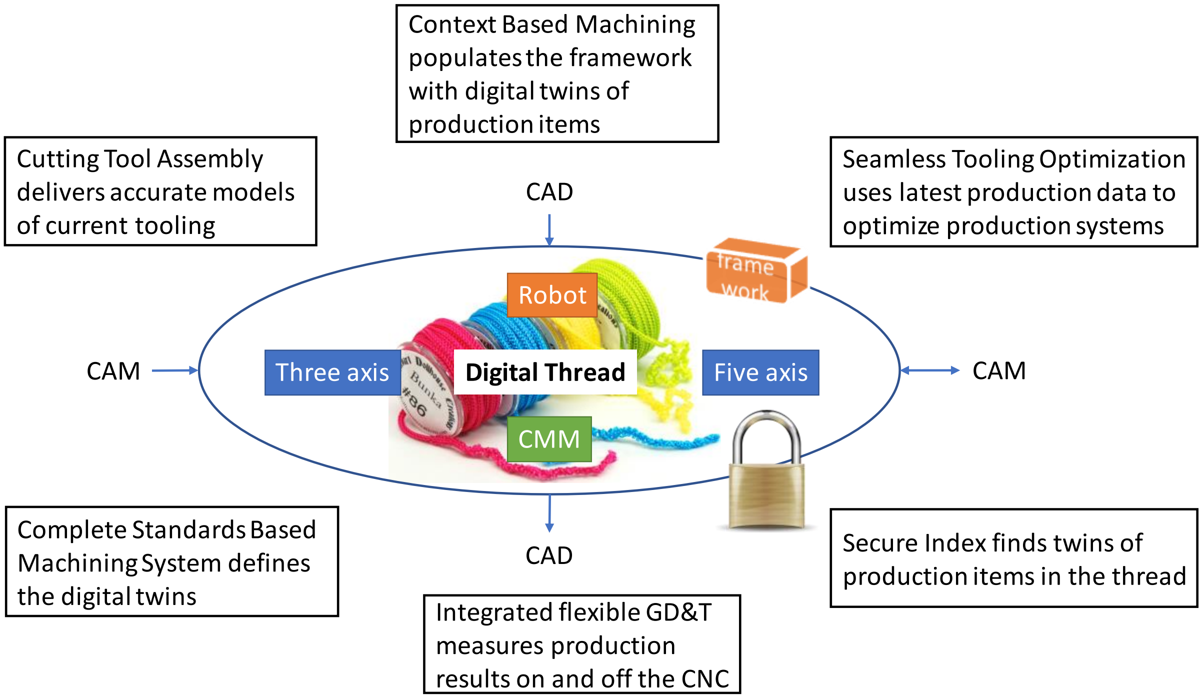


Figure 3 Strawman medium scale framework

At IMTS log files were used to record changes to the physical elements. These log files were played in real time by streaming data from the machine, and afterwards by replaying previously recorded demonstrations. In the proposed new framework, the four ordinary agents will read the log files of their devices and write a log file to the managing agent.

For example, when the three axis CNC finishes it writes a command to a system log file. The command is read by the managing agent. The managing agent then initiates a program in the robot to transfer the part to the CMM. When the robot finishes it also writes a record to the system log file. The managing agent then starts the CMM machine, and so on for each of the actions. These messages may be more suited to a Twitter protocol than MTConnect. The same may also be true of the explicit commands detailed in the last section.

A medium scale framework may contain a single agent connected to multiple devices, or multiple agents connected to single devices. If there is a single agent then it will have access to all the information in the framework which should be important for applications such as collision detection. If all the devices operate at the frequency observed at the IMTS demonstration then the necessary compute power will be formidable. Fortunately, fast server machine with as many as 128 cores are becoming available at reasonable prices. These servers use sophisticated caching algorithms to give the cores access to a shared memory space. Reading data from multiple Internet data streams is a common application, and the different cores can be dedicated to twinning different devices within the shared memory space.

A large-scale framework that operates at the scale of a manufacturing plant, or a supply chain may be even more challenging. Such a framework will need to include coordinated agents for people, products, processes and machines. As per the analysis of the second section, expectations for the functionality of a large-scale framework may be low, however. Specifically, if the framework can give meaningful visualizations of the current operation of a plant or supply chain, then owners and operators will be highly satisfied because they are not available today.

A large-scale framework must process data from many sources. The data will be defined by multiple information models some of which may be standards, some of which may be consortia agreements, and the remainder will be company specific. Making all these models inter-operate is challenging but a new protocol called the Administration Shell is becoming available to meet this requirement [5]. The team plans to prototype a medium scale framework by building a machining cell agent for IMTS 2020. Discussions will then take place with the developers of the Administration Shell about how to build a large-scale framework for aerospace plants.

Conclusion

This assessment of the digital twin manufacturing framework examples leads us to the following definitions for digital twin, digital twin agent and digital twin framework.

1. A digital twin is a measurable digital model of a physical element that can be observed in the real world.
2. A digital twin agent processes messages streamed from sensors, and uses them to synchronize the current state of digital twins with that of their corresponding physical elements.
3. A small scale framework manages one agent. A medium scale framework manages multiple agents in a shared memory space. A large scale framework manages multiple levels of agents distributed between multiple memory spaces.

If we can return to the Battle of Britain, then the agents are the Ladies with sticks pushing models of airplanes around a map. They get messages from aircraft spotters and radar installations and use them to update the positions of the models. The managing agent is the man sitting in the big chair at the head of the table. He uses the picture of the battlefield to take actions that add and subtract physical airplanes to the battlefield. This is a medium scale framework because there is one managing agent and multiple ordinary agents in a shared memory space. If we further include an air marshal who uses the bigger picture to add and subtract resources to airfields, then we have a large-scale framework.

Working Group 15 of SO TC184/Sc4 is developing the ISO 23247 standard in four parts. Part 1 describes the basic principles and concepts. Part 2 describes a reference architecture. Part 3 describes how to use information models to define twins. Part 4 describers how communication protocols connect physical elements to their twins. The small framework prototype shows the communication protocols must be able to stream large volumes of data very quickly. The digital twin agent reads the stream and makes measurable models. When issues are identified the models are shared with CAD, CAE and CAM systems to make optimizations that ensure the final accuracy of the manufacturing product.

[1] "A roadmap for STEP-NC-enabled interoperable manufacturing", M. Hardwick, Y. F. Zhao, F. M. Proctor, A. Nassehi, Xun Xu, S. Venkatesh, David Odendahl, Leon Xu, Mikael Hedlind, Magnus Lundgren, et al, International Journal of Advanced Manufacturing Technology, Volume 66, Nos. 1-4, Springer Verlag, March 2013

[2] "Improving Machine Tool Interoperability using Standarized Interface Protocols: MTConnect", Athulan Vijaraghavan, Will Sobel, Armando Fox, David Dornfield, Paul Warndorf, Proceeding of 2008 Symposium on Flexible Automation 2008, http://escholarship.org/uc/item/4zs976kx.

[3] "Embedding X.509 Digital Certificates in Three-Dimensional Models for Authentication, Authorization, and Traceability of Product Data." Hedberg TD, Jr., Krima S, Camelio JA. ASME. *J. Comput. Inf. Sci. Eng.* 2016;17(1):011008-011008-11. doi:10.1115/1.4034131.

[4] "QIF 2.0: A New Digital Interoperability Standard for Manufacturing Quality Data", Curtis Brown, Dimensional Metrology Standards Consortium, 2014, http://www.nist.gov/el/msid/upload/17_cBrown.pdf

[5] "The Structure of the Administration Shell: TRILATERAL PERSPECTIVES from France, Italy and Germany", Federal Ministry for Economic Affairs and Energy (BMWi) Public Relations E-mail: publikationen@bundesregierung.de, www.bmwi.de, 2018

Industry Readiness for Digital Manufacturing May Not Be as We Thought Preliminary Findings of MxD* Project 17-01-01

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ABSTRACT

Industry interviews conducted during this project have revealed some potential inaccuracies in the conventional thought as to the readiness of the US industrial base to adopt digital manufacturing processes and procedures. The performers in this project went into the research phase with the assumption that approximately half of the supply chain would be ready to implement digital manufacturing capabilities into their organizations. With this assumption the deliverable of the project would be a set of technically-oriented playbooks for Original Equipment Manufacturers and Small and Medium sized Manufacturers to use as guides for implementation. What was found during the interview process was that less than 30% of those companies were actually in a position to adopt digital capabilities and that there is a gap in awareness and knowledge in what digital manufacturing means. Additional research into other studies has revealed similar issues in adoption of these necessary skills and capabilities. This realization has led the research team to rethink the deliverables of the project to include a digital manufacturing awareness/education component. In this paper the authors will present the findings and discuss the meaning of these revelations to the digital manufacturing and model based enterprise community.

INTRODUCTION

The final deliverable for this project was originally to be a set of document-style playbooks for Original Equipment Manufacturers (OEMs) and Small and Medium sized Manufacturers (SMMs). These playbooks would help companies understand the need for becoming digitally enabled to participate in the supply chains of today and into the future, and provide guidance on what and how to get started [1]. The goal is to overcome the inefficiencies created by the inability to communicate accurate and timely technical data, which continues to be one of the most significant sources of waste and project overruns [2]. Industry has made consistent efforts to integrate and link data across the product lifecycle and enterprises for decades [3]. The benefits of reduced cost and time along with innovation would result in a better positioning of the U.S. industrial base to compete in the global market.

The project team is focusing on utilizing existing tools and technologies developed in previous commercial and government funded research to create a roadmap and set of playbooks for OEMs and SMMs to guide the implementation of secure digitally-enabled supply chain practices and technologies. But, revelations made during the research phase of the project showed a lack of readiness to adopt and have provided cause for the project team to reevaluate the best use of their work. Insights found thus far in the execution of the research portion of this project have indicated that what the digital manufacturing and supply chain community believed to be the current state of industry readiness may not be accurate. Interviews with tiered supply chain partners have indicated that industry is not as far along the digital capability maturation scale as the team originally thought.

Once the adoption barriers were more evident, the research team made a concerted effort to find other studies that were concerning the adoption of digital manufacturing and model-based enterprise capabilities. This search supported the revelations found during the interview process and shed new light on what the industrial base truly needs for moving closer to an Industry 4.0 capable supply chain. These discoveries have caused the team to pause and think about whether this effort is a “how to” playbook effort or does it have more of an education and awareness purpose?

METHODOLOGY

To develop a format and structure for the roadmap and playbook for both OEMs and SMMs, the research team approached the research review from several directions. The major components of the research effort are:

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- Input from industry on supplier-customer data interactions
- Interviews of suppliers with contacts made by industry partners
- Interviews made by the industry partners themselves
- Academic literature review
- Investigation of applicable and developing standards

This paper is focused on the outcome of the interviews and the academic research. The interview portion of this project was focused on three elements fundamental to digital manufacturing:

- Interactions - Determine what information is exchanged between customers and suppliers and how it is exchanged.
- Inefficiencies - Understand any impact from communications inefficiencies.
- Motivators and barriers - Identify potential motivations and barriers to the adoption of digital manufacturing for both customers and suppliers and the individual roles within.

The input from the participants in these areas will help the project team develop an approach and messaging designed to accelerate adoption. The industry members on the project team provided a list of potential suppliers for the research team to interview to gain insight into current state and digital capability of the traditional supply chains functioning in industry today. This primary research provides qualitative evidence to inform development of the playbook content and structure.

The interview targets were SMMs that produce both electronic and mechanical goods for large companies, OEMs, prime contractors and the DoD. These are the companies that typically lag in adoption of digital manufacturing but make up a significant portion of today's supply chains.

Targeted individuals for these interviews were in positions where they personally exchange data with trading partners and/or must use data that is exchanged. For this exercise, the team is most interested in subjects who exchange and use data related to the design and manufacture of goods. The subjects represent a good cross-section of size and type of goods manufactured, both mechanical and electronics. Only one company is highly reliant on DoD business, while the majority sell more commercial than defense products. Several interviewees did not know their mix of DoD vs. commercial revenue since they supply to OEMs that do not reveal where the product will be used. Companies spanned the country and ranged in size from 28 employees to 400, with half of those interviewed having fewer than 50 employees and the other half had between 50 and 500 employees. Industries served include aerospace, defense, medical, automotive, semi-conductor and robotics. The role of those interviewed was most often the owner or a senior executive, with program managers and engineers being the second largest group. These subjects had typically been in the industry for decades and in their role for more than five years.

Three different groups of interviews were conducted in different settings with different subjects. A discussion guide was developed to be used with each interview participant to provide consistency, enabling the findings from all three interview groups to be aggregated. Thirteen total interviews were conducted thus far.

- **MxD* Workshop Interviews** - Two interviews were conducted with MxD* supply chain workshop participants in June 2018. Although the subjects did not meet the target criteria, they were able to provide some insights.
- **OEM Interviews** - The project team OEMs conducted four face-to-face interviews of suppliers that were representative of their supply chains.
- **Dedicated Team Interviews** - Project team OEMs suggested 26 suppliers to be interviewed by The Lucrum Group and Auburn University. That list was pared down to nine suppliers based on selection criteria that included company size, type of goods manufactured and location. Of those nine suppliers, four agreed to participate in the interviews – two in person and two by phone. Most of the remaining OEM-suggested targets were unresponsive to interview requests. One declined to participate. Several small manufacturers known to the interview team were included to supplement the data. Additionally, several interviews were conducted with large companies to get supplier insights from the customer perspective.

An important note is that all companies interviewed primarily have a low-volume, high mix of products produced. These companies are typical of aerospace and defense supply chains. No interviews were conducted with companies that are primarily focused on high-volume, steady-state production.

EARLY FINDINGS

Industry interviews revealed a significant gap in the believed readiness or capability of suppliers to adopt digital manufacturing processes and participate fully in a digitally enabled supply chain. Findings from these interviews have been relatively consistent. Following are four of the most important findings.

Little understanding of what is "Digital Manufacturing"

When asked for their definition of digital manufacturing, most respondents said that it means going paperless. They view it primarily as a means to move data between operators and equipment without manual entry or intervention. None of those interviewed mentioned integration, modeling, collaboration, analytics or similar terms associated with digital manufacturing. One subject explained that most of their operators do not have computers. The organization still generates a significant amount of paper, such as quality inspection reports, corrective actions and first article reviews. They do not see an easy path to moving toward a paperless environment. A few subjects did say that it was something that could positively impact the entire manufacturing process. One interviewee recalled an instance where they had to ramp up from 30 items per month to 30 per day in response to a surge in demand from DoD. They said that they learned then that you must go from "heroics" to "systems" to be able to scale quickly and that digital manufacturing provides that kind of system.

While interviewing a large manufacturer about their SMM suppliers, the large company expressed concerns about the ability of SMMs to adopt digital manufacturing. "Smaller suppliers are focused on the work at hand rather than thinking strategically about the future". The subject said that even when they do look to the future, the SMM must set aside time and money to make those advances, which can often be challenging.

Despite those concerns, this large manufacturer had several good anecdotes of when they had brought in suppliers to educate them about the advantages of digital manufacturing. In one example, a subject matter expert from the large company was able to help the small supplier learn how to use Product and Manufacturing Information (PMI). The result was that the supplier then began producing more valuable 3D models than the 2D drawings they used to provide. The same large company also employed a third party to help their suppliers develop digital capabilities.

The findings in these interviews are echoed in a recent report on the adoption of digital manufacturing by the Information Technology & Innovation Foundation (ITIF) [4]. In addition to pointing out the lack of quantitative data on the status of digital manufacturing adoption, they found that most U.S. companies are still in the initial phases.

Significant challenges in technical data exchange

There continue to be significant issues in the use and exchange of technical data and specifications. STEP files were the most common format for exchanging data, although there were instances of suppliers receiving files in PDF or native CAD. There were even a few reports of receiving paper drawings. Most interviewees are doing some translation from one format to another, largely through software although a few are done manually. Some suppliers validate these translations on their own, one requires that the OEM validate the translation and others do not validate at all. Several interviewees reported having to create an entirely new model from scratch, one of them as much as 50% of the time.

Many companies still receive a mix of both drawings and models from customers. When a customer sends both, suppliers often find inconsistencies in data between the two. (This seems to be particularly true when the DoD is the customer.) In some cases, the customer has said that the drawing is the official version and the model only for visualization. That situation often results in the supplier creating an entirely new 3D model for quoting and to generate machine code.

Suppliers also find wide variations in the completeness and accuracy of data provided. Not only is there disparity between customers, but between different engineers at the same customer as well. One subject commented that they used to see multiple signatures of reviewers on a drawing and now they typically see one signature. They view this as an indication that there are fewer checks, which could cause some of the issues. Most interviewees reported that they often must go back to the customer for additional data or clarification. Usually the need for additional information is discovered in the quoting process, although it also happens after the work has begun. One example provided was a part that shows engraving on the model and the print calls out engraving, but neither has data about line width, depth, etc.

This need for clarification exposed another impediment, and that is the lack of a direct connection between customer and supplier engineers. Most of the interviewees said that they must forward questions to the customer's buyer or purchasing agent, who then forwards it to the engineer. The customer's engineer reviews the question and sends their answer back through the buyer to be forwarded to the supplier. This process can often take weeks, which places an additional burden on the supplier to meet their deadline.

In addition to issues about the actual data, there are significant inefficiencies in transmitting that data. Many of the subjects, particularly those associated with an OEM, use their customer's portals to exchange data and manage version control. The primary challenge with this approach is the cost and effort SMMs must bear to learn and work with a different portal for each of their customers. One benefit of portals is that a few OEMs include both buyers and engineers in all supplier communications, removing the buyer bottleneck. The greater challenge in exchanging technical data is that nearly all suppliers use email extensively as their primary means of communications. This leads to various issues ranging from delays to incorrect versions and loss of data continuity. That problem is exacerbated when those emails are sent to a large group of individuals or multiple companies in a supply chain. Two of the most often cited results from all technical data issues are additional costs and customer rejects. In both cases, subjects said that they typically had to bear those costs regardless of where the problem originated.

Very little design collaboration

Subjects reported limited up-front design collaboration. Suppliers that interact through a customer portal seem to be the most likely to collaborate on design, although the focus is typically manufacturability issues. Manufacturers that do not interact through a portal report less design collaboration. When these suppliers do collaborate, it is typically by email, although *fax was cited as a communications method for collaborating by nearly half of the subjects*. One supplier said that they must communicate with their customer several times weekly to address manufacturability issues that could be resolved by up-front coordination.

Two of the interviewees reported that the ability to collaborate on design is a selling point. One subject does extensive collaboration with customers on design, especially manufacturability, before the customer asks for a quote. The supplier considers this level of collaboration to be a sign of trust and a considerable competitive advantage. In cases where there is not up-front collaboration, this supplier will often return a quote with a price for the work as specified and then optional pricing if certain manufacturability challenges are removed.

Limited exchange of production data

Only a few interviewees reported providing any production data to the customer. The primary means was by email and tended to be in response to questions about order status or inventory. Several suppliers interacting through a customer portal said that they also provide data for items like material certification and inspections. Most of the companies interviewed are not leveraging the Internet of Things (IoT) in their production facilities. The two suppliers that said they are somewhat advanced in their use of IoT are sharing production data with customers primarily through email.

OTHER RESEARCH

Digitally enabled manufacturing is discussed using many terms that all mean something specific, but are quite often used interchangeably by manufacturers, government and academics. In the U.S. the term Smart Manufacturing is used to describe a set of capabilities of which digitally enabled processes and procedures are a significant part. Industry 4.0, which originated in Germany and is used predominantly in Europe, and Smart Factory, used in Asia and Europe are often used interchangeably as they both describe a set of capabilities that include digitalization and cyber physical systems. These three terms are used to describe the objective of enabling the industrial base in different countries to connect and adopt informational and operational technologies, as well as business and operating models, which can result in new revenue streams as well as cost and efficiency gains [5]. Regardless of the term used to name the effort, the components of the systems of operation include digitalization of processes and procedures along with the exchange of technical data based on the use of models as the authoritative source of information.

A DoD study in 2016 [6] provided insight into a number of issues with organizations, albeit government, adopting digital manufacturing/model-based enterprise (MBE) capabilities. In this research a historical review of documentation was performed to provide a baseline of issues encountered in implementing MBE which encompassed searching a library of past articles, presentations, white papers, and reports to collect issues or pain points from the documents that were hindering the adoption and integration of digital capabilities, such as MBE, through the lifecycle of products and systems. The list of issues naturally distributed into five categories. Component issues were aggregated into the five topical categories in an initial list and sent to a known group of subject matter experts (SMEs) for review. After this initial review of the categorized issues, some SMEs provided additional materials to add to the issue review and the reference list. In an effort to derive the true issues from those that may actually be on the fringe, the team compared the list of topics and the component issues with the Advanced Manufacturing Enterprise (AME) Subpanel taxonomy which allowed additional insight into issue credibility. The AME Subpanel operates under the DoD's Joint Defense Manufacturing Technology Panel (JDMTP). Once the categorized list of issues was developed, additional sources of issues were evaluated to either corroborate or modify the initial list. The main categories of issues found in the research, (1) Interoperability, (2) Data Reuse, Communication, and Archiving, (3) Advanced Manufacturing Vulnerabilities, (4) Analysis, and (5) Infrastructure, all affect the overall production costs and time of systems acquisition and sustainment [6]. Each of these issues independently can be a significant obstacle to overcome in adopting MBE, but most organizations encounter combinations of the issues which can stifle the energy necessary to transform to a digitalized system.

In 2017, International TechneGroup Incorporated (ITI) hosted several online webinars on subjects associated with adoption and implementation of MBE in organizations. ITI collected insights into problems with adopting MBE in organizations and found numerous similarities to findings of adoption issues in other studies. Many manufacturers are using digital tools such as advanced simulation and Product Lifecycle Management (PLM) supported by engineering systems to perform required functions in product realization. ITI is a provider of interoperability, validation and migration solutions for digital product data and related systems for manufacturing and engineering enterprises. Consequently, their webinars draw many seeking assistance in developing digital MBE capabilities [7]. The ITI marketing department collected responses to a set of questions in an effort to identify potential products for the company to meet current and future needs in manufacturing and engineering operations. The relevant information was collected as answers to open-ended questions which can be classified as unstructured data. This unstructured data was analyzed using tools developed to gain insight into the myriad of unstructured, open ended comments and found a similar group of issues as the DoD study in 2016.

Mittal, et al., found similar issues with European manufacturers with adoption of Industry 4.0 digital capabilities [5]. In this extensive study of maturity models, the authors identified studies throughout Europe that indicated the SMMs of the region realize that they need to engage in digitalization but do not know how and where to start. In this study the authors refer to a report by WirtschaftsWoche magazine stating that "two-thirds of over a thousand surveyed industries in Germany, Austria, and Switzerland are not aware of the basics regarding Industry 4.0 technologies and their enabling business and operating models" [5]. This study also found that many SMMs are "ignoring associated trends like digitization (digitalization) and automation" [5].

In a report looking at Korean and U.S. industries, Ezell, et al., found "… that, for all manufacturing digitalization's promise, U.S. manufacturers – especially small- to medium-sized enterprises (SMEs), the 250,000 of which account for 98 percent of all U.S. manufacturers – have been particularly slow to adopt digital manufacturing practices, with most companies remaining just at the initial stages of smart manufacturing technology adoption" [4]. In a study on industry in West Virginia, Wuest et al. found that "Overall, there is little awareness of Smart Manufacturing and related topics among manufacturing SMEs in WV" [8].

Even though each of these studies are probably not, in and of itself, convincing evidence of the state of the industrial base, the combined weight of the different samples these studies cover, and the similarity of findings, provides a preponderance of evidence that the supply chain is not as mature in digital readiness as the MBE community has been led to believe (or we have convinced ourselves). The issues identified in these studies and through the interviews performed for the MxD* 17-01-01 project are apparently significant barriers to the adoption of digital capabilities and a model-based enterprise.

SUMMARY

There are apparently many more issues than first thought to overcome before the full benefits of an MBE environment can be realized. Multiple studies are now indicating a serious gap between the OEMs which are working their way through the many issues to becoming a digitally enabled/MBE organization and the supply chain participants upon which these OEMs rely to produce their products. The technical issues of connecting the digital thread have dominated the landscape and the attention of the MBE community which has mainly consisted of researchers, solution providers and OEMs thus far. The missing piece has been the tiered suppliers in the manufacturing industries that do not possess the resources and funds to participate in the development of the technology. This leaves an awareness and knowledge gap that the supply base cannot overcome without assistance. It is time to pay attention to the development of the business case for digitally enabling the supply chain and provide the education and assistance needed to adopt and mature digital capabilities in the industrial base.

NEXT STEPS

Helping SMMs adopt digital capabilities requires a comprehensive understanding of the current state to inform the design and deployment of programs that more effectively accelerate the depth and breadth of digital manufacturing adoption throughout the U.S. Gathering those insights requires a coordinated effort that reaches a representative cross-sample of SMMs. A key element is capturing the differences between high-volume, low-mix manufacturers and those with a low-volume and high-mix of products. While previous research has focused largely on the former, recent work by Auburn University and others indicates the greater need and opportunity is on the latter. Such insights are particularly important to industries such as aerospace and defense, where low-volume and high-mix production is the norm. The companies with the greatest exposure in this engineering-centric work are those that design, machine, cast, forge, print and assemble discrete products. An additional effort should compare the state of digital manufacturing in the U.S. with Europe and Asia. The information should then be collated and analyzed to inform recommendations of how to best accelerate the depth and breadth of digital manufacturing adoption in the U.S.

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REFERENCES

[1] Harris, G.A. , Peters, C., Whittenburg, R., Hughes, R., Fischer, K., Hartman, D., Ma, K., Shubrooks, J., and Hedberg, T., 2018, “Digitally Enabling the Supply Chain,” *NIST Advanced Manufacturing Series, Proceedings of the Model Based Enterprise Summit 2018,* NIST Headquarters Gaithersburg, MD, April 2-5, (in publication).

[2] Subsystems Technologies, Inc., 2011, “Overcoming Key AME Inefficiencies Through Improved MBE Tools and Processes,” Air Force Research Laboratory, AFRL RFI-11-10-PKM, INDISTRIAL BASE INNOVATION FUND (IBIF), Request for Information (RFI) response submitted 2011.

[3] Hedberg, Jr., T.D., 2018, “Enabling Connections in the Product Lifecycle using the Digital Thread,” Ph.D. Dissertation, Industrial & Systems Engineering Dept., Virginia Polytechnic Institute and State University, Blacksburg, VA.

[4] Ezell, S.J. , Atkinson, R.D., Kim, D.I., and Cho, J., 2018, “Manufacturing Digitalization: Extent of Adoption and Recommendations for Increasing Penetration in Korea and the U.S.” Information Technology & Innovation Foundation, Washington, DC, August.

[5] Mittal, S., Khan, M.A., Romero, D., and Wuest, T., 2018, "A critical review of smart manufacturing & Industry 4.0 maturity models: Implications for small and medium-sized enterprises (SMEs)," *Journal of Manufacturing Systems*, vol. 49, pp. 194-214, Oct.

[6] Harris, G.A., Abernathy, D., Whittenburg, R., Holden, A., and Still, A., 2018 "Issues in Implementing a Model Based Enterprise*," in the NIST Advanced Manufacturing Series, Proceedings of the Model Based Enterprise Summit 2018,* NIST Headquarters Gaithersburg, MD, April 2-5, (in publication).

[7] International TechneGroup Incorporated (ITI), 2018, "About," [Online]. https://www.iti-global.com/company. [Accessed June 27, 2018].

[8] Wuest, D.T. , Schmid, P., Lego, B., and Bowen, E., 2018, "Overview of Smart Manufacturing in West Virginia," Bureau of Business & Economic Research, Industrial and Management Systems Engineering, West Virginia University College of Business and Economics, West Virginia University Benjamin M. Statler College of Engineering and Mineral Resources, Morgantown, WV, Winter 2018.

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Standards Needs for Maintenance Work Order Analysis in Manufacturing

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ABSTRACT
To bolster the efficiency and performance of maintenance work in manufacturing it is increasingly necessary to ensure that maintenance operations are capable of seizing on analysis techniques from prognostics, health-monitoring, and related disciplines. Despite a surge in availability for low-cost sensing and data processing generally, the bulk of available knowledge on any given maintenance workflow will exist within historical records, via Maintenance Work-Orders (MWOs). Additionally, despite burgeoning standards in sensing and the related analysis, there is a dearth of similar standards scoped to MWOs. To that end, this paper enumerates standards needs in MWOs; specifically, MWO data collection and storage, MWO data cleaning and parsing, and MWO data analysis needs.

MWO STANDARDS NEEDS

In any manufacturing operation, achieving proper maintenance practice revolves less around the mere act of executing maintenance work, and more around the key preparations and decisions made leading up to and/or following that work. Examples of key decisions being made include: how often to repair a component; whether to replace, or to repair a subsystem; who for, and when to schedule a job. These decisions help to minimize downtime, increase asset life-span and performance, or maintain production rate. However, making decisions holistically involves acquiring multi-scale input information from a wide range of sources, like individual machine conditions, cost, interactions between production lines, technician competencies and schedules, and complex supply-chain considerations. This complexity, especially under dynamic circumstances, necessitates continued reliance on human practitioners that are capable of adapting their cross-contextual expertise to unfamiliar circumstances, while also increasing the pressure on them to adapt faster and to more complex systems than ever before.

Analysis techniques for processing these data streams are theoretically able to assist in making these decisions, but rely on taking advantage of newly available data structures, software frameworks, and hardware capabilities capable of processing and acting on widely varying data types. Standardized methods and interfaces for parsing the information contained in these streams is a necessity to prevent untenably high adoption costs. While standards do exist in some areas of the maintenance space, serious gaps exist in standardization of data representation and processing for Maintenance Work Orders (MWOs). This must be addressed to enable innovation and broad adoption of computational techniques.

Multiple domains have related standards in Prognostics and Health Management (PHM). Oil and gas production operations have, in many cases, adopted a data structuring standard (ISO 15926-1, 2004) and developed subsequent ontologies based on it. Within discrete manufacturing, standards do exist having relation to maintenance, especially concerning key performance indicators (KPIs) for manufacturing operations management (ISO 22400-2, 2014); however, only a small number have been designed specifically with maintenance in mind. A key issue in creating such standards is the necessity to account for human-generated data sources. Although the sources and types of useable data in performing maintenance analysis are many and varied, MWOs tend to be the common available source of information across all maintenance tasks. Each MWO represents an "event," containing relevant asset information, timestamps, and importantly, notes from the technician performing the work, which contain valuable tacit expertise on a system, while being generally unstructured and inaccessible to computation.

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Data Collection and Storage

The way in which these MWOs are stored/archived can vary wildly, from stores of handwritten notes, to spreadsheets of row-event entries, to fully-fledged computerized maintenance management systems (CMMS) that record metadata on each asset and MWO to enable automated data analysis workflows downstream (when fully utilized). This variation in *how MWO data is recorded* and *stored* makes research and development of more unified analysis architectures incredibly difficult. This issue is compounded if not every operation requires the full amount of information the CMMSs are capable of capturing. Such records could become taxing on teams that do not need complex system interactions. Additionally, in many cases the amount of time needed for a maintenance technician to structure data into predefined fields via CMMS software takes time from the technician's ability to efficiently perform other maintenance tasks, and often misses vital notes by limiting their expressiveness.

A better solution would determine what data is likely to be useful from existing technician culture. This could likely capture fields such as "asset ID" or "technician name," but would allow the technician to input other relevant data in a flexible manner. Any standardization must be done in a way that does not prohibit flexibility in representation of MWO data, but rather *encourages it*. With that in mind, standards are still needed to determine what types of data, formats, and storage needs are necessary for maintenance analysis. These standards should keep the flexibility of human-driven input in mind, and be independent of specific CMMS solutions to promote development of independent analysis methods. Some research has been done determining what data is captured in MWOs and the potential Key Performance Indicators (KPIs) in Brundage et al, 2018; however, guidance is necessary to formalize these methods for all MWOs and CMMS systems. The following topics need to be addressed by data collection and storage standards in MWOs:

- MWO Terminology Definitions
- Atomic data types and formats for information flow in MWOs
- Adaptive database schemas for storing varied MWO data
- Mapping from disparate CMMS solutions into standard data types.

Data Cleaning and Parsing

Counter to the need for enabling this flexibility in MWO data capture is the difficulty in parsing and analyzing unstructured datasets. However, forcing maintenance technicians to describe problems in a specific, potentially imprecise or irrelevant way invariably leads to "bad data." Research efforts have found success in pre-processing the human-driven MWO text to enable high quality maintenance analysis (Ho, 2015; Sexton, 2018). Other possibilities include mappings to pre-existing ontologies, or the use of pre-trained language embeddings like word2vec and statistical diagnostic classifiers. (Lilleberg, J. et al., 2015; Sharp, 2016) While a number of solutions for structuring free-form data are available, it is difficult for manufacturers to know which solution will work best for their needs. These solutions are dependent on a number of factors: the number of work orders, the amount of time that can be spent cleaning the work orders, and the types of analysis that is to be performed.

Standard guidelines would benefit manufacturers not only in selecting which analysis technique is useful, but also the steps necessary to parse through the data and enable analysis of the MWOs. Standards for cleaning and parsing MWOs should address:

- Guidance on how to select data cleaning methods
- Guidance on strengths and limitations of specific data cleaning methods
- Metrics to determine validity of data cleaning methods for use in PHM

Data Analysis

Once the data is parsed and cleaned, manufacturers can perform various analysis techniques to use the MWO data for actionable decisions. The type of analysis that can be completed is dependent on the collection, storage, cleaning, and parsing decisions that were made beforehand. When developing standard guidelines, it is important to understand what types of analysis are available in a given context, and when they should be used in each component of the maintenance workflow. (Sharp, M. E., 2019) Understanding the different roles of the decision makers (e.g., the maintenance manager has different decisions than a maintenance technician) when developing and using these analysis techniques is also integral in developing standards.

The developed standards need to include validation components to determine if the required analysis was performed correctly and produced valid results. While this paper focuses on MWO standards needs, these documents are not the only datasets used in analysis. Guidance is necessary on how to merge MWO analysis with other data sources, such as sensor data or MTConnect data. Standards specific to these data sources are being developed in the ASME Prognostics Health Management (PHM) subcommittee[1] (Weiss, 2017). The following areas should be addressed by MWO analysis standards:

- Guidance on available analyses, and how they tie to maintenance decisions
- Guidelines on how to perform analysis techniques
- Validation methods and benchmarking for MWO analysis
- Guidance on multi-modal data fusion (e.g., merging MWOs+sensor data)

CONCLUSIONS

This paper discusses MWOs in manufacturing and the high level steps required for MWO analysis. Three areas are presented for potential standards development for MWOs: (1) data capture and storage, (2) data cleaning and parsing, and (3) data analysis. The next step in this work involve developing roadmaps and white papers around specific standard needs as outlined. These roadmaps and white papers will enable standards groups in the creation of more formal standard guidelines that incorporate rich human expertise into the use of data-driven techniques for PHM.

DISCLAIMER

The use of any products described in this paper does not imply recommendation or endorsement by the National Institute of Standards and Technology, nor does it imply that products are necessarily the best available for the purpose.

REFERENCES

Brundage, M. P., Morris, K. C., Sexton, R., Moccozet, S., & Hoffman, M. (2018, June). Developing Maintenance Key Performance Indicators From Maintenance Work Order Data. In ASME 2018 13th International Manufacturing Science and Engineering Conference (pp. V003T02A027-V003T02A027). American Society of Mechanical Engineers.

Ho, M. (2015). A shared reliability database for mobile mining equipment (Unpublished doctoral dissertation). University of Western Australia

ISO 15926-1. (2004). 15926: Industrial automation systems and integration–Integration of life-cycle data for process plants including oil and gas production facilities. Technical report, ISO.

ISO 22400–2. (2014). Automation systems and integration–key performance indicators (KPIs) for manufacturing operations management–part 2: definitions and descriptions. Geneva: International Standard Organization (ISO).

Lilleberg, J., Zhu, Y., & Zhang, Y. (2015, July). Support vector machines and word2vec for text classification with semantic features. In 2015 IEEE 14th International Conference on Cognitive Informatics & Cognitive Computing (ICCI CC) (pp. 136-140). IEEE.*

Sexton, R., Hodkiewicz, M., Brundage, M. P., & Smoker, T. (2018, September). Benchmarking for Keyword Extraction Methodologies in Maintenance Work Orders. In PHM Society Conference (Vol. 10, No. 1).

Sharp, M. E., Sexton, R. T. B., & Brundage, M. P. (2016). Semi-Autonomous Labeling of Unstructured Maintenance Log Data for Diagnostic Root Cause Analysis.

[1] https://cstools.asme.org/csconnect/CommitteePages.cfm?Committee=102342234

Sharp, M. E. (2019). Observations on Developing Anomaly Detection Programs with Case Study: Robotic Arm Manipulators (No. International Journal of Advanced Manufacturing Technology).

Weiss, B. A., Alonzo, D., & Weinman, S. D. (2017). Summary Report on a Workshop on Advanced Monitoring, Diagnostics, and Prognostics for Manufacturing Operations (No. Advanced Manufacturing Series (NIST AMS)-100-13).

Selecting Optimal Data for Creating Informed Maintenance Decisions in a Manufacturing Environment

Don't Drown in Trash: Curating 'Minimum Viable' Data Sets

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ABSTRACT

Data availability within a manufacturing enterprise directly drives the ability of decision makers to effectively function and operate. The information needs of decision makers can vary greatly, based not only on the level at which the decision is being made, but also the perspective and desired effect of that decision. For example, an equipment-level operator needs direct knowledge of that equipment's condition when deciding whether to operate that machine today; a production manager needs to know the number of operational machines when planning system-level operations; a maintenance manager needs knowledge of what maintenance tasks are in the queue and the availability of technicians. Although each decision is related, the information required to support each decision is distinct, and generated from sources that are often independent of one another. The granularity of information needed to make a decision is informed directly by what that decision is and any consequences of that decision. This paper discusses information and data requirements for maintenance decisions in manufacturing from multiple perspectives, including system, equipment, and component -level decisions. These decisions include both structured maintenance (planned and scheduled in advance of failures) and unstructured maintenance (performed immediately after a failure) decisions. The goal of this paper is to guide manufacturers who have limited resources to invest into a monitoring program to select a minimum viable set of data items to collect that supports the decisions they want to make.

INTRODUCTION

The competitive edge in many industries, including manufacturing, is built upon fast, informed, and experienced decision making. Knowledge needed for informed decision making differs based on the perspective and role of the decision maker. Decision support information requirements vary based on both the type of decisions being made and the level the decision affects, such as asset level, plant-wide level, or enterprise level. Reliability, maintenance, and operations planning all require specialized information resources to develop highly informed decisions in manufacturing facilities. What all these levels and perspectives of decision making have in common is the need for information, i.e., data. However, not all facilities are equipped or have resources to devote to developing fully integrated or exhaustive data collection systems.

Sources of data are varied in modern manufacturing facilities. Each day a wealth of potential information is generated from equipment, sensors, and routine activities performed by plant personnel. Unfortunately, even in facilities with existing data collection systems, most of this information is not being properly captured and documented in a manner that allows for proper utilization of that data. While ideally data would always be managed with end uses and goals in mind, that is often not feasible as new uses and needs evolve with changing technologies and environments of factory floors. To maximize resource utilization and effectiveness it is important to continually assess the minimal set of decision-making information needs and verify that the manufacturing facility's current information capturing policies and technologies can support them. When considering areas and systems with 'critical information', the goal is to develop a plan to collect a minimally viable amount of data that allows sufficient characterization and modeling of the system for intelligent decision making without devoting resources to unneeded or ineffective information. Too much data collection adds unnecessary processing costs and time as well as increasing the demands on properly storing and curating the information. Too little data

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collection could increase uncertainty or erroneous assumptions leading to suboptimal planning and lost productivity. These inefficient and ineffective scenarios can be avoided by structuring monitoring and analysis activities to collect and curate the smallest amount of data that sufficiently answers decision support questions for maintenance and operations management.

This paper is the first in a series making recommendations to help manufacturers develop viable monitoring programs and reference data sets to support informed maintenance decision making at various levels of the enterprise. Before focusing on technology solutions to capture and store data, it is also important to understand what constitutes useful amounts and types of data. This requirement list is largely informed by the intended use of the data being gathered. Both qualitative and quantitative sources of information are needed to produce comprehensive assessments of the condition, capability, and capacity of systems at all levels of the manufacturing enterprise. Finding the minimum viable information set requires identifying how much and what kinds of data are needed to enable efficient informed decision making necessary for competitive operations.

BACKGROUND AND MOTIVATION

Gathering and assessing information as it moves in a manufacturing facility is a never-ending task aiding in all levels of facility functions. In many instances, manufacturers benefit from both quantitative data coming from embedded/OEM (original equipment manufacturer) and third-party sensors, as well as qualitative data coming from human operators. Tools for collecting, storing, and processing these sources of information have evolved to allow the generated data to contain both more content and volume [Lee et al 2018]. Technologies for visualizing and interpreting data have also grown, promoting further utilization, understanding, and justification of any decisions made within or about a facility [Sackett et al 2006]. However, a number of concerns still exist in practical implementations of decisions using these data sources including: 1) potential for data capture to impede normal operating procedures, 2) lack of data interoperability, and 3) lack of validation guidance.

One concern when implementing information collection procedures and technologies is to ensure the information collection does not significantly interfere or impede normal operating procedures. This is true with both digital sensing, such as Industrial Internet of Things (IIoT) where computing and communication resources (bandwidth) for controlling the system may compete with data collection and transmission. Similarly, personnel performing value-add activities, such as completing maintenance tasks, often competes with time spent on filling out work orders and maintenance logs. While such procedures can provide large benefits for analysis and planning, they compete for time that could be spent performing other tasks.

An ideal reference data set would have balanced amounts of information representing all possible expected states of the equipment and facility. In most situations, creating this is impractical while maintaining normal operations. For example, many predictive diagnostic models at the asset or component level require one or more observed failures of a given type to characterize incipient fault symptoms. Generally, in real-world environments, every precaution would be made to prevent such failures making them impossible to observe and record. There is a need to develop different points/sources of data or model types to overcome this. Additionally, some system conditions could be exceedingly rare, or just not practical to enact at the time that the model is initially being created or tested. For these reasons, it is important to have mechanisms for adapting, updating, or replacing any information and decision support models as new data becomes available during the life of the system.

Unfortunately, even with modern data capturing technologies and procedures, it is rare for manufacturers to capture or have access to the ‘perfect’ data set for any given end goal. What limits the usefulness of a data set is not only the lack of balanced coverage of the information, but also a lack of annotation and context within data that is available. Ideally, when disparate sources of data relate to similar (or identical) kinds of system(s) or asset(s), those sources of data would be semantically linked or annotated in a manner that allows alignment and concurrent use for models and analysis. Rarely can a single source of information fully characterize a system or asset. Both quantitative and qualitative sources, such as maintenance reports [Sexton et al 2018] and sensors [Kong et al 2017] are needed for a full picture of the production facility. Manufacturers rely on standards for product information (e.g., STEP [ISO 10303], G-code [Kramer 2000], QIF [QIF 3.0, 2018]); equipment data (e.g., MTConnect [MTConnect Standard 2018]); and non-standardized data collected from Computerized Maintenance Management Systems (CMMS), as well as raw and processed sensor logs. Despite the availability of these data standards, the lack of interoperability of the associated data sources and integrated third party tools highlights practical concerns of linking dissimilar file formats. This also points to a need for intermediate platforms for information extraction and collection that can be accomplished in a practical way useful for various levels of informed decision making. More basic than information extraction, there is a need for a standardized manner to discover and/or assign connections between the files that can facilitate information discovery.

There are few standardized methods for determining how much and what kinds of data are necessary to build models or perform validation on decision support platforms at a given level of the enterprise. Even when restricting to a single decision level, such as the equipment or component level, available models each have their own requirements regarding active and historic data [Si 2011]. Adding to this, even if a ‘perfect’ data set were to exist that could translate information across all levels of the enterprise, no consistent guidance is given on how to turn this data into actionable intelligence for decision making.

When developing an information and decision support structure, there are two philosophies for approaching this: ‘what is the minimum data I need to answer my questions?’ versus ‘what questions can I answer with the data I have available?’. The authors approach the issue from the first perspective, which implicitly requires decision makers to understand and focus on fewer, but higher impact questions. This builds from the idea that it is not realistic, useful, nor feasible to capture all information. Our research goal is a framework guiding the development of minimum viable data collection and storage that satisfies all critical decision support needs without over burdening employees or other resources with unnecessary tasks of curating and dissecting information of limited value. The next section examines some practical steps that can be used in developing both historical and ongoing data sets for characterization and modeling of system states for informed decision support.

METHODOLOGY

This paper explores methods for developing ‘minimally viable’ data sets required for informed, intelligent decision making. The first step in determining the minimally viable amount of data collection focuses on decomposing the functions and assets of the factory into linked levels and subdivisions that represent the physical and functional structure of the facility [Li et al 2018]. This architecture can be used to help model and identify the most critical links that either contain or transmit data and information needed to make useful observations about the state of the facility [Sharp 2018]. The ISA-88 and ISA-95 family of standards prescribe an enterprise hierarchy: field device (sensors and actuators), control device (control devices, controllers, embedded controllers), and station (machines, robots, intelligent logistics/material handling). For the purposes of this paper, the authors focus on a simplified hierarchy: system, equipment, and component levels. Some additional context and characterization of the component, equipment, and system is provided below.

Within the context of maintenance decisions, the “bottom” of the decomposition hierarchy is defined by the lowest repairable unit (LRU) and any associated performance or condition indicators that are monitored. The specific list and level of LRU assets will be unique to each enterprise, but the definition generally centers on the lowest level component that can be maintained, fixed, or replaced on site, and whose failure would have a negative impact on the site’s performance or efficiency. Some examples of LRU could be bearings, sealed motors, hydraulic actuators, or other assets that are generally repaired or replaced on site. Given this list, it is important to note that although most LRUs are found at the component level, in certain situations this could be found at either the equipment or even system level. For example, if a specialized milling machine must be maintained by an outside contractor, it may only be necessary for the factory to monitor if the milling machine is maintaining high level performance indicators. A system level LRU could be a digital software system, such as a third party off the shelf CMMS that might simply be replaced with another if it fails to meet the facility’s needs or proves faulty / obsolete.

Components are physical entities defined by a single, static functional capability controlled parametrically by well-defined inputs and expected effects. Each can be maintained (or replaced) independently of the equipment it's a part of. Components can be composed of other components (i.e., sub-components). Most LRU assets are found at the component level. Examples of components could be pumps, bearings, actuators, wiring, etc.

Equipment are composed of components and/or other equipment, and are described as "functionally complete" units. Information and data from them supports decision-making focused on real-time process execution. Concerns regarding the equipment level are embodied in supervisory control systems (SCADA), advanced-process control and optimization (APC-O) and programmable logic controllers (PLC). From the maintenance perspective, the availability and capability of the equipment is directly impacted by its components. While an equipment asset may be "maintained" or inspected, maintenance activities most often address the lower level components that comprise the equipment. Examples of equipment level assets could be milling machines, robotic manipulators, casting machines, or other assets that perform one or more tasks facilitating production and have components within them that can be replaced or repaired on site.

Systems are composed of equipment and subsystems and focus on completing one or more production tasks. Information relating to systems is used for decision-making focused on material/job flow, resource utilization and contention, and enterprise concerns such as throughput, cycle-time, quality, and cost. These concerns are often embodied in manufacturing operations management (MOM) and manufacturing execution systems (MES). Additionally from the maintenance perspective, systems are not individual units that can be directly maintained, but rather has its capability, capacity, and performance defined by its constituent units (subsystems and equipment assets). Work cells, work stations, production lines, or even full facilities could be considered systems and collections of subsystems from an enterprise level.

Each level of this relatively simple hierarchy (component, equipment, system) provides state, capability, or performance information that is aggregated upwards to inform the next level (Figure 1). In this simplified scheme, information from component and LRU level assets is propagated upwards to inform about the operations state and condition of the associated equipment. Equipment state and condition, in turn, is used to inform its system's operations and performance. The system state, aggregating many pieces of information, is input into an operations planner that prioritizes and schedules both production and maintenance tasks that are fed back through the various levels. Should additional information be required at a higher level than it is typically transmitted to, it would ideally be a simple matter to drill down and query any information set without losing any information. Figure 1 is a simplified flow chart that represents an implementation of this process. Alternatives or variants of this diagram could also exist, but the basic structure of condensing and feeding information upwards to a planner that then directs operations is the idea explored in this paper.

Figure 1 indicates that it is the primary job of the component level to populate maintenance tasks based on both condition- and calendar-based events for any given LRU. The equipment level information may also provide maintenance tasks that cross-cut multiple components, or may not have been easily discoverable based upon component level monitoring. Evaluating the criticality of each maintenance task is mostly performed with contextual information from the equipment level. Equipment level information also supports coordinating maintenance tasks that should be performed together. Coordinating maintenance tasks is possible when a planned operation provides an opportunity to performance additional maintenance while minimally impact operations, e.g., replacing a faulty valve when a machine is on a planned service outage for routine lubrication change. This coordination function can similarly be performed at the system level when managing linked equipment. Full maintenance scheduling is best accomplished at the system level where all available information about scheduled operations can be synthesized and optimized into a plan that incorporates all relevant resource and criticality information.

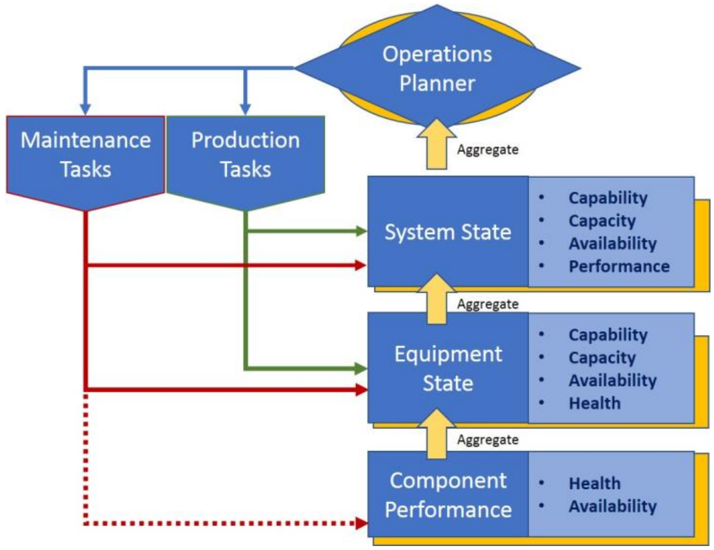

Figure 1: Information Level Flow Diagram

The definitions of the various information tiers are intentionally flexible, leaving room for interpretation on how a system is decomposed into its constituent subsystems, equipment, and component assets. Ultimately, the use and interpretation of these definitions can be application-specific to best suit user needs. For example, equipment may be composed into other equipment such as a machining center being decomposed into a constituent material handling robotic arm and a machine tool. Additionally, one could define digital equivalents of each of these levels that can be monitored and maintained in an analogous fashion to the physical assets presented in this paper. For simplicity, digital assets of this nature such as communications exchanges, cyber security protocols, operating systems, etc. are largely ignored with regards maintenance in this paper. The decisions and data requirements for each level are described in the sections below.

System level:

At the system level, we are primarily concerned with how maintenance decisions impact performance metrics such as throughput, cycle-time, and cost. From the maintenance perspective, important information is current and future equipment state and characterizing dynamic behaviors, such as availability, capability, and capacity. Equipment standards, such as MTConnect, report whether a machine is available or unavailable (up/down) and possibly busy/idle. The second aspect related to planning and scheduling focuses on creating and incorporating predictions of future unavailability -- whether due to scheduled/planned maintenance tasks or estimated unplanned maintenance. There are several ways to incorporate information about expected availability into scheduling methods, dependent upon the specific available information [Vieira et al, 2003].

Accurate descriptions of equipment capability, capacity, and state are essential for operations management decision-making; primarily the scheduling of production and maintenance operations. This data collection enables identifying and characterizing bottleneck equipment (workstations and systems). Maintenance operations management decisions can then incorporate this information to determine maintenance priorities.

A summary of general system-level decision information and corresponding data requirements is presented:

<u>Classes of decisions:</u>

Which production jobs can be assigned to a piece of equipment? Is it available and capable?
When should maintenance tasks be generated (planning) and performed (scheduling)?
How to prioritize maintenance jobs? When should jobs be performed and to what extent?
Which replacement components (or equipment) should be stocked in inventory?

Supporting Data:

- Equipment State (*Current and Future*)
    - Capability
    - Availability
    - Capacity
- Maintenance Queue
    - Priority/Criticality of tasks
    - Availability of resources (personnel, material, parts, etc.)
    - Impacts on throughput
    - Coordination of tasks (i.e. opportunity-driven priority)
- Production Queue
    - Priority/Criticality of tasks
    - Availability of resources (personnel, systems, material, parts, etc.)
    - Current buffer states

Equipment level:

At the equipment level, decisions are less about if the equipment *should* be run, and more about if it *could* be run. This centers around the determination of both the equipment health and availability, as well as capability and capacity; the determination if there is a configuration of the equipment that will allow for safely fulfilling all requirements of the requested duty cycle. Synthesizing health information from the constituent components' health and making determinations of overall health as well as capacity will largely be diagnostic in nature. This information is also used to assess criticality of and assign priority to component maintenance requests.

Root cause investigations and determinations of potential solutions to the problem provide critical information for decision makers in the event of a failure. Additional information, such as the amount of required time/effort for a given solution, is also useful. Determinations of impacts on production and throughput would generally be made in context of the system level.

Another equipment level decision is the coordination between maintenance tasks. This is different than the assignment of criticality of the task, and focuses on the benefits from performing simultaneous maintenance activities --- effectively judging if the extra time spent at this piece of equipment will affect other maintenance jobs in the queue. These 'opportunity-driven' tasks can be aligned to minimize the total downtime of a given equipment.

Based on these decision requirements, much of the data and information collected around this level should support investigations relating to failure diagnostics, prediction, and prevention. The decision makers need to predict when the equipment will go down next, what will cause the failure, how long the corresponding maintenance will take, and how much additional time is required for the equipment and any associated process to resume normal operations. While a large portion of this information is fed from the component level, the prioritization and alignment of maintenance tasks can only be determined with the contextualization of the equipment level. Common examples of equipment level information come from raw and processed sensor signals from the component level (e.g., vibration data) as well as qualitative data in Maintenance Work Orders (MWOs) (e.g., description of the problem).

The different decisions and supporting data are summarized below:

Classes of decisions:

- Should I operate this equipment?
  - Are all critical components in a state to allow safe completion of the planned duty cycle?
  - Can the equipment produce parts or perform services to the required minimum level of quality in its current state?
  - Can the equipment be in a different configuration to better meet requirements?
- What maintenance activities should be prioritized?
  - How critical are component level maintenance requests?
  - What, if any, is the equipment level relationship between diagnosed component degradation?
  - What is the criticality and time horizon of potential faults or failures?
  - Should any maintenance activities be grouped for simultaneous execution?
  - What are the maintenance solutions to prevent (or delay) failure and are these solutions cost effective to implement? If so, how long will it take to implement the solutions?
  - What is the root cause for an observed failure?
  - Has this failure happened before?
  - What can be done to fix observed faults, failures, inefficiencies, or other problems and how long will it take to fix?
  - How can I prevent similar problems in the future?

Supporting Data:

- Maintenance Work Order Data
  - Descriptions of previous faults/failures/etc. and corresponding solutions
  - Time spent on faults/failures and solutions
  - Technician(s) sent to solve fault/failure/etc.
  - Resources (e.g., parts, tools) used in addressing the fault/failure/etc.
- Equipment Data
  - Equipment manuals and schematics
  - Taxonomy of components in equipment
  - Population fault/failure rates
- Component States
  - Health information
  - Predicted faults/failures/etc.
  - Component level maintenance requests

Component level:

Component information monitoring focuses on two areas. The first area determines the current capabilities of the equipment: if and at what capacity or workload a component can be operated. The second relates to populating maintenance tasks via degradation monitoring, diagnostic fault cause analysis, and prediction of probable future states of the component. Some of this information needs to be contextualized at the equipment level, where understanding the relationships between components is essential, e.g., will this component hurt production efficiency, lower product quality, etc.? Even so, the bulk of the data/information regarding maintenance needs and even some decisions are collected/made at the component level.

The most simple information that can be captured is if the component currently able to operate, or if it is currently exhibiting a ‘failure’ condition. This can be a soft failure where the component is unable to perform at a minimal operating level or has deviated beyond allowable limits from expected behavior; or a hard failure, typically catastrophic, where the component is unable to function at any capacity. This class of information could loosely be categorized as a minimum state observation for the component. While this observation can provide decisions on ‘go/no-go’ scenarios, the amount of insight given is very minimal.

The next progression of component level decision information involves accessing the overall health and capacity of the component. This demand for extra information creates a corresponding amount of additional demand on the data required. There are an abundance of sensor types, algorithms, and models that can be used to access the current condition of a component. These assessments can be qualitative, quantitative, definitive, or probabilistic, and are determined by either direct or indirect measurements about the system [Si 2011]. While different models and algorithms may impose different data needs for their construction, the general class of tools that measure or estimate the specific condition of a component all rely on some level of sensing capabilities. In some cases, certain condition monitoring tools can even benefit from higher level operational data, such as workload plans, maintenance activities, etc. A more in-depth breakdown of the data requirements for various modeling approaches (physics, rules-based, data driven, etc.) is beyond the scope of this brief paper, but will be addressed in future works. One metric useful at this information tier is the Current Life Consumed (CLC), which often corresponds to the current amount of degradation detected in the component, normally as a percentage of some failure threshold. This information tier encompasses active monitoring of a component.

The component conditions assessment can also extend to predicting future states. This is accomplished by first knowing what are the current/future needs and expectations from the system, and second - given these expected stresses and demands - predicting the probable future condition and capacity of the component. These information types and analysis broadly fall under the category of prognostics. The ‘prognosing’ of future states can be longer term (e.g., for scheduling, maintenance, and planning), or shorter term that focuses exclusively on the current or immediately upcoming duty cycle. Some form of either definite or probabilistic operational plan must be defined or inferred for this analysis, which yields information beyond that available at the component level. This shows the relationships between multiple information levels and areas of a factory setting. Again, the specific tool or algorithm used for the prognostic assessment of the equipment will have specific needs of the component level information, either historical or current. A common metric for these types of analysis is a component's Remaining Useful Life (RUL). A brief summary of general component level decisions and corresponding data requirements is presented below:

Classes of Decision:
- Can a component, within a piece of equipment, be marked available for a requested operation?
  - Is the component currently occupied with some other task?
  - Is the component functioning or has it failed?
  - What are the state and time horizons of any currently identified incipient faults?
  - Can this component meet the current/future needs?
- What are the current or future maintenance actions required for this component?
  - Are any calendar-based or cycle-based preventive maintenance actions upcoming?
  - Are there any condition-based maintenance actions upcoming?
  - Are any corrective repairs needed?

Supporting Data
- Capacity Specifications
  - Possible configurations of component
  - Nominal work loads
- Condition assessment information
  - Human interrogators
  - Predictive models
  - Sensors

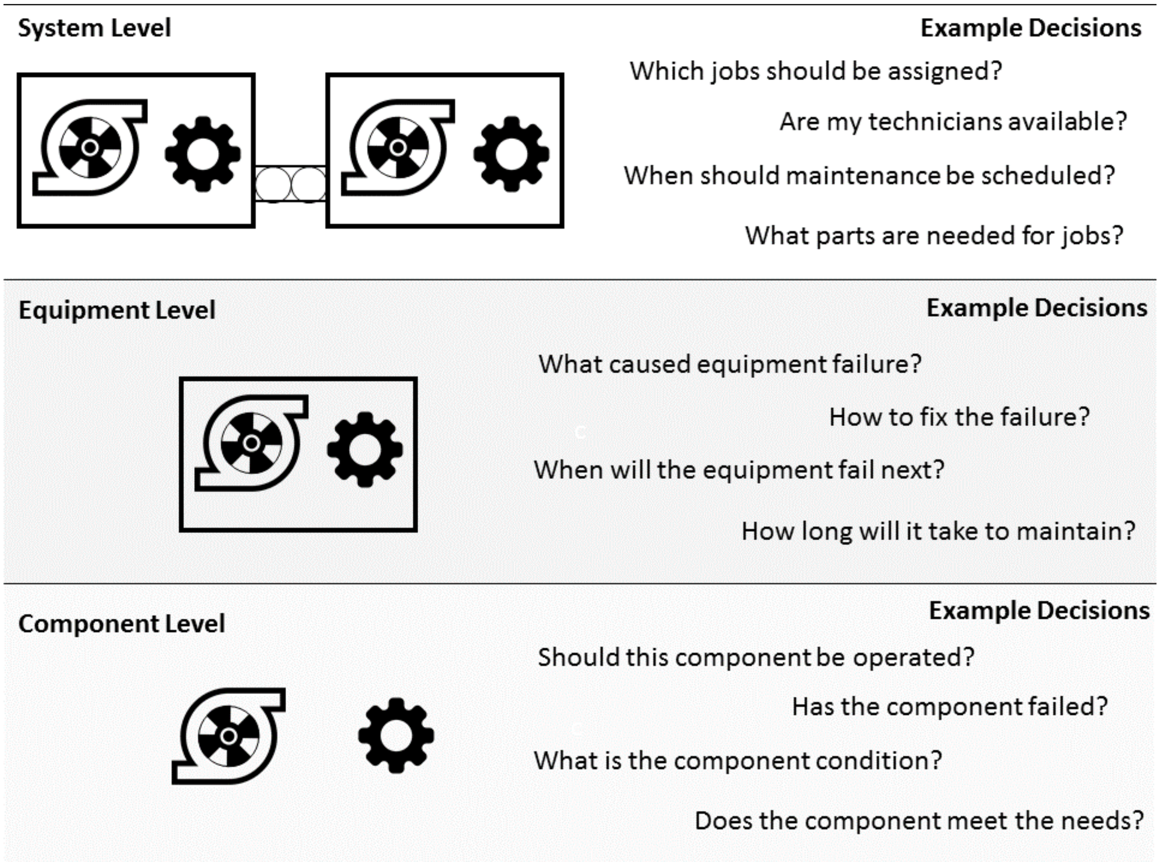

Figure 2: Maintenance Decisions and Corresponding Levels

- Anticipated Future Performance
  - Planned duty cycles
  - Probabilistic modeling
- Maintenance planning
  - Needed resources
  - Maintenance work order data
  - OEM Maintenance recommendations

SUMMARY AND CONCLUSIONS

This paper discusses maintenance decision making and data needs at three levels: component level, equipment level, and system level. There is strong interplay between these levels with information flowing upwards from the component level LRUs, into a more contextualized equipment level of information and finally into system levels of information with pertinent decision support at every tier. The primary blocks of creating a maintenance action plan have different information needs at each of the three levels. A summary of example decisions and supporting questions for the various information levels is shown in Figure 2. These are not the only decisions or possible groupings of information that could be applied to a factory setting.

The primary goal of this work is to present some common questions and decision support needs by way of information gathering. This is intended as the beginning steps to creating a working guide for industry practitioners to develop their own optimized information gathering and decision support network. Resources dedicated to gathering specific sources of information should be tailored to the explicit decision support needs of the managers, operators, and technicians. If an asset is not deemed mission critical, or is otherwise placed into a 'repair on failure' category, there is no need to invest in expensive data collection and storage tools.

Conversely, if an asset is *highly* critical, there is a strong case for extensive monitoring and modeling tools to ensure that the asset rarely, if ever, experiences a failure. Other assets that could merit more monitoring tools are those that are creating large amounts of maintenance work orders, either calendar or condition-based. The extra monitoring and analysis could help to optimize the amount of maintenance and/or discover different operations or maintenance practices that could optimize the types of maintenance performed and thus reduce downtime.

The next steps in this work will look at a specific decision at the system level and create a framework for determining the correct data from both the equipment and component levels. This implementation will lead to a more appropriate roadmap of standards and research needed in this space.

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REFERENCES

ANSI QIF 3.0, October 5, 2018. http://qifstandards.org

Kong, Dongdong, Yongjie Chen, Ning Li. Gaussian Process Regression for Tool Wear Prediction. Mechanical Systems and Signal Processing. 2018. Vol, 104 (pp 556-574).

Kramer, Thomas R., Frederick M. Proctor, Elena R. Messina. The NIST RS274NGC Interpreter - Version 3. NIST Interagency/Internal Report (NISTIR) - 6556. August 01, 2000.

Lee, Gil-Yong & Kim, Mincheol & Quan, Yingjun & Kim, Min-Sik & Joon Young Kim, Thomas & Yoon, Hae-Sung et. el. (2018). Machine health management in smart factory: A review. Journal of Mechanical Science and Technology. 32. 987-1009. 10.1007/s12206-018-0201-1.

Li, Rui, Wim J.C. Verhagen, and Richard Curran. A Functional Architecture of Prognostics and Health Management Using a Systems Engineering Approach. European Conference of the Prognostics and Health Management Society, 2018.

MTConnect Standard. 2018 MTConnect Institute. https://www.mtconnect.org/

Sackett, J., P & F. Al-Gaylani, M & Tiwari, Ashutosh & Williams, D. (2006). A review of data visualization: Opportunities in manufacturing sequence management. Int. J. Computer Integrated Manufacturing. 19. 689-704. 10.1080/09511920500504578.

Si, Xiao-Sheng, Wenbin Wang, Chang-Hua Hu, Dong-Hua Zhou, Remaining useful life estimation – A review on the statistical data driven approaches, European Journal of Operational Research, Volume 213, Issue 1, 2011, Pages 1-14, ISSN 0377-2217, https://doi.org/10.1016/j.ejor.2010.11.018.

Sexton, Rachael, Michael P. Brundage, Melinda Hodkiewicz, Thomas Smoker. Benchmarking for Keyword Extraction Methodologies in Maintenance Work Orders. 2018 Annual Conference of the Prognostics and Health Management Society. September 24-27, 2018. Philadelphia, PA.

Sharp, Michael, Brian Weiss. Hierarchical modeling of a manufacturing work cell to promote contextualized PHM information across multiple levels Manufacturing Letters, Volume 15, Part A, January 2018, Pages 46-49.

United States, Congress, “ISO 10303-11 Industrial Automation Systems and Integration: Product Data Representation and Exchange.” ISO 10303-11 Industrial Automation Systems and Integration: Product Data Representation and Exchange, ISO, 1994

Vieira, G. E., Herrmann, J. W., & Lin, E. (2003). Rescheduling manufacturing systems: a framework of strategies, policies, and methods. Journal of scheduling, 6(1), 39-62.

Machine Learning Model for Surface Finish in Ultra-Precision Diamond Turning

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ABSTRACT
In diamond machining freeform and symmetric optics, it is essential to ensure that surface characteristics are maintained. Optics for imaging applications require tight tolerances on surface roughness, mid-spatial frequencies, and form. This work predicts surface roughness in diamond turning as a function of machining parameters using machine learning. Diamond turning is chosen for its relative simplicity when compared to other machining operations. No tool wear is expected, and the surface is generated by a simple geometric replication of the tool into the surface for a wide range of parameters. Machine learning algorithms are trained by associating machining characteristics / parameters with the resulting surface finish performance measures. Surface finish prediction results obtained with traditional regression machine learning algorithms are reported, including a general regression neural network. Work is ongoing to further validate results and use additional diamond turning machining data to train the neural network. In addition, work continues to better interpret the effects of machining parameters on the surface function estimates obtained by the machine learning algorithms.

INTRODUCTION

In manufacturing of optics, research institutes and industries alike are making use of ultra-precision manufacturing techniques to produce high quality optics and optical mold surfaces [1]. Techniques such as single point diamond turning on an ultra-precision machine tool can be employed to manufacture precision, rotationally symmetric optics with optical quality surface roughness and form [3]. In the past decade, optics manufacturing has become increasingly challenging with the implementation of freeform optics [3]. The major benefits of freeform surfaces are the reduction of components necessary in a product and the ability to contain multiple reflective or diffractive functions in a single optic. Freeform surfaces can be described as asymmetric, or lacking a single axis of rotation about which symmetry can be defined. These complex geometries require the use of multi-axis (>2) ultra-precision machine tools; the associated sub-aperture manufacturing techniques introduce new challenges not encountered in traditional diamond turning.

For both freeform and symmetric optics, maintaining the key surface characteristics is of critical importance. Optics for imaging applications, including telescopes, spectrometers, energy concentrators, and thermal imaging optics, require tight tolerances on surface roughness, mid-spatial frequencies, and form that are related to the wavelength of light in a particular application. Suleski et al. showed the degrading effect on imaging quality of raster milled versus turned surfaces for visible light applications [4]. Another example includes high-powered

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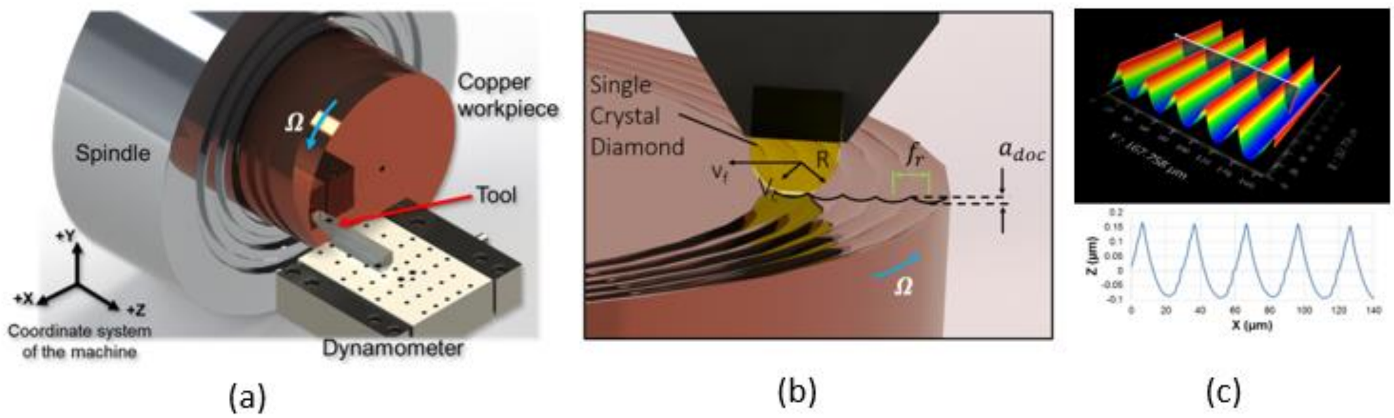

Figure 1: (a) Diamond turning arrangement; (b) diamond turning parameter definitions; and (c) measurement of typical diamond turned surface under ideal cutting conditions.

laser applications that use reflective optics manufactured from oxygen-free high-conductivity (OFHC) copper [2]. Surface finish, or roughness, is crucial in laser applications due to the effect of light scatter [5,6] and subsurface defects that act as energy concentrators. These cause heat spikes in the material which can degrade the surface and subsurface over time [7].

In diamond machining, key process signatures can be directly detected in the machined specimen surface. In traditional diamond machining, an extremely sharp (~100 nm edge radius) round-nosed tool cuts a surface, leaving circular cusp structures by direct geometric replication of the tool shape into the diamond turned surface (see Figure 1(c)). However, geometric replication of the tool is a very simplified description of the process. Diamond machining involves complex, high-strain rate material flow and the physics of this flow can affect surface structure. In addition, the tool is not infinitely stiff. Deflections and dynamics from the machine tool or cutter interacting with the workpiece will result in lower quality surfaces. Further, dimensional changes occur due to temperature variations. In cutting complex freeform optics, for example, cycling of the machine chillers have been observed to add other more slowly varying time fluctuations that can translate into surface structures at various length scales. These undesired effects drive manufacturers to employ more conservative machining parameters which results in longer machine times and higher costs. Because the surface characteristics result from such a complex interaction of machining parameters, they have not been fully captured by existing physics-based models. Thus, the goal of this work is to develop a machine learning model for the prediction of surface quality in diamond turning as a function of machining parameters, with the end goal of providing manufacturers with a tool for optimizing the processes and reducing costs.

Until recently, statistical methods including regression, ANOVA, and the Taguchi method among others, have guided the search for models that capture the relationship between surface roughness and the optimal cutting parameters that achieve the desired surface roughness [8-16]. As noted, the complex interaction of machining parameters contributes to model error, which can lead to disagreement between the surface finish predictions from data-learning models and (admittedly incomplete) physics-based models. Machining relationships, in addition, are highly nonlinear requiring simplifying assumptions in the physics-based models that compromise predictive performance; in fact, existing physics-based models are used mostly for guidance and not for prediction. Data learning models, on the other hand, have demonstrated higher accuracy in surface roughness prediction and associated optimal cutting parameters due to their ability to represent both linear and nonlinear relationships among and between cutting parameters, and to learn these relationships directly from experimental data. In additional to their predictive capability, data learning models can identify unexpected dependencies between surface finish results and parameters that suggest new physical models.

While there has been a great deal of work predicting surface finish in complex machining operations where many physical phenomena including tool wear and complex material flow are operative [8-9,11], the focus of this paper is a more tractable problem, the prediction of surface roughness in diamond turning of OFHC copper. For a large range of parameter values, the surface generation in the turning of OFHC copper can be approximated by a pure geometric replication of the round tool nose into the material surface. Under these conditions, the roughness is dominated by two machining parameters. However, for other ranges of parameters, the surface finish is dependent on more complex chip formation processes and machining parameters that relate to other physical effects, such as material behavior, tool vibration, and short-term thermal fluctuations. The logic of the approach is to provide a training set that will enable the machine learning model to identify a known physical model for some parameter ranges while providing new physical insights for observed behavior over other ranges of parameters.

EXPERIMENTAL ARRANGEMENT

The simplified diamond turning experiment is described in Figure 1. A single crystal diamond tool generates a nominally planar cusped surface on a rotating copper workpiece as shown in Figure 1(a). The tool is mounted on a dynamometer to measure cutting forces; however, for simplicity, force data is not used here. The input parameters for the machine learning models are illustrated in Figure 1(b) and summarized in Table 1: spindle speed or rotation rate Ω, in rev/min (rpm), tool nose radius R, in μm, rake angle α, in degrees[a], cutting speed V_c, in m/s, feed velocity V_f, in mm/min, axial depth of cut a_{doc}[b], in μm, and feed per revolution f_r[c], in μm/rev. Figure 1(c) shows an example surface measurement from a coherence scanning interferometer (CSI), and a cross section of the surface demonstrating the geometric replication of the tool geometry into the surface. Under ideal conditions, there is a cusp structure with spacing f_r and radius R. This cusp structure dominates the surface micro-roughness.

Table 1: Parameter ranges

R (μm)	α (deg)	V_c (m/sec)	f_r (μm/rev)	a_{doc} (μm)
250	0	3	{0.1; 0.3; 1.0; 2.0; 5.0; 10; 20; 30; 40}	{1.0; 10}
250	0	0.3	{0.1; 0.3; 1.0; 2.0; 5.0; 10; 20; 30; 40}	{1.0; 10}

There are many mathematical parameters used to quantify surface roughness (e.g. Sq, aerial root-mean-square, Sz, areal peak to valley, etc.). Here the arithmetic mean surface roughness Sa is applied, which, for geometric replication, has a simple analytical relationship to the machining parameters.

$$Sa \cong \frac{f_r^2}{9\sqrt{12}R} \quad (Eq.1)$$

Based on the geometric replication model, smaller f_r will decrease cusp spacing for the same radius R thus lowering Sa. Increasing R does not change the cusp spacing but changes the cusp height, again reducing Sa. Target values for Sa are in the range of 1 nm to 2 nm (or better) for visible light applications and on the order of 30 nm for infrared applications. Since there are practical and cost limits to increasing R (e.g., larger diamonds, limiting inventory, etc.), decreasing f_r is the primary option for meeting a roughness specification. However, reducing f_r linearly increases machining time, introducing other problems, and cost. The goal is to machine an optic as fast as possible while meeting the necessary surface finish specification by minimizing the time for changes in other parameters, such as temperature, that cause issues such as form and mid-spatial frequency errors.

The parameter ranges chosen for training the machine learning model are given in Table 1. It was expected that for low f_r (< 1 nm) and for high f_r (> 20 nm) the measured Sa will deviate from the simple geometric model. Under these conditions, the effects of other parameters become important and these dependencies can be identified by the machine learning model. Thus, it may be possible to use the machine learning model to suggest new hypotheses about the physics of the diamond machining process.

[a] The rake angle is the angle between the tool front face and the line perpendicular to the surface being machined.

[b] The axial depth of cut is the depth of tool penetration into the initial surface.

[c] The feed per revolution is the motion of the tool per revolution of the workpiece given by $f_r = V_f/\Omega$.

MACHINE LEARNING MODEL

In recent years, the growth in data availability and computational power, coupled with advances in data learning modeling approaches, has led to broader uses of machine learning techniques and has shown increased success in solving highly complex tasks, such as image object identification, voice recognition, and self-driving cars. Supervised machine learning algorithms approximate a nonlinear function by mapping, or modeling, the relationships between input(s) and corresponding output(s) guided by input-output pairs of observation measurements of a system. This is the "model training" phase of the machine learning process. In a subsequent "model testing" (simulation) phase, the model can then be used for predicting output values of the function when provided with new input data. For this work, input parameter values listed in Table 1 define the diamond turning process that was used to collect 78 measurements of the resulting surface roughness Sa. The set of 78 input-output pairs constitutes the dataset used for experiments with two traditional machine learning regression algorithms, Support Vector Machine (SVM) and Gaussian Process Regression (GPR) models, as well as a Generalized Regression Neural Network (GRNN).

A GRNN is a one-pass neural network algorithm that provides estimates for continuous dependent variables and converges to the (underlying) regression surface [17]. This artificial neural network has several advantages in comparison to other nonlinear regression modeling techniques, including fast learning, generalization from sample examples, insensitivity to the local minima problem, and consistent convergence to global solutions.

There are two reasons for selecting a GRNN to predict surface roughness. First, this type of network is capable of producing reliable predictions even with a small observation set for model training. The prohibitive cost of collecting a large number of sample measurements from ultra-precision diamond turning experiments makes GRNNs an appropriate choice. Second, a GRNN is capable of handling noise within the inputs. The observation samples are inherently noisy in this domain. Surface roughness is a function of many parameters which are connected only indirectly to the measured input parameters: high strain rate thermo-plastic material flow, vibrations, environmental temperature fluctuations, and other factors. These dependencies are more pronounced for very low and high f_r values.

The overall architecture of the implemented GRNN is shown in Figure 2. The GRNN is a two-layer network similar to a radial basis function network, but with a slightly different second layer. As shown, the GRNN network has a highly parallel structure and implements a one-pass learning algorithm that does not require an iterative training procedure as in back propagation [17]. The input for the network is formed with nodes in equal number to the independent input parameters to be modeled. The machining parameter values are fed to the GRNN via the input nodes that provide these values to each neuron[d] in the radial basis (hidden) layer. The first (hidden) layer comprises nonlinear radial basis neurons with as many neurons as the number of sample observations available for training, i.e., 78 neurons for the 78 experiments. Each neuron in the first (hidden) layer is associated with only one of the sample observations and stores its corresponding dependent output parameter, Sa. Similar to biological neurons, each neuron in the neural network receives one or more inputs from the previous layer, performs a mathematical transformation on these values and sends the results to the next layer. The special linear layer has purelin transfer function neurons equal to the number of sample observations, i.e., 78, and the number of neurons in the first layer. This second layer computes a weighted function of the values received from the first layer and uses a linear transfer function to determine the second layer's output which is sent to the output node. The value of the output node corresponds to the surface roughness predicted value.

[d] An artificial neuron is a mathematical function conceived as a model of the biological neuron in the brain. Neurons are the basic units typically used to build artificial neural networks (ANN). A neuron receives input values, processes and passes them to the next layer of the network. ANNs simulate the network of neurons in the human brain and are capable of learning from data and making decisions in a human-like manner.

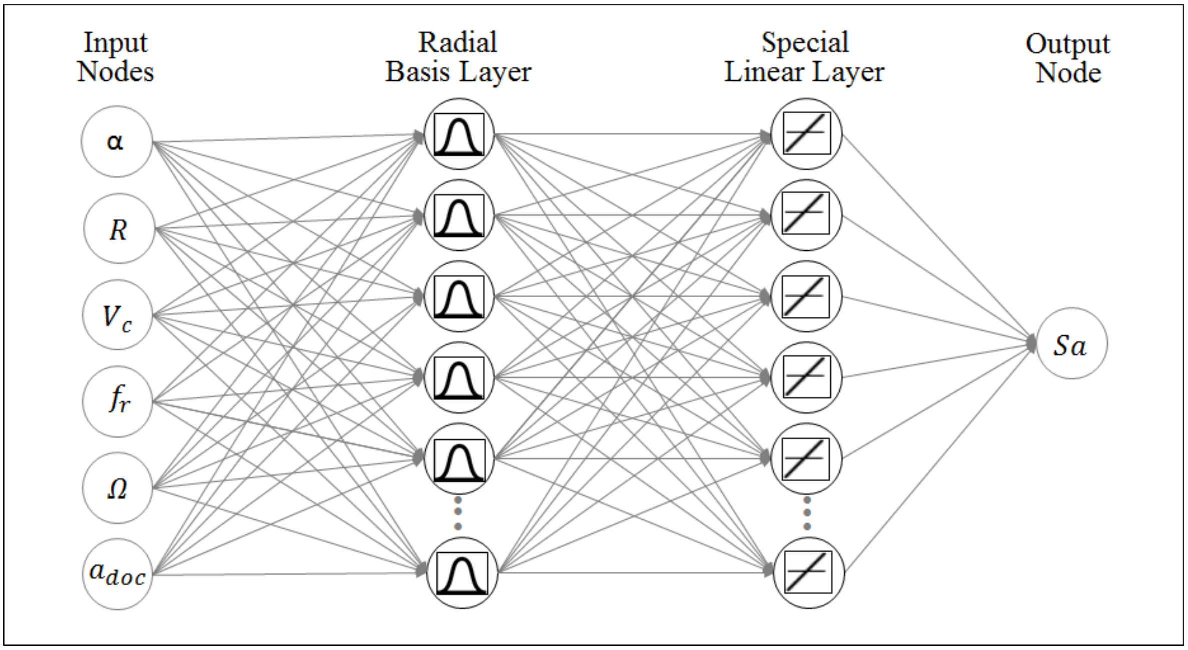

Figure 2: Generalized regression neural network architecture

For brevity, a detailed explanation of the GRNN inner-workings is not provided here, but it is important to mention that the GRNN has only one unknown, free parameter, the *spread* constant σ. The radial basis layer computes bias as a constant 0.8326/*spread.* Thus, the spread controls the area around the input parameters and affects the radial basis function's slope in the first layer neurons. Larger *spread* values produce a smoother slope causing more neurons in the network to respond to the input parameters, thus increasing their contribution to the weighted output. The result is that the network approximates the input parameter values to the output value associated with the training set of input parameters closest to the new input parameters. A main disadvantage of the GRNN is that their size grows very quickly with the number of input sample observations used for training, thus rendering large networks computationally intensive. This is not a concern for this work, however, because the high cost of obtaining experimental data limits the size of the training dataset.

RESULTS

Prior to applying the data learning model to the experimental data, a set of computational experiments with different sets of input parameters, or input vectors, was developed. For example, one input vector consisted of parameters: Ω, V_c, a_{doc}, and f_r, while another consisted only of V_c, a_{doc}, and f_r, etc. Using the MATLAB R2018b Statistics and Machine Learning Toolbox™, 19 traditional regression machine learning algorithms (e.g., SVM, GRP) were trained for each set of input vectors to evaluate the available data and obtain insights about individual machining parameters and how their behavior, together and separately, affect surface roughness outcomes. Since the input machining parameters have various units and ranges, a best practice is to scale the data to a common notional scale. In this case, the data was normalized to have "unit" standard deviation and zero mean. The input parameters in our sample dataset with invariant values, tool nose radius R and rake angle α, have zero standard deviation and were removed from the dataset. Next, the 78 normalized inputs and their associated output values were split into training and testing sets using a five-fold cross-validation strategy. For each input parameter vector tested, the model with the smallest root-mean-square error (RMSE) was selected as the best model among the 19 models generated. Table 2 describes the four input parameter vectors tested, the best model found, and its corresponding RMSE results. These initial models provided a basis for analysis of the behavior of the machining data features/parameters.

Table 2: Traditional regression machine learning algorithm results

Experiment	Input Parameter Vector	Selected Best Model	RMSE
1	$V_c,\ f_r, \Omega, a_{doc}$	Squared Exponential GPR	5.8344
2	f_r, Ω, a_{doc}	Quadratic SVM	5.2207
3	f_r, Ω	Squared Exponential GPR	4.7141
4	f_r	Squared Exponential GPR	3.7359

The GRNN model was implemented using the MATLAB R2018b Deep Learning Toolbox™. A GRNN was trained using the 78 input-output experimental dataset, where the input vector parameters consisted of the four machining parameters listed in Experiment 1 of Table 2 and *spread* equal to 0.7. For a true blind test of the GRNN model, 20 new sample values of the input parameters were selected—never seen before by the neural network and for which the corresponding surface roughness had not being measured—which were then fed to the GRNN model to obtain a resultant Sa prediction. Figure 3 illustrates the Sa results obtained with the GRNN model.

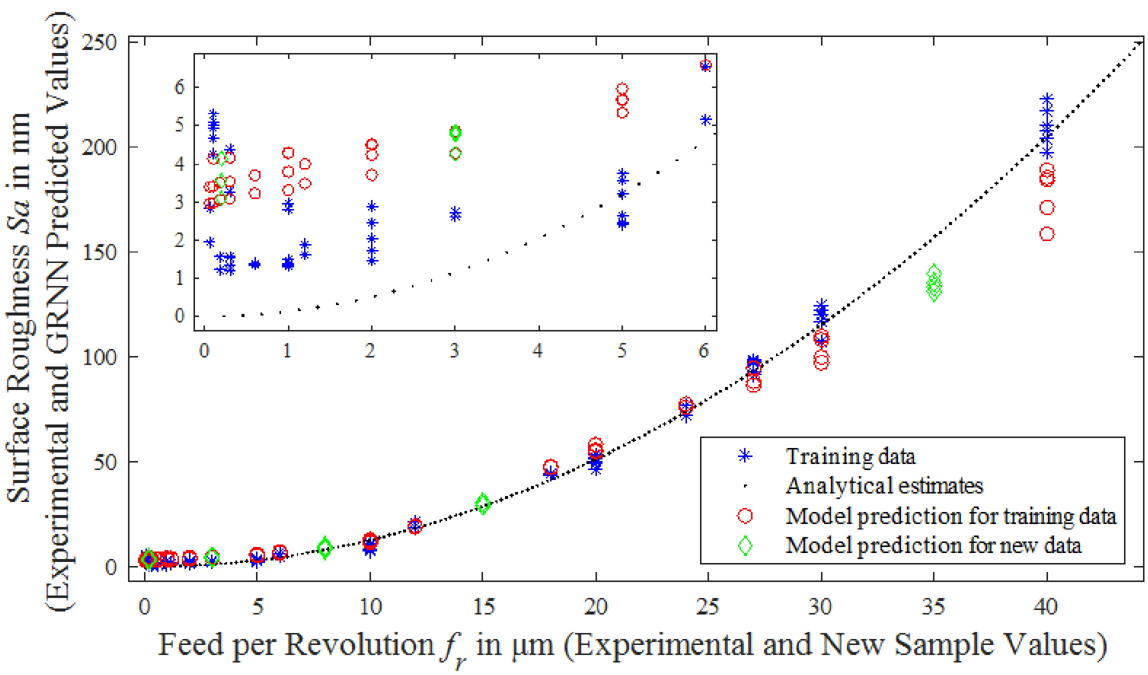

Figure 3: Plots of the experimental results, the geometric analytical model, and the predicted results of the machine learning model.

Figure 3 shows four different sets of results. Data points labeled "training data" correspond to the original 78 input-output sample observations used for training the model. Equation 1 was used to calculate "analytical estimates" of Sa for all values within the f_r range resulting in the smooth dotted curve. Once the model was trained, the original 78 input sample observations were fed to the model to obtain "model predictions for the training data" and the 20 new sample values of the input parameters for the blind test to produce the "model prediction for the new data" data points. The inset overlaid on Figure 3 shows in detail the resulting Sa for the lower f_r range.

Figure 4 provides a comparison of the measured and predicted values of Sa for the GRNN model, where the input vector parameters consisted of the four machining parameters listed in Experiment 1 of Table 2 and *spread* equal to 0.7. While Figure 3 plots Sa against only one of the input parameters, the feed per revolution f_r, Figure 4 captures the collective influence of all four machining parameters in assessing the predictive performance of the GRNN model.

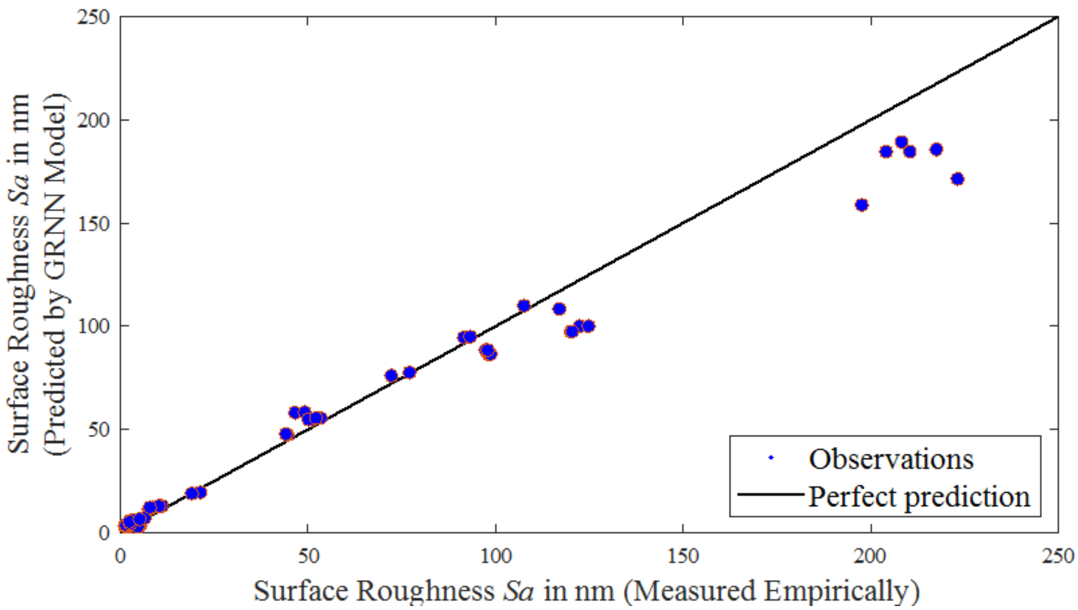

Figure 4: Comparison of measured and predicted surface roughness

DISCUSSION

The training data plotted in Figure 3 generally follows the analytical (geometric) curve. However, it diverges from the analytical estimate for lower values of f_r, which, as discussed earlier, may be due to more complex material flow effects, thermal fluctuations, or other physical phenomena. Both data learning models mimic the increased roughness at lower feed rates. The GRNN predictions that appear well below the analytical estimate at higher feed rates are physically impossible. While some deviation below the estimation curve can occur due to rounding of cusps peaks, it is unclear what parameter is driving the model down. The predictions produced in the middle range of f_r agree with the analytical and training data. This provides insight and motivation that the models need to incorporate the more complex effects that occur during the cutting operation. Figure 4 also indicates three sub-regions of performance. At the higher values of Sa, predicted values of Sa fall significantly below measured values, while at the lower values of Sa, the predicted values of Sa fall slightly above measured values.

CONCLUSIONS

This work introduces a general regression neural network (GRNN) model for estimating the surface roughness Sa of an ultra-precision diamond turning process in OFHC copper. The model input consists of the spindle speed or rotation rate Ω in rev/min (rpm), tool nose radius R in μm, rake angle α in degrees, cutting speed V_c in m/s, feed velocity V_f in mm/min, axial depth of cut a_{doc} in μm, and feed per revolution f_r in μm. The Sa values predicted by the GRNN model are compared to experimental data collected in laboratory tests and Sa data calculated using the analytical (geometric) model defined by Eq. 1. The GRNN model was able to generalize the training dataset results to a new dataset not utilized during the network training.

This is a first step to demonstrate the feasibility of using ANNs for determining the surface finish of diamond turning processes. The simulation results obtained with the GRNN model are encouraging as it significantly outperformed the analytical model estimates on the lower end of the inputs' range. Of particular interest for further study are the three sub-regions of model performance across the spectrum of feed per revolution f_r. Current results suggest that aspects of high-strain rate material flow, among other factors, may not be adequately reflected in the current model, especially in regions of low surface roughness. Next steps include the implementation of physics-guided ANNs that are able to improve model performance to conform with physical constraints. At the higher regions of surface roughness, physics-guided ANNs are able to penalize the model for predictions below the geometric limit. Further experiments with other complex materials will be conducted to both confirm the superior performance of the GRNN model and validate the complex behaviors observed across the spectrum of feed per revolution. To supplement the training data we will be using machining simulation data in addition to experiments. Further, the ANN model will be augmented with physical models that, for example, penalize predictions that are below the geometric prediction and are thus physically not possible.

Finally, the machining operation considered here is quite well behaved in that it follows the geometric model over a wide range of parameters fairly closely. Particularly for applications in infrared optics which must be manufactured in brittle materials, the material behavior is much more complex. For these more complex situations, a machine learning model that predict the most productive machining parameters that meet the specifications is of great practical benefit.

References

[1] Rhorer, R., Evans, C. (1995) Handbook of Optics – Fabrication of Optics by Diamond Turning; Chapter 41. McGraw-Hill.

[2] Zhang, H., Zhang, X. (1994) Factors affecting surfaces quality in diamond turning of oxygen-free high-conductance copper"; Applied Optics, 33(10):2039-2042. doi: 10.1364/AO.33.002039.

[3] Davies, M.A., Owen, J.D., Troutman, J.R., Barnhardt, D.L., Suleski, T.J. (2015) Ultra-precision diamond machining of freeform optics, 2015, Imaging and Applied Optics 2015, OSA Technical Digest (online) (Optical Society of America, 2015), paper FM1B.1, doi:10.1364/FREEFORM.2015.FM1B.1.

[4] Shultz, J.A., Davies M.A., Suleski, T.J. (2015) Effects of MSF errors on performance of freeform optics: Comparison of diamond turning and diamond milling, Imaging and Applied Optics 2015, OSA Technical Digest (online) (Optical Society of America), paper FT4B.3.

[5] Thompson, A.K. (1998) Scattering effects of machined optical surfaces. Source DAI-B 59/03, UMI, 151 pages.

[6] Taylor, J.S., Syn, C.K., Saito, T.T., Donaldson, R.R. (1986) Surface Finish Measurements Of Diamond-Turned Electroless-Nickel-Plated Mirrors. Large Optics Technology Proc. SPIE 0571. 25(9) 251013. https://doi.org/10.1117/12.950369.

[7] Owen, J.D., Troutman, J.R., Harriman, T.A,. Zare, A., Wang, Y.Q., Lucca, D.A., Davies, M.A. (2016) The mechanics of milling of germanium for IR applications. CIRP Annals - Manufacturing Technology, 65(1):109-113.

[8] Özel T., Karpat Y. (2005) Predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks. Intl Jour of Machine Tools and Manufacture, 45(4–5):467-479. https://doi.org/10.1016/j.ijmachtools.2004.09.007.

[9] S.K Choudhury, G Bartarya, Role of temperature and surface finish in predicting tool wear using neural network and design of experiments, Intl Jour of Machine Tools and Manufacture, 43(7):747-753, 2003, https://doi.org/10.1016/S0890-6955(02)00166-9.

[10] Liang, S.Y., Hecker, R.L., Landers, R.G. (2002) Machining Process Monitoring and Control: The State–of–the–Art. ASME International Mechanical Engineering Congress and Exposition, Manufacturing 599-610. doi:10.1115/IMECE2002-32640.

[11] Paturi, U.M.R., Devarasetti, H., Narala, S.K.R. (2018) Application of Regression and Artificial Neural Network Analysis Modeling of Surface Roughness in Hard Turing of AISI 52100 Steel. Materials Today, Proceedings, 5:4766-4777. https://doi.org/10.1016/j.matpr.2017.12.050

[12] Wang, X., Feng, C.X. (2002) Development of Empirical Models for Surface Roughness Prediction in Finish Turning, Int J Advanced Manufacturing Technology, 20(5): 348–356.

[13] Petropoulos, G., Mata, F,, Davim, J.P. (2008) Statistical study of surface roughness in turning of peek composites. Materials and Design, 29(1):281-223.

[14] Muthukrishnan, K., Davim, J.P. (2009) Optimization of machining parameters of Al/SiC-MMC with ANOVA and ANN analysis. Jour Materials Processing Technology, 209(1): 225-232. https://doi.org/10.1016/j.jmatprotec.2008.01.041.

[15] Palanikumar, K., Karthikeyan, R. (2007) Optimal Machining Conditions for Turning of Particulate Metal Matrix Composites Using Taguchi and Response Surface Methodologies, Machining Science and Technology. 10(4): 717-433. https://doi.org/10.1080/10910340600996068.

[16] Gupta, M. Kumar, S. (2015) Investigation of surface roughness and MRR for turning of UD-GFRP using PCA and Taguchi method. Engineering and Science Technology: An International Journal. 18(1):70-81. https://doi.org/10.1016/j.jestch.2014.09.006.

[17] Specht, D.F. (1991) A general regression neural network. IEEE Transactions on Neural Networks, 2(6): 568-576.

Low Cost Development Testbeds for Implementing the Digital Thread

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ABSTRACT
A number of manufacturing demonstration and research cells have been developed that address key Digital Thread use cases. Free, open-source software and relatively affordable desktop 5-axis machine tools, along with detailed documentation and publicly available data provided by NIST, has allowed researchers to 1) create their own research platforms; and, 2) prove out fundamental concepts of Digital Thread. This paper identifies system components and architectures, as well as target research areas, for development testbeds that realistically and usefully model key areas of manufacturing while avoiding the expense of industrial CNC machines.

BACKGROUND

The Digital Thread promises closer ties between design, manufacturing, and supply chains leading to better feedback through the product lifecycle. This will in turn lead to dramatically shorter times to market, better quality, or lower costs.

Adoption of the Digital Thread is increasing in industry, but most real-world implementations remain narrow in scope and incomplete in breadth. The thread concept necessitates complete, comprehensive, end-to-end systems integration, but commercial applications have yet to realize that concept. Current technology looks ahead to Digital Thread but remains focused on specific process steps. This technology is incomplete because it may address inspection (but not manufacturing), design (but not inspection), or supply chain management (but not design).

Digital Thread implementations will inevitably be mashups of hardware, software, systems, and standards. Because the Digital Thread is, by definition, interwoven with the entire product lifecycle, projects in the space have the potential to significantly disrupt existing processes and production. Small scale pilots and test installations, though, avoid production interruptions while allowing key concepts to be proven out and important lessons learned. A variety of public and private testbeds have surfaced that target Digital Thread use cases or are well suited for further research into those use cases, and best practices for effective testbeds are emerging. These testbeds benefit industry primarily by appealing to next generation design, engineering, and production talent and by serving as a proving ground for research on business practices, data flow, traceability, standards implementation, quality, etc.

Two testbed examples are cited here: AMT Pop Up Shop and NIST Smart Manufacturing Systems Testbed. These testbeds are specifically intended as platforms for further research and development. Additionally, two low cost demonstration cells are described: an integrated computer-aided manufacturing (CAM)-CNC system that enables direct control of a machine tool without G-Code, and an MQTT-based data flow architecture for collection, storage, and analysis of machining process data.

CRITERIA

For this paper, “low cost” is a total cost under $10,000 for a reasonable facsimile of a manufacturing cell. Items that are re-used, re-purposed (i.e. Raspberry Pi), and multi-purpose (i.e. Laptop) are included with estimated replacement costs to indicate total expenditure if starting from scratch. The equipment listed here has capabilities like those used in an industrial environment, uses components or software that are used in industry, and/or are a small-scale stand-in for their industrial equivalent. While many Digital Thread concepts

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can be tested in simulation, the discussion here is focused on practical implementations with little or no software simulation.

AMT POP UP SHOP

AMT – The Association For Manufacturing Technology set up a technology testbed in its headquarters office space for education and training for staff and to develop the MTConnect standard. Hands-on demonstrations in the Pop-Up[1] Shop facilitate discussion of manufacturing fundamentals and knowledge transfer from industry veterans to newcomers. The Pop-Up Shop is an affordable on-site supplement to factory tours, trade shows, and conferences while offering a more concrete and student-led experience than textbooks, eLearning, and YouTube videos, and has become an invaluable tool for aiding and improving technical discourse.

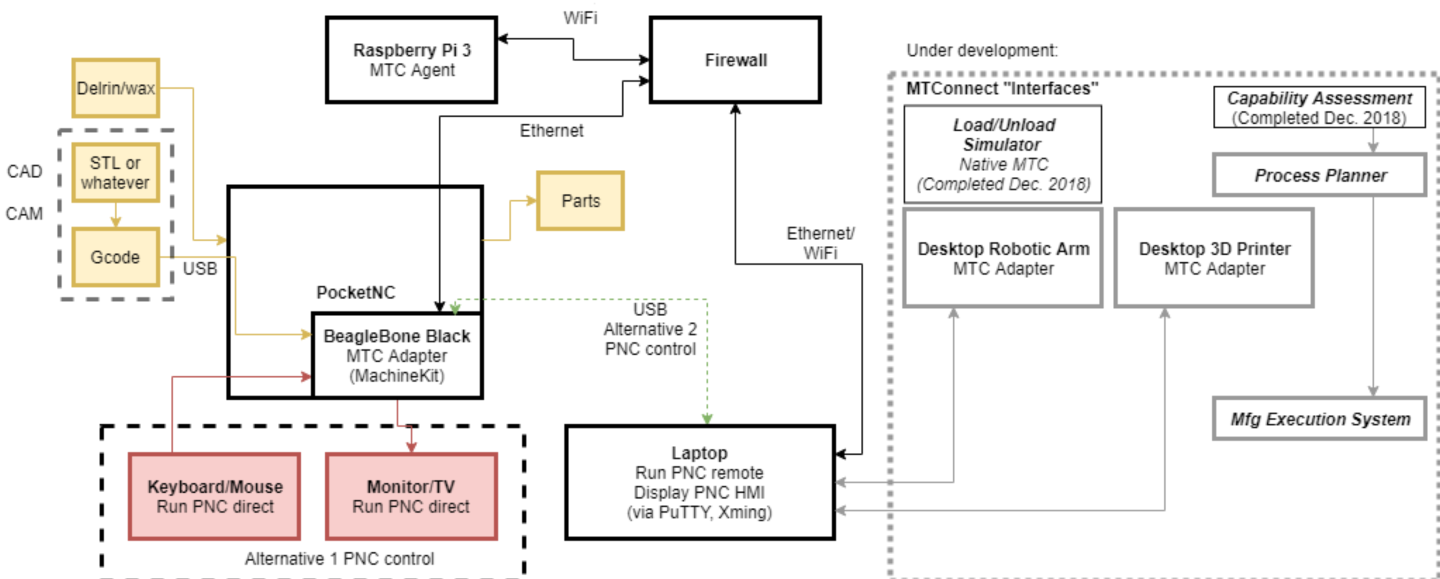


Figure1. AMT "Pop Up Shop" components and layout

In addition to serving as a technology demonstrator, the Pop Up Shop serves as a small scale testbed for developing new functionality related to MTConnect in two key areas:

1. Interfaces demonstrates and tests information exchange patters for orchestration of an automated cell and follows "Robot Control Integration Enhancements Using ROS-Industrial and MTConnect"[2] and "Cost Effective Coordinated and Cooperative Robotics Enabled by Open Technologies."[3] Robotic load/unload is modeled in simulation and a desktop robotic arm will be added in 2019.
2. Capability assessment is a foundational requirement for completing the MTConnect parts and processes model and follows "SPEC-OPS: Standards-based Platform for Enterprise Communication enabling Optimal Production and Self-awareness."[4] The capability assessment (complete) will relate device level data to process level data via a process planner (incomplete) and to the enterprise management level via Manufacturing Execution System (incomplete).

[1] From "pop-up retail," "pop-up store," or flash retailing.
[2] NIST Project Number 17NCDMM12
[3] NIST CFDA Number: 11.609
[4] DMDII-15-03-02

AMT Pop Up Shop, current scope

Pocket NC	$5,500 (V2)
Pocket NC enclosure	$549
Vise	$60
Travel case	$299
Raspberry Pi (bundle)	$85
Laptop	$600
TOTAL, Desktop CNC	**$7,093**

AMT Pop Up Shop, future scope

Ufactory xArm	$7,000
xArm gripper	$1,500
TOTAL, Desktop CNC + Desktop Robotic Arm	**$15,593**

Table 1. AMT "Pop Up Shop" component list

NIST SMART MANUFACTURING SYSTEMS TESTBED

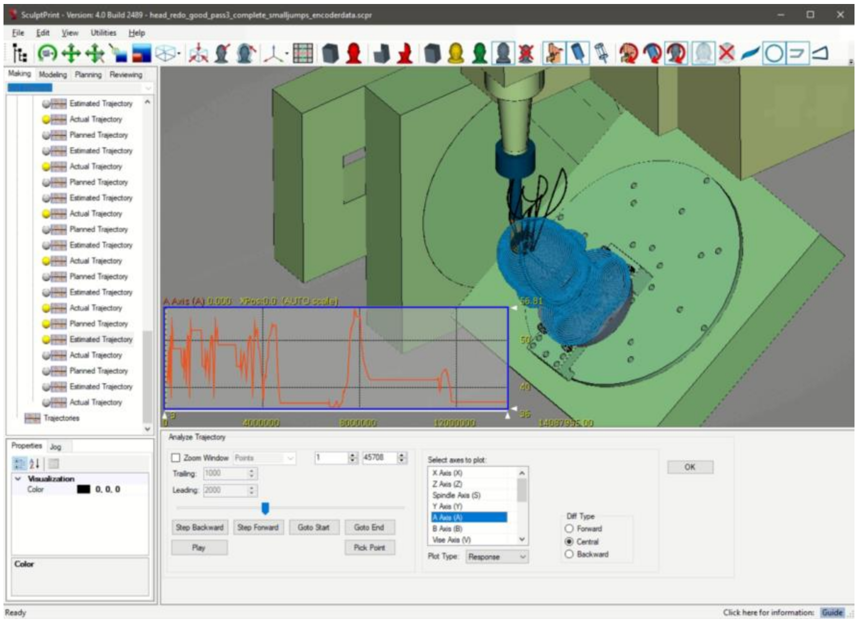
The AMT Pop Up Shop setup is heavily influenced by the NIST Smart Manufacturing Systems (SMS) Testbed, which is a public-facing physical and virtual laboratory for management, design, and manufacturing validation and testing across the product lifecycle. The Pop Up Shop network infrastructure and standards implementation very closely resemble that of the SMS Testbed, albeit at a smaller scale. The SMS Testbed also includes data storage and presentation via volatile data stream and query-able database, which the AMT Pop Up Shop may install in the future. Finally, the SMS Testbed provides public data access to data collected from equipment in the NIST Manufacturing Lab. The Pop Up Shop includes much simpler equipment and generates only a very small volume of data; therefore, there is no plan to allow public access to the Pop Up Shop.

The NIST SMS Testbed offers an example for universities and research laboratories to follow in their own existing machine shops or manufacturing labs. The AMT Pop Up Shop also shows that the SMS Testbed can be also usefully emulated on a small scale with limited space and budget using widely available commercial off the shelf tools.

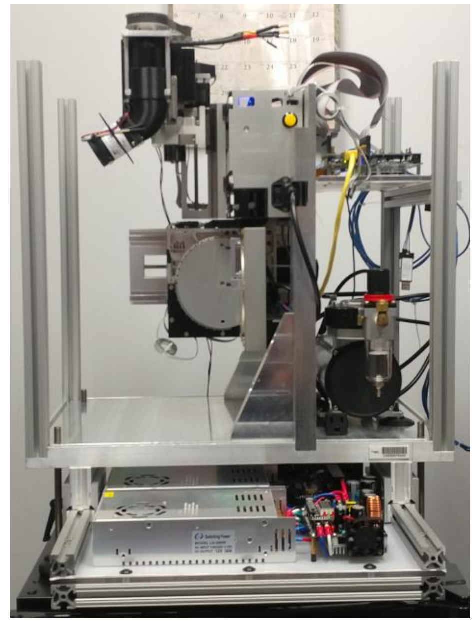
CONTROL OF MACHINE TOOLS USING THE DIGITAL THREAD

In response to a need for superior data exchange between computer-aided manufacturing (CAM) systems and CNC machine tools, Lynn, et al, developed a tightly-integrated CAM-CNC system using a PocketNC[5] that enables more controllable machine tool motion profiles. Instead of relying on typical G-Code, the highly-modified PocketNC is directly controlled by a CAM system known as SculptPrint at the 1ms servo rate of the Machinekit CNC system. This system offers both a high level of controllability and high frequency process data feedback to the CAM system in near realtime. The approximate cost breakdown of the directly-controlled desktop CNC system is presented in Table 2.

[5]Lynn, R. "Realization of the 5-Axis Machine Tool Digital Twin Using Direct Servo Control from CAM." NIST Model Based Enterprise 2018



a. Software Interface



b. Modified PocketNC

CAM-Controlled PocketNC

Pocket NC	$4000 (V1)
Frame	$700
Electronics	300
Sensors	$600
Control PC	$2000
TOTAL, Directly-Controlled Desktop CNC	**$7600**

Table 2. CAM-Controlled PocketNC component list

DESKTOP IMPLEMENTATION OF DIGITAL TWIN ARCHITECTURE

Saleeby et al demonstrated MTConnect with MQTT on a cell comprised of a PocketNC on a network shared with full-scale industrial machine tools[6]. An MTConnect adapter was configured and installed on the PocketNC's BeagleBone Black control system. The adaptor aggregates the machine state at a given frequency, formatting the data according to the MTConnect standard and providing visibility of the machine state to other components outside the machine. A RaspberryPi Zero W with NodeRed was used to stream this data via Wi-Fi to an MQTT message broker, hosted locally on a Linux based miniPC. The message broker operates with a publish/subscribe topic structure, allowing auxiliary services to selectively choose which topics are received and which topics are ignored. To store the data, NodeRed was again used to subscribe to the relevant topics and deposit the data in a MySQL database.

The message broker was designed to operate in a cloud environment, as well as in a closed network. For many machine shops, cloud services are acceptable to use because the parts produced are not sensitive to exposure, and the security of the cloud service is appropriate. However, for many government operations, data

[6] Newman, D., and Saleeby, K., 2018, "Future Factory Software Architecture & Supporting Applications," Boeing / GT Yearly Review.

security is of the utmost importance and cloud services cannot be used. This PocketNC testbed demonstrates the ability to work in a closed network environment, as well as with commercial cloud service providers, providing classified manufacturers the ability to securely leverage the benefits of Digital Twin technologies.

CONCLUSION

Affordable hardware and widely available free and/or open source tools are accelerating research and development on Digital Thread. For a fraction of the cost of industrial scale equipment, and without the risk of production interruptions, desktop machines offer a useful stand-in for standards deployment and integration, design-to-part data exchange, and other foundational Digital Thread application areas. This speeds research, but also accelerates technology transfer from the laboratory to industry.

A QIF Case Study – Maintaining the Digital Thread from OEM to Supplier

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ABSTRACT
The Quality Information Framework (QIF) standard was used to facilitate a Model-Based Definition (MBD) pilot at a Tier 1 Manufacturer. The pilot specifically addressed the 3D data interoperability gap that exists when 3D data is passed from an Original Equipment Manufacturer (OEM) to a supplier. QIF v3.0 is an American National Standard that provides a common interface for digital interoperability that maintains the digital thread (3D data traceability) and enables closed loop feedback throughout product manufacturing. For example, it captures measurement results in the product model adjacent to the design requirement (i.e., tolerance). QIF defines, constrains, and provides for the exchange of MBD, quality planning, measurement results, and enterprise connectivity via a persistent unique identification method called the QIF Persistent Identifier (QPId). QPIds are universally unique identifiers (UUIDs). The use of QIF and QPIds allows for the digital capture of the design requirements and measurement results without manual data entry. The techniques and tools used in this pilot resulted in reduced lead time, increased data reporting accuracy, and improved OEM-to-supplier collaboration.

QIF MBD Pilot Case Study: The Problem

Passing 3D model data without a drawing from an Original Equipment Manufacturer (OEM) to a supplier generally creates interoperability chaos. This chaos inhibits the opportunities available in manufacturing today. NIST estimates there are $100 Billion annual savings available to industry if we [1]:

1. Adopt open standards
2. Adopt model-based methods
3. And move to advanced manufacturing

Because the manufacturing industry relies so heavily on static documentation methods (e.g. drawings) that are not machine readable, the industry cannot leverage the $100 Billion annual opportunity.

To date, native and derivative solutions have been employed, but lack automated data traceability. Today's methods rely on manual human analysis to compare design requirements against actual measurements (e.g. the inspector copies and manually enters data from the drawing into Excel® to capture measurements).

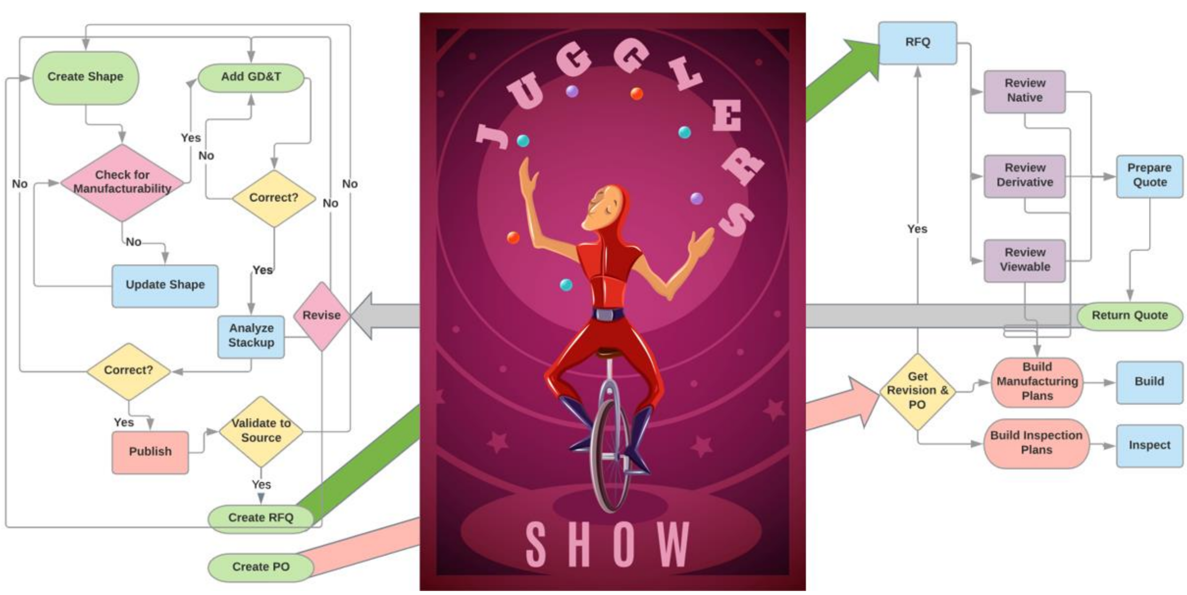

Figure 1: Today, passing data from the OEM to Supplier is a complex workflow of human checking to ensure data integrity. The reason for this is due to the 2D nature of drawing-based documentation methods. Uncertainty and suspicion in the accuracy of this static data drives some industries to spend millions of dollars each year on intensive, error-prone data exchange. [2]

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Because manufacturers and especially suppliers are caught up in the way they have always done business, they are not able to see a new method. The pilot conducted at the Tier 1 Manufacturer and their Tier 2 Supplier successfully tested methods that move beyond the status quo.

The problem is not that manufacturers and suppliers do not have the tools and knowledge necessary to implement Model-Based Definition (MBD). The problem is that each of these companies has likely created their own standards and methods for how information is disseminated throughout their ecosystem. The information includes data that is both machine-readable and human-interpretable. While introducing a new language (MBD) that offers so much potential savings by enabling advanced manufacturing capabilities, it does require a framework of standards and methods to ensure that data being transferred across the enterprise, including the supply chain, retains its authority and integrity. This also ensures that everyone in this ecosystem will be able to benefit from this new language.

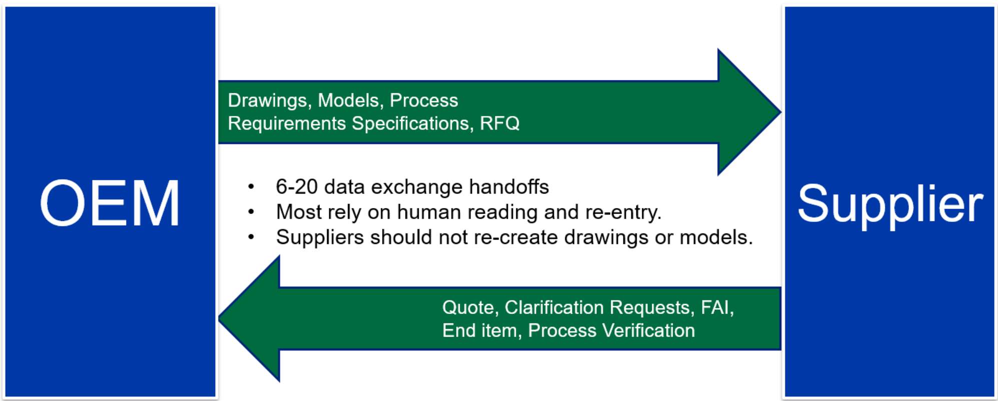

Figure 2: During the assessment and requirements phase of the pilot project, 6 to 20 manual data exchange handoffs were identified from OEM to Supplier. This is a significant amount of manual data handoffs. The pilot proved a reduction of these handoffs.

Success Overview

A large OEM and high precision supplier collaborated on a pilot project of a machined part. The part was designed using Siemens NX to capture the product definition using MBD principles. The design data package was released to the supplier via 3D PDF and without releasing a 2D drawing. The supplier was able to use the native Siemens NX model as well as validated derivatives and contents of the data package to quote, engineer, and produce a part that passed First Article Inspection Report (FAIR) [3] qualification. 3D data interoperability was accomplished by leveraging derivatives as 3D PDF and Quality Information Framework (QIF) files. The Supplier used SOLIDWORKS to create in process models for machining, and Origin International's CheckMate plugin for CMM [4] programming and inspection. Not only were the OEM's supplier quality requirements met, the supplier also realized some very real qualitative and quantitative benefits in their engineering and manufacturing processes.

Together, by standardizing how the product definition model-based design data was characterized and transferred between the two parties, they achieved the goal of capturing the data needed at the OEM and maintaining that data in a 3D data format throughout the entire procurement cycle. Furthermore, the product characteristic data maintained digital traceability every time data was shared between the two companies.

At the core of what NIST is asking for (adoption of open standards, model-based methods, and advanced manufacturing) [1] is that the source native CAD model must:

1. Capture data
2. Interoperate amongst the internal enterprise
3. Be published in a traceable way to external contributors
4. Maintain data integrity during all data exchange for all data elements.

Our conclusion is that MBD is the foundation of the enterprise that can leverage advanced manufacturing.

Solution Overview

The Quality Information Framework (QIF) standard was used to facilitate a Model-Based Definition (MBD) pilot at a Tier 1 Manufacturer. The pilot specifically addressed the 3D data interoperability gap that exists when 3D data is passed from an Original Equipment Manufacturer (OEM) to a supplier. QIF v3.0 is an American National Standard that provides a common interface for digital interoperability that maintains the digital thread (3D data traceability) and enables closed loop feedback throughout product manufacturing. For example, it captures measurement results in the product model adjacent to the design requirement (i.e., tolerance).

By standardizing the language of MBD within the context of Quality Characteristics, both the OEM and the supplier were able to define and disseminate product definition information and data consistently. Both parties were still able to leverage their own tools and processes that are tailored to their own needs. For instance, the OEM used Siemen's NX as their CAD system and the supplier used SOLIDWORKS.

Software Tools used during this pilot are:

- Capvidia CompareVidia
- Capvidia MBDVidia
- Elysium ASFALIS
- ITI CADIQ
- Origin International's CheckMate
- Siemens NX 11.0
- Dassault SOLIDWORKS 2018

The pilot specifically tested the passing of Annotations from NX to SOLIDWORKS using QIF MBD, QIF Planning, and QIF Results [5]. The data passed was both machine and human readable and allowed quality a valid process for comparing design requirements against inspection measurements of the end item. By identifying model-based characteristics in the NX model (created using associated 3D annotations) which was the authoritative source for the product definition, the characteristic definitions remained consistent throughout the manufacturing and quality processes. This product definition is comprised of 3D CAD geometry, annotations authored for machine consumption as well as human readability, attributes (metadata) and presentation states for human interpretation [8].

QIF defines, constrains, and provides for the exchange of MBD, quality planning, measurement results, and enterprise connectivity via a persistent unique identification method called the QIF Persistent Identifier (QPId). QPIds are universally unique identifiers (UUIDs). The use of QIF and QPIds allows for the digital capture of the design requirements and measurement results without manual data entry. For each annotation in this pilot, a 3D ID (commonly called an inspection balloon) was attached to each product characteristic.

The QIF format was able to capture both the geometry and associated annotations that could be consumed by the supplier and leveraged by their tools and processes. Re-modeling and re-design at the supplier were avoided and automation opportunities were possible for some manufacturing and quality processes. This was made possible by leveraging the machine-readable elements of the product definition. However, some risk was introduced due to the creation of data derived from the NX source model. The risk is the loss of data integrity during 3D data exchange of geometry and annotations which if not discovered could result in costly mistakes and/or re-work. To mitigate loss of data integrity, the derivative data was compared to the NX source. Not only was geometry validated, but also the characteristic definitions which were comprised of 3D annotations, their associated geometry and the 3D ID (commonly called an inspection balloon).

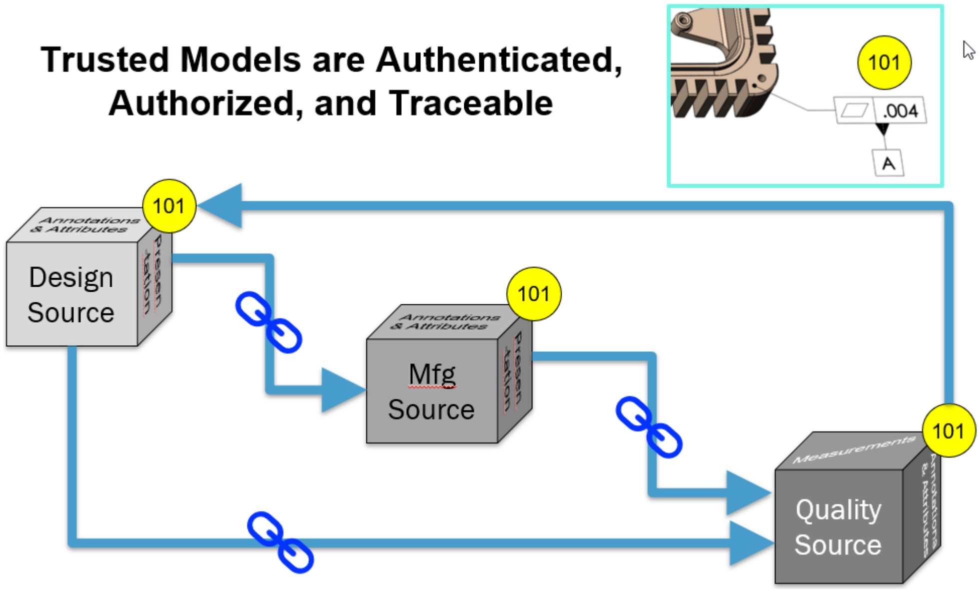

Figure 3: This pilot showed that data can pass from the Native NX Design Source to the SOLIDWORKS Manufacturing Source and record measurement results that can be viewed in 3D space (Quality Source). The 101 balloon is the persistent unique identification that persists through all file formats.

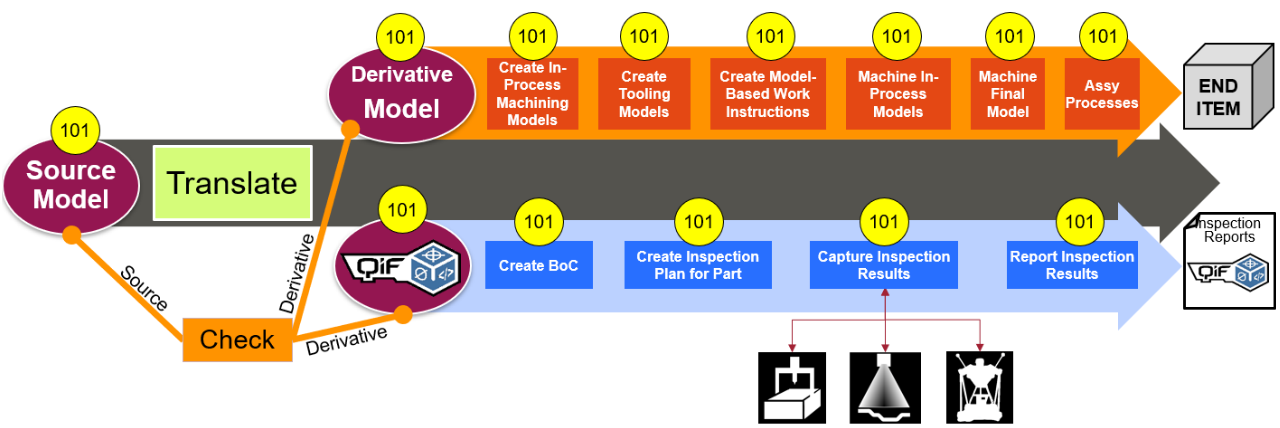

Figure 4: Validation of 3D data sets is crucial to building trust in 3D models. Every product characteristic persists through the supplier handoff because it is enabled by the QPId.

The QIF derivative was successfully validated against the native Siemen's NX file using Capvidia's CompareVidia software prior to releasing the data package to the supplier. This ensured that all data sent to the supplier was trusted and validated.

In addition to the OEM validating the QIF derivative, the supplier derived SOLIDWORKS data was also validated against the OEM's native NX file to further build confidence that data integrity was maintained, establishing a digital thread. While the geometry and attributes (metadata) were able to be validated using any of the several validation tools evaluated (CADIQ, CompareVidia and Elysium), the 3D annotations had to be validated manually by opening both the NX design authority and the SOLIDWORKS derivative. The 3D annotations were not imported as native SOLIDWORKS DimXpert annotations but rather as FormatWorks annotations, and as such, validation required manual visual inspection of the FormatWorks annotations to ensure the text content, display location and geometry associations were retained.

Data Element		Validation Tools / Methods
Geometry	✓	CompareVidia
Annotations	✓	CompareVidia
3D IDs	✓	CompareVidia
Tolerances	✓	CompareVidia
Notes	✓	CompareVidia
Attributes	✓	CompareVidia
Presentation States (Model Views / 3D Views)	✓	CompareVidia

Figure 5: Siemen's NX / QIF derivative validation results

By leveraging the validated MBD derivatives the supplier was able to re-use the data with confidence thereby eliminating the need to re-create the product definition data in their own environment. Once the MBD information was available in their CAD environment, SOLIDWORKS, they were able to build upon that product definition to create several SOLIDWORKS configurations that digitally represent the part as it would exist after each manufacturing operation. These SOLIDWORKS configurations were referred to as Manufacturing Work Instructions. Using SOLIDWORKS MBD the supplier was also able to create their own semantic annotations that could be used to streamline the CMM programming process for in-process inspection and final inspection.

Finally, using Origin's CheckMate plugin for SOLIDWORKS all the MBD annotations, were able to be used to automate much of the CMM programming and inspection reporting tasks. The QIF QPIDs were maintained at every step of the manufacturing and quality inspection processes. The results obtained by running the CMM programs were also sent back to CheckMate for further analysis within the context of the model to reconcile any characteristics that failed inspection. Using CheckMate and the QIF format again, the FAIR results were automatically sent to Net-Inspect thereby satisfying the OEM's quality requirements.

The following resource drain and gaps were filled with the MBD methods employed in this pilot.

Resource Drain: Drawings are often not clear enough for suppliers to generate accurate quotes, so they re-create the 3D model [6].

Data Element	Validation Tools / Methods
Geometry	Validation Tools
Annotations (Require FormatWorks)	Manual Check
3D IDs	Manual Check
Tolerances	Manual Check
Notes	Manual Check
Attributes	Validation Tools
Presentation States (Model Views / 3D Views)	Manual Check

Figure 6: Siemen's NX / SOLIDWORKS derivative validation results

Benefits Realized: Utilizing the 3D PDF files in the quoting process.

- Gives the supplier a complete 360-degree view of the part, removing ambiguity from the quoting process.
- Associated annotations and general notes provide the supplier with the related specifications.
- Clearly defines features and associated tolerances.
- No longer need the native CAD as a resource for proper quoting.

Resource Drain: Forty percent of respondents in a Lifecycle Insights study state that suppliers or downstream consumers re-create the 3D model [6]. Many tool designers re-create the design model because the drawing is often not enough to develop a model for tooling, especially for designs with complex geometry [6].
Benefits Realized: Utilizing the MBD/PMI native and translated CAD files.

- Suppliers can use the CAD file to produce the manufacturing processing part models.
- Create internal 3D PDF operation sheets which eliminates manufacturing process ambiguity.
- Now have the potential to use PMI to minimize machine programming time.

Resource Drain: 60% of Quality planning time is spent on manual data entry [7]
Benefits Realized: CMM programming automation needs to improve considerably. Nonetheless, we were able to partially program the CMM by utilizing a derivative from the QIF file.

- Partially automated creation of inspection plan utilizing the PMI from the QIF file.
- The supplier experienced a 30% CMM programming time savings.
- There is potential to achieve a 70% CMM programming reduction.

Conclusion

Defining a product utilizing MBD principles and the QIF standard for transferring product definition data between OEMs and suppliers enables an OEM to adopt MBD principles in their product definitions as well as the supplier to manufacture a product to the OEM's quality requirements. The pilot identified gaps to be addressed by software suppliers to enable a complete digital thread of 3D CAD with machine and human readable annotations from the OEM's CAD system (NX) into the Supplier's CAD system (SOLIDWORKS) and back into the OEM's enterprise-level inspection database (Net-Inspect). Industry has estimated cumulative enterprise labor savings in the 20 to 40% range and results of this pilot is in-family with those savings and include the perilous OEM to supplier handoff. The techniques and tools used in this pilot resulted in reduced lead time, increased data reporting accuracy, and improved OEM-to-supplier collaboration.

References

1. Thomas Hedberg 2017 GPDIS Presentation https://gpdisonline.com/wp-content/uploads/2017/09/NIST-ThomasHedberg-EngineeringA100bParadigmShift-Keynote-Open.pdf
2. Jennifer Herron 2017 MBE Summit Presentation https://www.nist.gov/sites/default/files/documents/2017/04/18/07_herron_mbe17-040-mbd_supplier_readiness.pdf
3. Wikipedia https://en.wikipedia.org/wiki/First_article_inspection
4. Wikipedia https://en.wikipedia.org/wiki/Coordinate-measuring_machine
5. Quality Information Framework http://qifstandards.org/
6. The State of Model-Based Enterprise Report (2014, Lifecycle Insights)
7. Jennifer Herron, Curtis Brown, and Daniel Campbell 2018 MBE Summit: QIF and the Future of Digital Metrology
8. ASME Y14.47-2013

Use Collaborative Robots to Easily Program Complex Automated 3D Scanning for Dimensional Quality Control (QC) across Supply Chain

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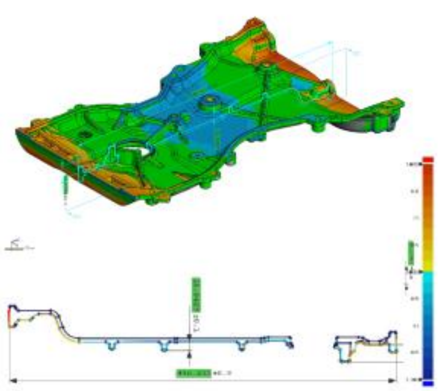
ABSTRACT

In this paper, we seek to provide multiple comparison studies to present use cases of automated 3D scanning both for in-lab and in-line applications. The primary goal of these comparison studies is not only to assess the return on investment from utilizing automated 3D scanning compared to the existing inspection methods, such as CMM or 3D scanning heads on CMMs, but also evaluating state-of-the-art robotic and 3D scanning technologies. First study calculates the cost savings from replacing CMM using a reference automated 3D scanning system with an area-laser based 3D scanner. Second study calculates the return from deploying the same reference system in-line to reduce scrap. Third study compares the benefits of using collaborative robots over traditional industrial robots and also using multi-line laser based 3D scanners over popular structured blue light scanners. Throughout this paper, in addition to evaluating the productivity of robotic automation of 3D scanning, we also seek to articulate the value of data automation that results in easier human-machine interaction in setting up complex inspection programs and advanced data analytics that maximizes the return from collecting high resolution 3D measurement at high frequency.

EXECUTIVE SUMMARY

Study I: Replacing CMM with an automated robotic 3D scanning system



<Figure 1>

The first study is comparing a structural part inspection, between CMM and automated 3D scanning using an area-laser scanner. The part is manufactured by Fiat Chrysler Automobiles, where this structural part has warping issues due to its shape and size. It is critical for the part to fit the mating casting with tight tolerance. In the current process, CMM takes a dedicated operator and 20+ minutes per part to measure approximately 100 points.

The first study is comparing a structural part inspection, between CMM and automated 3D scanning using an area-laser scanner. The part is manufactured by FCA, where this structural part has warping issues due to its shape and size. It is critical for the part to fit the mating casting with tight tolerance. In the current process, CMM takes a dedicated operator and 20+ minutes per part to measure approximately 100 points.

As this part does not have features such as deep holes, which are hard to measure with optical sensors, the entire inspection process can be replaced using automated 3D scanning. As a result, the CMM which is currently being used for inspecting this structural part production can be freed up for more optimal applications.

In the current production and quality process, 2 parts per shift are inspected, and there are 3 shifts per day. Therefore the total number of inspected parts per month is 180. We assume the labor cost per part is $25 and the CMM machine capacity per part = $50 (i.e. opportunity cost of using CMM machine hour for this part). In sum, the total cost of using CMM for this structure part is $75 per hour.

Therefore, we conclude that there is $13,500 (180 * $75) cost savings per month arising from replacing the CMM process with automated 3D scanning. For this particular 3D area-laser scanning automation, the total inspection process takes up only about 25% of its full machine capacity, which implies that 3 other similar production lines can use the same machine, resulting in $54,000 per month potential cost savings.

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Study II: Use an automated 3D scanning system inline for scrap reduction

The second study is estimating the reduction of scrap metal from a structural part production line based on the inputs provided by FCA. On this particular production line, when an error is detected, it tends to continue over the entire shift. In other words, the scrap amount can be up to 800 (number of part produced per shift).

In the current production and quality process, 800 parts are produced per shift, where the production cycle is about 3 minutes per part. We assuming the same reference system as in Study I is used for this study, and the measurement cycle time is about 15 minutes per part (i.e. implied inspection rate is ~20%).

For simplicity, we assume scrap value of $20 for part with dollar value of $50. With 2 failure incidents per month, as we inspect 1 out of every 5 parts, the maximum scrap amount decreases from 400 to (i.e. assume continuous uniform distribution) to 5 parts. In conclusion, there is $250,000+ annual savings from scrap reduction (i.e. $11,850 (395 * $30) savings * 2 (failure / month) * 12 month = $284,400). As a result, there initial CAPEX investment of $250,000 can be recouped in 1 year just from the savings from scrap reduction.

Study III: Replace a CMM with a 3D scanning head with a collaborative robotic 3D multi-line laser scanning

The third study is comparing a transmission housing inspection, between a CMM with a 3D scanning head and collaborative robotic 3D multi-line laser scanning. The part, fixture and the comparison data were provided by Ryobi Die Casting. As part of this study, we also compared the reference collaborative robotic 3D multi-line laser scanning system against other systems with conventional industrial robots with structured blue-light scanning.

Traditional Industrial Robot vs Collaborative Robot

In advance to selecting the collaborative robotic 3D scanning as a test process against CMM with a 3D scanning head, we evaluated the productivity of collaborative robots compared to traditional industrial robots.

<Figure 2>

	Traditional Industrial Robot	Collaborative Robot
Setup	Program: 7~10 hours Report: 3 hours	Program: 2 hours Report: 3 hours
Training	3 days	5 hours
Integration	Software: 4 weeks Mechanical: 2 weeks	Software: 1 week Mechanical: 1 weeks

<Table 1>

The comparison study validated the easiness of using a collaborative robot instead of a traditional industrial robot and showed significant productivity improvements from a minimally trained worker to perform a program setup of automated 3d scanning. The primary difference comes from a worker being able to program the robot locations by moving the robot arms with hands, instead of using teach pendent.

Structured Blue Light Scanning vs Multi-Line Laser Scanning with External Tracking

	Multi-Line Laser Scanning with External Tracking	Structure Blue Light Scanning
Need to spray	X	O
Time for data acquisition	3.5 mins	5-15 mins
Need to use markers	X	O
Accuracy (for non-shiny surface)	1.5 thou	.5-5 thou
Accuracy (for shiny surface)	3-5 thou	Lack of data
Resolution	.3-1mm	.013-.05mm

<Table 2>

Multi-Line Laser Scanning (with External Tracking) on Collaborative robot vs Robotic Structured Blue Light vs Current Process (CMM Plus 3D Scanning Head)

Currently, the facility goes through a manual process of checking the color map and identifying errors. When the 3D scanner mounted on a CMM completes scanning, the deviation between the scan data and the CAD is depicted in a in a heatmap, a worker performs visual check manually. This inspection process takes 47 minutes, while using automated 3D multi-line laser scanning with a collaborative robot results in less than 7 minutes cycle time.

<Figure 3>

	Multi-Line Laser + Cobot	Blue Light + Industrial	Current
Setup Time (FAI)	5 Hours	10 Hours	Days
Total Cycle Time	7 Minutes	20 Minutes	47 Minutes

<Table 3>

CONCLUSION

ARIS has performed automated robotic 3D scanning at UI Labs for the die casted, CNC machined, and additive manufactured real-life production parts. The studies were performed in a way that one automated robotic 3D scanning system emulated manufacturing QC to verify and validate the quality of manufactured components before shipping, and supplier QC to verify and validate the quality of sourced components pre-machining or assembly. This exhibits the relationship between a Tier 2 manufacturing supplier with a Tier 1 OEM. The manufacturing QC results showed highly precise measurement, which can be replicated when the measurement is repeated, implying the flexibility, stability, and portability in utilizing automated robotic 3D scanning for inspection. The manufacturing QC also showed significant productivity enhancements; one study showed 85% reduction in total inspection cycle time compared to a CMM with a scanning head (47 minutes to 7 minutes); the other study showed 75%+ engineering cost reduction in performing the first article inspection (FAI) from start to finish compared to CMMs. It is noteworthy that programming of the robotic 3D scanning system was performed by an engineer with little experience in robot programming. The amount of training needed was significantly reduced when a collaborative robot arm was used instead of traditional industrial robot arms. The supplier QC results at the Tier 1 OEM can use the same measurement process to collect 3D scan data on the sourced part from the Tier 2 supplier. By collecting measurement data with the same process, the Tier 1 OEM can reliably compare the QC inspection data provided by the Tier 2 manufacturer side by side with QC inspection results they have created. The original CAD and the raw 3D scan data is saved at the edge of the Tier 2 for security, and the QC results in a form of QIF and visual PDF are available to be transferred to the Tier 1 OEM via secure cloud. The supplier QC results showed that the manufacturing QC data can be easily saved on a secure server and be accessed remotely from the component buyer’s perspective. From the Tier 1 OEM side, this measurement can be connected to MES (Manufacturing Execution System), so that supplier QC results can inform the supply chain decisions in real-time. It is an important note that both incoming inspection (supply QC of die cast parts) and outgoing inspection (post-machined die cast parts) were measured using one system, showing the seamless connectivity of data not just inter-companies, but intra-company.

ACKNOWLEDGEMENTS

A very special gratitude goes out to both R&D and Quality teams at Ryobi Die Casting, Shelbyville for not only providing inputs to the real-life case, including the part, fixture, and current process data for the comparison study, but also evaluating the state-of-the-art collaborative robotics from the R&D perspective. We also want to express special gratitude to FCA, Kokomo for partnering in 2 different case studies for both in-lab and in-line application of robotic 3D scanning.

Standardized and Persistent Product Characteristics, a Critical Knot on the Digital Thread

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ABSTRACT

Product acceptance has often been identified as the primary inhibitor towards an impactful MBE implementation for digital product realization. Assurance for a successful MBE implementation requires both the maturity to authorize a fully semantic model-based definition (MBD) and the ability to accept product from an authorized MBD. Realizing an end-to-end model-based quality solution will enable the manufacturing quality function to become a primary advocate for MBE and it starts at the MBD and with common, persistent, model-based product characteristics. This paper suggests a lexicon for product characteristics, a human-readable symbols with tag for product characteristic and criticality designation, and recommends the use of a persistent universal unique identifier for machine-readable applications.

Threading the MBE process from design, to manufacturing, to Inspection by intelligently mapping a set of persistent product characteristics can offer connectivity with product requirements, product and manufacturing information, measurement methods, and inspection results. Within digital manufacturing quality this becomes a critical enabler for evaluating first article inspection and production acceptance. Product characteristics have been known and used within different industries as many different names and each may have a synonymous or slightly different interpretation.

CURRENT SITUATION

Some terminology for product characteristics on 2D drawing, and annotated part models include:

- Key characteristic
- Critical characteristic
- Control characteristic
- Major characteristic
- Minor characteristic
- Inspection requirement
- Significant
- Safety critical
- Key ID
- Process control

Furthermore, these may be grouped into items that are

- Process related
- Manufacturing related
- Safety, use or regulatory related

Finally, the human-readable symbols that are used to communicate these characteristics to consumers downstream are varied, inconsistent, and at best locally standardized by company or industry. Below are some example symbols that are being used by companies to communicate design & engineering information with the analysis, manufacturing, inspection, operations, support, and service organizations. The special feature symbols used are:

The symbol geometry typically identifies the feature or annotation as an important product characteristic, but then add the letters that describe the product critically area such as

- **S** Safety
- **P** Performance
- **D** Design
- **E** Engineering
- **F** Fit
- **A** Appearance
- **M** Manufacturing
- **P** Process
- **A** Assembly
- **Q** Quality
- **R** Regulatory
- **T** Test

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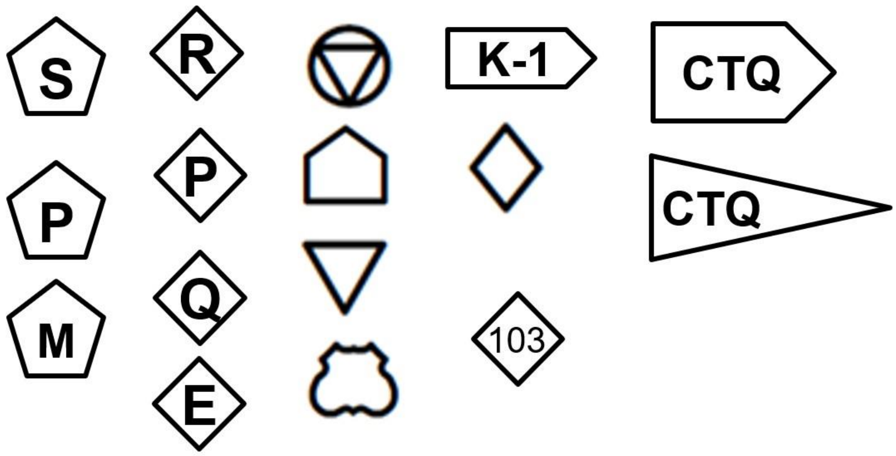

Figure 1. Variety of Symbols used on Drawings across Industries

PROPOSED LEXICON

This paper proposes some principal definitions for a common lexicon within this domain. Starting with the following:

- **Product Characteristic**: is a tolerance or specification applied to a feature or product that requires verification.
- **Key Characteristic:** is a product characteristic that exists because of a product requirement.
- **Critical Characteristic:** is a product characteristic that has a criticality designation associated with it.

A product characteristic is essentially an inspection requirement. This is what a Quality Engineer needs to plan to for inspection to certify that the product satisfies requirements. A Product Characteristic can be:

- Dimensional Tolerance
- Geometric Tolerance
- Unless Otherwise Specified Tolerance
- Specification
- Surface Finish
- Flagged Notes
- General Notes
- Other Symbols that require validation
- Visual Workmanship
- Specified Attributes (e.g., color)

A group of Product Characteristics can be called a Bill of Characteristics (BoC), a list of product characteristics that a Quality Engineer must inspect via various measurement methods.

Some Product Characteristics can be "Key" characteristics. A Key Characteristic explicitly exists to satisfy a product requirement. As a result, a Key Characteristic can be traced back to one or more product requirements, a product requirement can reference one or more Key Characteristics. Next, for those Product Characteristics that have a critically associated with it, then they are Critical Characteristics.

The usability and identification of a product characteristic must be both:

- **Human readable** with a unique identification within the part domain,
- **Computer readable** with a digital universally unique identifier (UUID).

PROPOSED SYMBOL FUNCTIONAL REQUIREMENT

Towards proposing a new human-readable product characteristic symbol, the following functional requirements were deemed as important:

1. The symbol must be a recognizable unique shape
2. The symbol must be easily creatable using existing office/CAD tools
3. The symbol must be able to contain lengthy alpha numeric identifiers

4. The symbol must not conflict with other major symbols in related ASME / ISO standards
5. The symbol can be easily associated to a drawing or model annotation (DimTol, GeomTol, Surface Finish, General Note, Flagged Note)
6. The symbol must be able to accommodate a Criticality Symbol before or after
7. The symbol must be able to be chained with one or more Product Requirement Symbols
8. The symbol must be easily created in an ASCII text field
9. The symbol must be applicable for both 2D drawings and 3D MBDs
10. The symbol should be able to support other to be determined attributes

The following symbol shapes were considered. Each shape was evaluated for its uniqueness and its ability be contain alphanumeric characters and that the shape may be elongated at times if long text strings are applied within the symbol. As a basic requirement, the shapes should not conflict with other, standard shapes, balloons, item numbers, flag notes or general callouts. Simultaneously a new symbol shape should integrate with inspection balloons, control characteristics and product requirements.

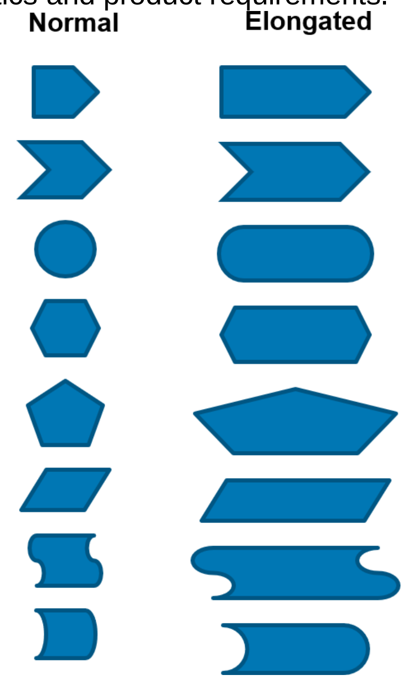

Figure 2. Potential Candidate Shapes for Standardized Product Characteristic Symbols

Text within the symbols must convey a variety of information including the product characteristic identifier, the criticality type, possibly the risk priority, and a reference to any driving product requirement(s). To maximize implementation and to accommodate written text, a method to convey the symbol within common ASCII text character set was deemed paramount.

PROPOSED SYMBOL

After reviewing the candidate symbols shown in Figure 2, the hexagon and the left & right directed chevron shapes have emerged as meeting all the functional requirements defined above. Additionally, as shown in Figure 3, these symbols can be simplified using basic text with the “greater than” and “less than” symbols commonly found in nearly all alphanumeric character sets. These symbols are also commonly presented in desktop software for documents and presentations. Examples of a textual product characteristic with id PC007 is: <PC007>. Then if a Safety Criticality needs to promote a product characteristic as a critical characteristic we can use textually communicate that as: < S < <PC007>. Likewise, if we add product requirement tagged as MD-44 to the <PC007>, then we have a textual key characteristic of <PC007> >REQ-MD-44>.

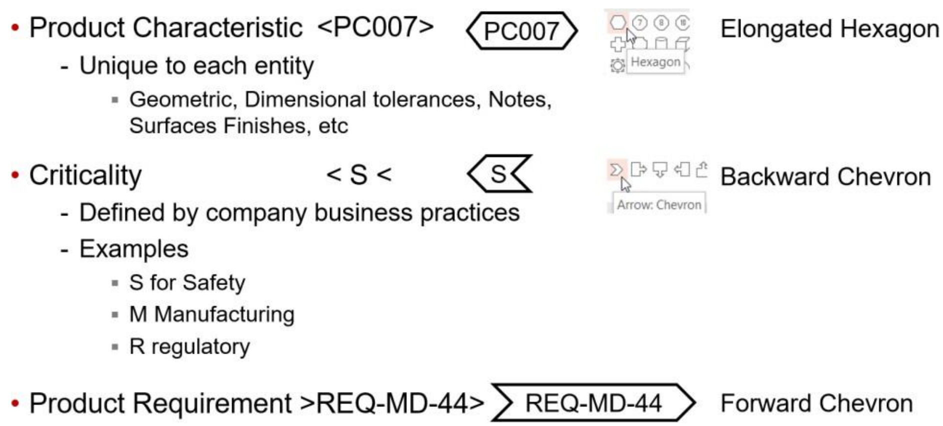

Figure 3. Proposed Symbology

Another functional requirement is that these symbols can be linked together, they visually interlock with each other, implying an order and specific pattern for the type of information. Symbols are the marker for the human readability which needs to be applied to the models in the CAD or drawing tool. Within the modeling software these new symbols will need to be applied to and associated with the product and manufacturing information (PMI) typically represented as annotations. For example, a Product Characteristic (PC) symbol with its human-readable id (e.g., PC007) must be applied to a dimensional tolerance, geometric tolerances, notes, or surface finishes. Then both the PMI and the PC knows that they are digitally linked together. Then a criticality may be associated with the <PC007>

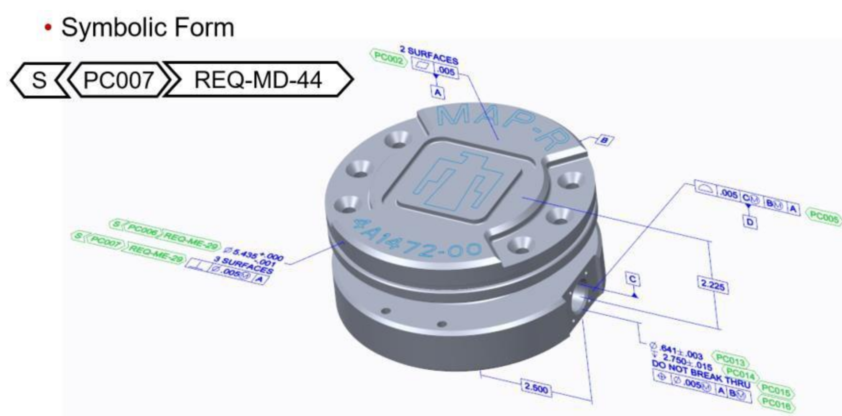

Figure 4. Model-Based Product Characteristics (MBPC)

SYMBOL USE EXAMPLE

Using MBD, with semantically correct product & manufacturing information (PMI), one can easily organize all the dimensional and geometrical tolerances into a Bill of Characteristics (BoC). This BoC becomes the measurement scope for product validation and listing of each tagged product characteristic becomes a line item for inspection. Further refinement is made by defining and displaying the critically level (e.g., safety, manufacturing, function) and the criticality area of definition using special symbology in the model.

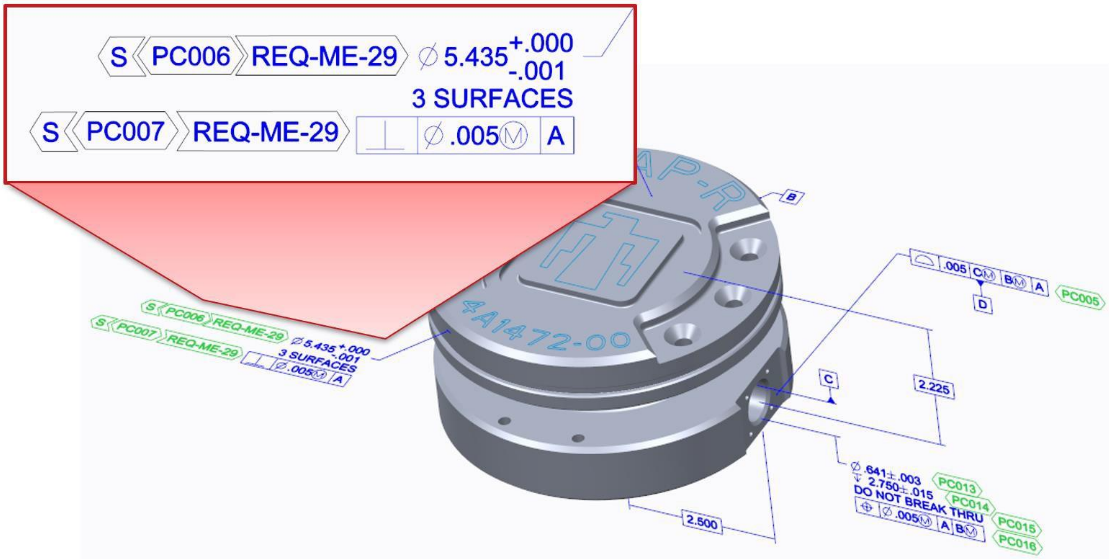

Figure 5

PERSISTENCE & DIGITAL (UUID)

A product characteristic should have both a human-readable symbol containing a part unique identifier (e.g, PC007) and a persistent machine-readable universal unique identifier. It is suggested that within the modeling software, each product characteristic symbol with tag will also have an associated UUID attribute for digital accessibility. This will allow downstream applications such as quality planning and inspection equipment to access information, act upon it as necessary, and report results as required. To connect the digital thread, this product characteristic must become a persistent digital knot that provides connective to many other disciplines and use-cases. Therefore, one must introduce persistence and a universally unique identifier (UUID). UUIDs are commonly used and defined and standardized as part of ISO/IEC 9834-8:2005. Per the standard, UUID is a 128-bit number used to identify information in computer systems. The term globally unique identifier (GUID) is also used and referenced within Microsoft systems. In its canonical textual representation, an ISO UUID takes the form of: xxxxxxxx-xxxx-Mxxx-Nxxx-xxxxxxxxxxxx and an example UUID looks like: 123e4567-e89b-12d3-a456-426655440000. Therefore, it is recommended that for each human-readable product characteristic symbol with tag will also own a UUID attribute that contains the preferred ISO UUID value scheme.

Therefore, once the requisite product characteristics are properly generated, associated with PMI within the 3D model and an UUID attribute is assigned, then a complete digital inspection report can be produced automatically.

Finally, based on the type of characteristic, the precision of the tolerances to be measured, the type of inspection plan or report desired, the verification method and frequency of inspection for the characteristic may be automatically associated. These may be visually color coded and grouped by inspection method or tool to streamline the inspection process.

The process flow for creating a persistent model-based product characteristic is to:

- Define Product Characteristics on the model
- Show human-readable identifier unique for the part
- Tag machine-readable universal unique identifier
- Link criticality designation
- Associate appropriate product requirement identifiers

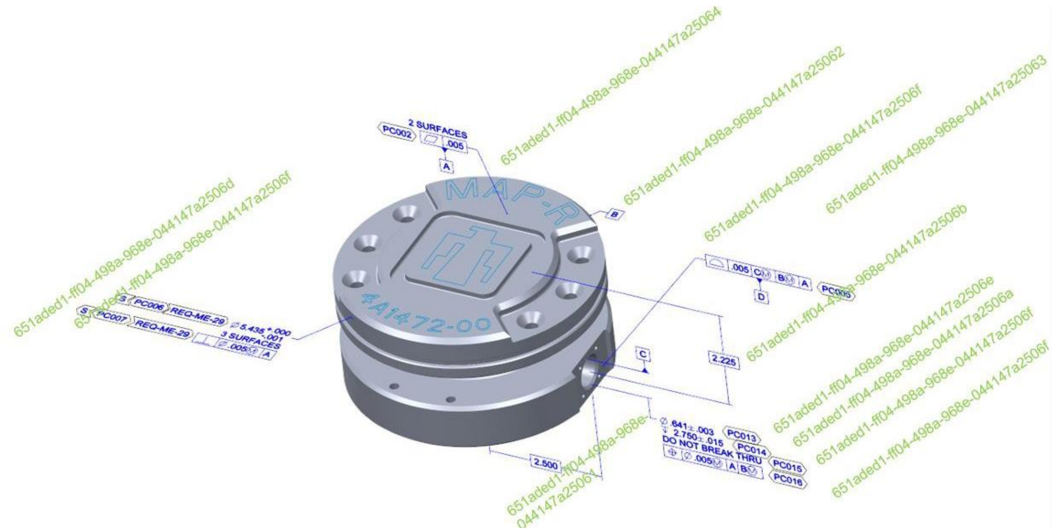

Figure 6: Model-Based Product Characteristics (MBPC) with Persistent UUID

DIGITAL OPPORTUNITIES

For each product characteristic, one can digitally connect various attributes such as:

- Criticality
- Product requirement
- Inspection method
- RPN risk priority number
- Producibility rating
- Process Capability from the inspection results
- Histogram of all inspection results
- Access to individual S/N part's inspection results

This information can be applied to the model via the symbology defined above. Ideally when implemented within a CAD tool one can toggle on and off the display of the various symbols independently or as group. Additionally, if selected, a product characteristic symbol would have detailed information available form a pick list when the right mouse button is depressed.

As an example of extending the digital thread, users implementing lean manufacturing techniques may want to apply a risk priority number (RPN) as driven from process or design failure modes effect analysis (FMEA). This requires a value for the traits of

- **S** Severity level, 1 – 10
- **D** Detection level, 1-5
- **O** Occurrence level, 1-4

This RPN number could be placed with a chevron symbol for immediate and clear visual notification to users as displayed in the appropriate MBD presentation state.

SUMMARY

In summary, the industry has multiple definitions and representations of "characteristics". The industry needs a common standard approach for both graphical and semantical Product Characteristics. This paper recommends a core lexicon, a human-readable symbology for both drawings and models-based definition, and the requirement for a digital persistent UUID for each model-based product characteristics.

Product acceptance from a MBD is a primary inhibitor to MBE implementation. Assuring product acceptance from a MBD is a critical driver toward achieving maximum MBE return on investment (ROI). Quality can become a primary advocate for MBE and it all starts with MBD and persistent Model-Based Product Characteristics.

Strategy for an Intelligent Digital Twin (IDT)

(An environment where Information replaces wasted resources)

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ABSTRACT

It is Newport News Shipbuilding's (NNS) strategy and commitment to advance the FORD CLASS Aircraft Carrier's digital Model Base Enterprise (MBE) to support the entire lifecycle for these ships. This means NNS will develop and advance tools & processes, and integrate disparate systems, which are necessary to support a "Product Model" centric "Digital Twin" and "Digital Thread". The FORD CLASS Product Lifecycle Management (PLM) environment must be capable of providing data configuration management for billions of data objects for a 60 year ship's life time frame.

This paper will focus on NNS's strategy, vision, and the development of an Aircraft Carrier "Intelligent Digital Twin" for lifecycle sustainment. The concept of an Intelligent Digital Twin is completely consistent with NNS's efforts to integrate digital capabilities based on smart technologies throughout the Digital Thread. The lifecycle sustainment objectives drive NNS's plans to provide the Navy a configuration managed Intelligent Digital Twin. The new capabilities will utilize connected digital information to form a holistic view of operations. This view is necessary to perform work safer, more efficiently, and with reduced downtime to allow assets to remain in service longer.

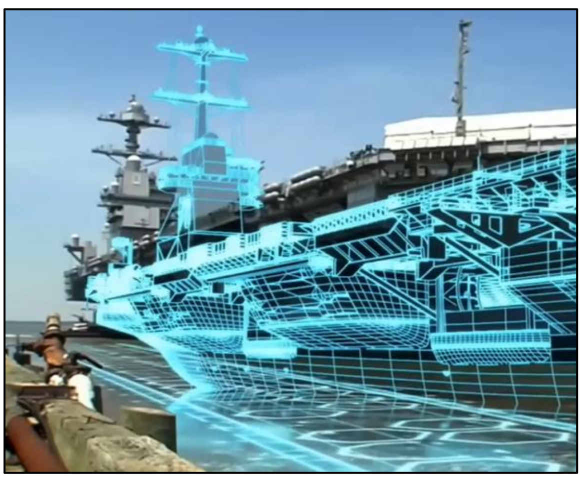

Figure 1. Lifecycle Sustainment "Digital Twin"

Newport News Shipbuilding (NNS) - Overview

- NNS is the largest industrial employer in Virginia, employing about 20,000 people, many of whom are third- and fourth-generation shipbuilders.
- NNS is the only company capable of designing, building, refueling, overhauling and inactivating nuclear aircraft carriers for U.S. Navy.
- NNS is one of only two companies capable of designing and building nuclear submarines for U.S. Navy.
- NNS is in the process of transforming our 130+ year company's paper-based processes to the Digital Age.
- NNS is in the process of eliminating drawings and moving towards a Model-Based Enterprise.
- NNS is adopting technologies like laser scanning, digital twin, mobile computing, and augmented reality.

Introduction

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Newport News Shipbuilding (NNS) is currently in the process of building the 3rd ship of the class of FORD CLASS Aircraft Carriers.

During this design & build period, NNS has continuously advanced its transition from 2D drawing centric paper-based products to data centric digital & 3D products. This complex and challenging digital transformation included evolution of NNS's Shipbuilders culture, processes, and products, along with its hardware & software infrastructure.

As CVN78 the Gerald R. Ford enters naval service, NNS and the Navy will be redefining what it means, and what it takes to support a digital product model-based ship.

The objective of this paper is to provide a view of what the FORD CLASS Aircraft Carrier Lifecycle Sustainment environment will look like in the future.

We will discuss NNS transition from its current state to the ultimate end-state of an On-Board Ship Intelligent Digital Twin.

We will further discuss the strategy NNS is taking to integrate processes; which have previously been done disparately and disconnected from each other, and how this strategy aligns with DOD efforts for Lifecycle sustainment.

NNS & Navy Strategic Alignment

This paper will discuss the direct parallels between Newport News Shipbuilding's (NNS's) **"Product Model Centric Strategy"** and the Office of the Under Secretary of Defense for Research and Engineering (USD(R&E)) **"Digital Engineering Strategy"** (DES) (Reference 1).

These NNS and Navy strategies can be related through the five DES foundational elements (listed below, *NNS related efforts*) necessary for a Digital Engineering Ecosystem to thrive:

1. Formalize the development, integration, and use of models to inform enterprise and program decision making (*NNS-Strategy for Digital Thread and Digital Twin*)

2. Provide an enduring, authoritative source of truth (*NNS-Configuration Managed links between Navy Databases and Digital Product Model*)

3. Incorporate technological innovation to improve the engineering practice (*NNS-Implementation of AR/VR, laser scanning, IOT and other technologies into production processes*)

4. Establish a supporting infrastructure and environment to perform activities, collaborate, and communicate across stakeholders (*NNS-Integrated, Secure Cloud Environment*)

5. Transform the culture and workforce to adopt and support digital engineering across the life cycle (*NNS-integrated Digital Shipbuilding (iDS) for digital manufacturing*)

The basic premise for a Virtual / Physical "Digital Twin" stems from the concept of a continuum of data flow & configuration management through the Design-Build-Sustain phases of a ship's lifecycle. This is referred to as a "Digital Thread" and is depicted in Figure 2.

An architectural view of the environment NNS is developing to meet these Lifecycle Sustainment strategic goals is shown in Figure 3. Note how the data center focused on Sustainment integrates critical data from multiple authoritative sources to provide needed Navy & Shipyard maintenance and modernization information in a digital format.

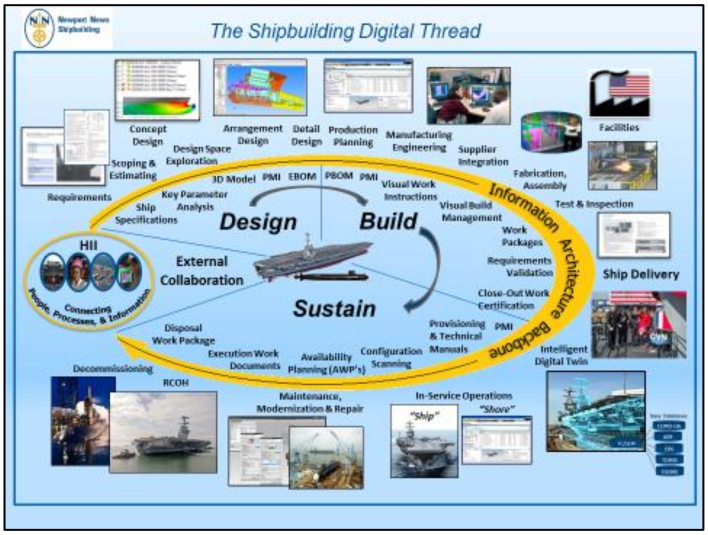

Figure 2: Shipbuilding Digital Thread

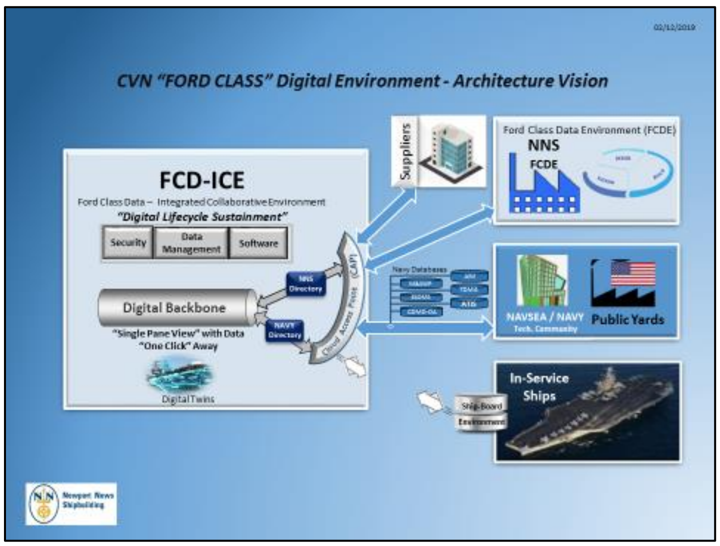

Figure 3. Lifecycle Sustainment Environment

Intelligent Digital Twin (IDT) – Conceptual View of Benefits

The goal, development, and use of an Intelligent Digital Twin is to reduce total ownership cost (TOC) to the Navy. By creating and maintaining a virtual product model of the ship which matches the physical vessel, we can perform activity simulations to reflect actual process operations and prepare in advance for ship maintenances and modernization activities.

The listing below identifies potential benefits that result from the development and management of an Intelligent Digital Twin. It is critical to understand the importance of the data configuration management aspect of the IDT. This function insures confidence by the end users that they have the most recent information to make educated decisions and perform their jobs. In this respect our *Focus is on information Availability.*

- In an IDT Configuration controlled ship *"work gets safer"* and there are *"less failures"*
- With an IDT "Uncertainty of System conditions is minimized"
- An IDT would "Reduced Execution Risks" for Type Commanders with digital functions/capabilities; visual analysis of AWP's, to "Tell me what's happening tomorrow, not what my problems are today"

- An IDT would provide Information that is consistent across the organization – replace wasted resources (data mining, data structure, visualization)
- An IDT would provide Operation readiness improvements based on *Continuous Maintenance Strategy*
- An IDT would provide Operation readiness improvements based on *Planned Obsolescence Strategy*
- IDT provide a Pathway to cultural change; initial implementation stages are supplemental to current processes
- IDT provides oversite of artificial intelligence (AI) applied to data mining-decision making (simulation proven)
- IDT supports additive manufacturing (AM) for part printing and new design (spare part planning)
- IDT allows Shipbuilder and Navy to change technologies together

Use-Cases, Operating Benefits, CM, and Infrastructure Supporting an Intelligent Digital Twin (IDT)

The development of IDT **Use-Cases** is based and prioritized upon the following areas:

- Economic Value (Identify and improve pain points)
- Data Control (direct access to authoritative source, traceability & validation)
- Minimum Information for the job, what do we have to produce?
- Definition of success; digital integration/automation, safety
- Operation procedures for new digital processes

Operating Benefits from an IDT include: (saving time/energy, compress schedules, reduce material costs)

- Strategy for reduction of FORD CLASS out-of-service maintenance period
- Time reductions for ship availability “open & inspect” activities
- Time reductions for ShipAlt activities from sensor-based condition monitoring
- Connected Information from Authoritative Sources (CDMD-OA, AIM)
- Improved Spare part management
- De-confliction of work (organize work in a space)
- Reduced availability growth work (ship check capturing more information - material condition)

Identification of IDT Data **Configuration Management** requirements is based on factors of:

- Reliability; criticality of component / system
- Cost; traceability path complexity
- Ergonomics; safe working environment
- Failure reduction; functioning of systems

On-Board Ship IDT **Infrastructure/Application** profile is defined early in the development processes, is maintained throughout the lifecycle, and is based on:

- Data types, hardware requirements, performance
- COTS products, level of configuration required, and complementary & augmented systems
- Definition of Technical Network & system compliance
- Develop Infrastructure Investment profile
- Plan for System Integration, authoritative source of data, traceability

IDT Lifecycle Sustainment Roadmap

Figure 4 shows the Model Based Enterprise (MBE) Tenants and Technology Capabilities that lead to an Intelligent Digital Twin.

Tenants for MBE development and integration include:

- Continuous Development through entire Ship Value Stream with increasing MBE Capability Levels
- Providing Agility & Responsiveness to make Business Decisions
- Creating a connected Digital Enterprise is providing Real-Time information
- Leveraging the Navy Investments in a Digital Environment
- Providing Agility to Introduce New Technologies
- Developing Data Driven Intelligence

High level **Categories** for MBE Integrated Collaborative Environment advancement include addressing requirements for:

- Collaboration
- Security & Infrastructure
- Data Enrichment
- New Technology Capabilities

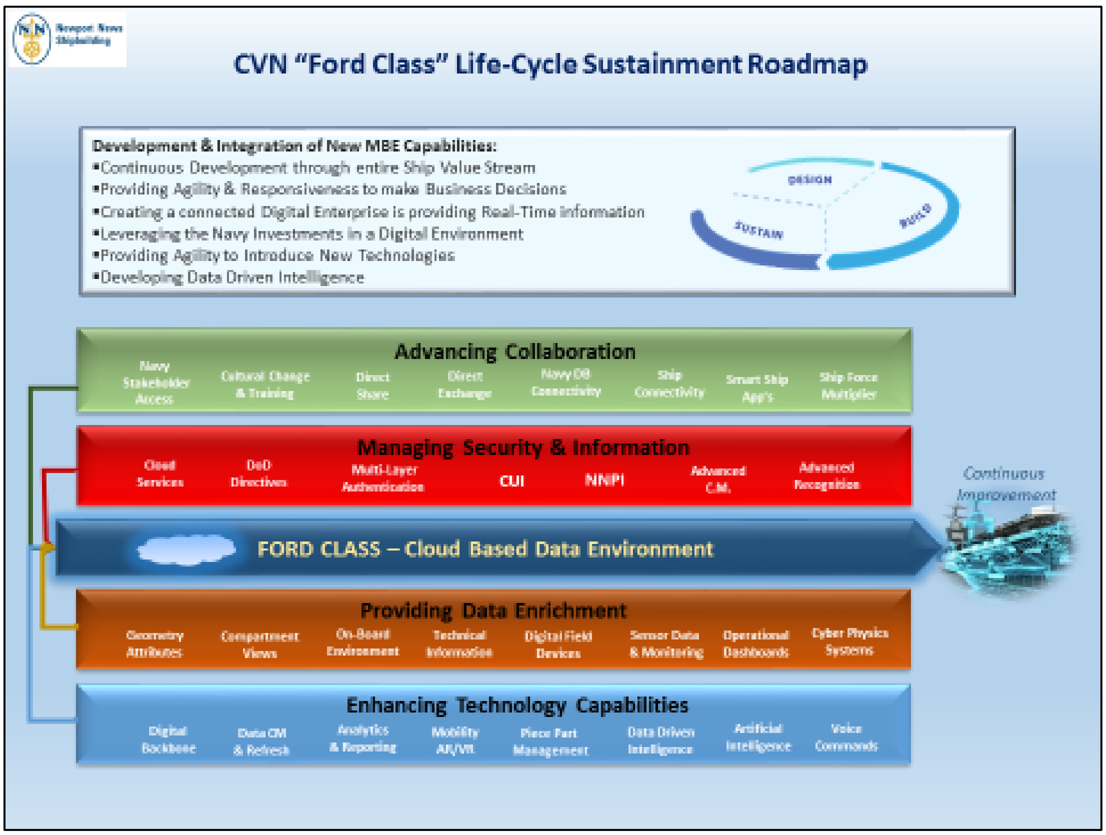

Figure 4: Lifecycle Sustainment Roadmap

SUMMARY

As part of the CVN digital transition, it is NNS's goal to ensure strong alignment with the Department of Defense (DoD) Digital Engineering (DE) initiatives that will transform the way the DoD designs develops, delivers, operates, and sustains systems. DoD defines digital engineering as an integrated digital approach that uses authoritative sources of system data and models as a continuum across disciplines to support lifecycle activities from concept through disposal.

- NNS has relevant experience implementing digital ship design & build applications, and the evolution of processes from drawing centric to digital model-based content. This evolutionary process has required organizational and technical agility.

- Critical aspects learned from this transition to a Model Base Enterprise (MBE) are now being applied to the Lifecycle Sustainment Phase of the Shipbuilding Digital Thread.

- NNS has planned for this Sustainment evolution by implementation of the initial critical infrastructure objects into our production environment. This environment can meet the Navy's basic Lifecycle requirements.

- NNS is now in the process of developing and implementing a strategy to provide advanced and innovative practices to the CVN Lifecycle Sustainment environment utilizing SIEMENS and 3rd party applications.

- These new practices provide "Structure for Complexity" that allows for effective advancement of Lifecycle Product Model centric capabilities to create an Intelligent Digital Twin.

- The topics discussed in this paper will help provide the basis for successful production process transitioning and alignment with DOD "Digital Engineering Strategy" (DES) initiatives.

References:

(1) DOD Secretary of Defense James Mattis's "Digital Engineering Strategy" (DES) dated June 2018 https://www.acq.osd.mil/se/docs/2018-DES.pdf

AUTHORs BIO's

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Mark has over 30 years of Shipbuilding experience and is currently responsible for data/information architecture strategy, planning, and implementation of Model Base Enterprise (MBE) and "Digital Thread" goals for NNS's. His responsibilities are cross program creating an "Integrated Digital Shipbuilding" environment which drives convergence on common processes and products. Mark is also an Information Technology - Major Initiative Team Lead for the NSRP organization.

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Generating the Digital Thread for Backlogged Parts that Lack TDP

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ABSTRACT

Sometimes aerospace manufactures of the defense industry go out of business or the parts are so old there are no TDP or performance requirements available. This paper will provide a methodology for a rapid response to organizations that need to generate a Technical Data Package (TDP) and manufacture backlogged spare parts. Since there is no access to Computer Aided Design (CAD) model data for these components a reverse engineering (RE) technique need to be employed to generate the geometry of the Baseline Geometry in a parametric feature-based CAD format. If complex surfaces are present a Sub-divisional surface modeling technique (Sub-D) is deployed. The static load levels and the natural frequency limits can be determined by assuming that the existing design meets all structural and dynamic performance requirements.

Enhancing this Reverse Engineering process with Generative Design and Lattice Structure generation techniques presents an opportunity to not only reproduce the part but improve its performance, reduce its weight and reduce its time to manufacturing.

Since the additive manufacturing (AM) industry continues to grow with new machines, faster processes and a large selection of materials there is a great opportunity to redesign these parts using Lattice Structures and Generative Design Techniques. Lattice structures such as Gyroid minimal surfaces are very effective for light weighting, energy absorption, dynamic damping, ballistic protection, etc. This presentation will demonstrate how to combine Sub-Divisional surface modeling, Topology Optimization, manufacturing constraints and Lattice Structure generation tools to generate optimum designs.
Introduction

Introduction

Sometimes aerospace manufactures of the defense industry go out of business or the parts are so old there are no TDP or performance requirements available. This paper will provide a methodology for a rapid response to organizations that need to generate a Technical Data Package (TDP) and manufacture backlogged spare parts. Since there is no access to Computer Aided Design (CAD) model data for these components, a reverse engineering (RE) technique need to be employed to generate the geometry of the *Baseline Geometry* in a parametric feature-based CAD format. If complex surfaces are present a Sub-Divisional surface modeling technique (Sub-D) is deployed. The static load levels and the natural frequency limits can be determined by assuming that the existing design meets all structural and dynamic performance requirements.
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Methodology

The proposed process includes the following steps:

1. Generate CAD Models of Baseline Part
   The scan data files are reviewed and “cleaned up” by filling the missing holes and smoothing the rough surfaces. A feature based parametric CAD model of the Baseline Part can be built using the scanned data. The model is validated using the mass properties of the Baseline Part. In collaboration with the stakeholder team GD&T is applied for a complete model based definition. The CAD model must also be manufacturable and mesh-able for downstream applications (i.e. AML, CNC, FEA, Optimization, etc.)

2. Estimate Structural Performance Requirements
   If the Structural Performance Requirements, such as load cases and safety margins, are known they can be used in the Optimization tasks. If the requirements are not known they can be estimated using the "as good or better" approach. Since the components have been certified and used in the field, we will assume that they have typical safety margins with respect to the yield and ultimate stresses. The support locations and load directions will also be assumed. A FEA model can be built and the magnitude of the load can be increased till the assumed safety margins are reached. It may be necessary to generate multiple load cases. In collaboration with the stakeholder team all critical loading cases can be determined.

3. Material and Manufacturing Technique
   In collaboration with the stakeholder team the material and the desired manufacturing techniques such as CNC Machining, 3D printing, Casting, Hybrid (additive & subtractive) can be determined. The appropriate manufacturing constraints such as extrusion direction, casting direction, number of CNC axes, lattice structures, AM build direction etc. can also be determined. Multiple manufacturing options may be selected.

4. Establish the Part’s Design envelope using Mechanism Motion Analysis
   Build an assembly of CAD models of the adjacent parts that participate in the motion of the main part. Build a Mechanism dynamic simulation model that can generate the motion of the assembly that contains the component under consideration and its adjacent components. Establish the space claim envelope of the adjacent moving parts and determine the main part’s available design space that cannot have any interference or collisions with the adjacent assembly parts. The available design space (design domain) of the part can be used in the topology optimization process.

5. Generative Design
   Utilize the *design domain* of the Baseline Part and perform Topology Optimization for all load cases with manufacturing constraints. This process can generate an optimized part that sheds excess weight from the Baseline Part without reducing its strength. The results of the topology optimization are usually faceted parts.

6. Generate CAD Model of Optimized Part
   Build a new CAD model of the Optimized Part using a sub-divisional surface modeler and lattice structures if appropriate. The CAD model can also be manufacturable and mesh-able for downstream applications.

7. Structural Analysis of Optimized Part
   Build a new FEA model of the Optimized Part in order to perform *validation* of stress levels and virtual certification. All critical load cases can be applied to the Optimized Part model.

8. Testing Plan
   Perform a design of experiments (DOE) study to establish the testing plan. Using each parts performance requirements establish the type and number of structural tests per part (i.e. tension, bending, torsion, fatigue, etc.). Collaborate with the stakeholder, participate and execute the testing plan.

9. TDP with PMI
   Generate a technical data Package with all CAD data for CNC code generation of both Baseline and Optimized Parts for manufacturing and testing. Additive manufacturing parts require a *unique PMI* information such as:

   a. Material Specification
   b. Printer type and software version
   c. Print Orientation
   d. Parameters setup for Printing
      i. Laser power
      ii. Pulse rate
      iii. Spot size
      iv. Velocity
      v. Scan Line Spacing
   e. Post Processing requirements
   f. Strain Relief
   g. Support Removal
   h. Sanding / grit blasting
   i. Painting / coating
   j. Heat Treatment
   k. Hot Isostatic Press (HIP) plan
   l. Storage
   m. Surface Finish
   n. Machined Features
   o. Inspection Dimensions
   p. Datums
   q. Inspection points for acceptable warping/distortion and
   r. Inspection Plan

Conclusion

The process which reintroduces backlogged parts that lack TDP into the Digital Thread will be presented and demonstrated. Examples of light weighting helicopter components using Lattice Structures and Additive Manufacturing will also be presented. As manufacturing is shifting rapidly, our decision to embrace emerging generative design and manufacturing technologies determines our ability to compete and thrive in the years ahead. The Figure below sows pictorially the technique that reduces weight and improves safety margins and reintroduces part’s TDP into the Digital Thread.

Figure 1 Technique that reduces weight and improves safety margins and reintroduces part's TDP into the Digital Thread.

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Point Cloud Management: An Overview of Current Practices and Technology

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ABSTRACT
Laser scanning allows for the capture of as-built products and structures. Point clouds are generated from the scans, which enables the use of software for multiple use cases such as comparison of as-built vs. as-designed. Multiple different technologies exist for capturing point clouds, just as multiple software packages exist for the processing of point clouds. Workflows in organizations shift constantly, point clouds are being targeted for their ability to enhance communication throughout the lifecycle. We discuss BIMs, scanning hardware, the capture and processing of point clouds and problems that exist with point clouds today. While laser scanning and the processing of point clouds are the primary focus of this paper, a brief introduction to other technologies is presented. Finally, an existing software for consolidating the point cloud workflow is discussed.

INTRODUCTION

When a digital representation of an object (3D model, point cloud, etc.) retains logic, relationships to data stored within it and to other objects related to it, the object can be defined as "semantically rich". Building information models (BIMs) are typically considered semantically rich digital models of various architecture. BIMs are gaining traction in multiple different communities because of the multitude of cases in which they can be utilized [4]. Building information models can be captured in a variety of ways, even images from cameras have shown promising results recently [3].

One way to create as-built BIMs is using laser scanners. Laser scanners are capable of quickly and accurately capturing and measuring the shape of the environment. There are three steps involved in attaining a BIM from a laser scanner. Data collection, data preprocessing and modeling the BIM are all steps involved in gathering, refining and producing semantically rich BIMs [7]. The first step, data collection, is where laser scanners come into play. Scanners rapidly capture the 3D shape of the environment by gathering measurements to nearby surfaces with centimeter to even millimeter accuracy. Each measurement gathered is a single point in the scan, and each scan can contain millions of points.

Point clouds are those millions of points created by a scanner, all clustered together to form an environment or definition of a three-dimensional space. This point cloud can be one scan or multiple scans fused together to form a larger environment. These scans are utilized in numerous ways, one of which is the creation of BIMs. Building information models are formed through the utilization of computer-aided design (CAD) software or BIM-specific software to generate 3D geometry for the intentions of design and planning. Scanners, on the other hand, capture the as-built geometry and can provide many benefits such as comparison of as-built vs. as-designed models.

The benefits of point clouds reach far beyond comparison of models. Having a digital representation of an as-built environment allows you to take measurements, experience scale, plan for changes to the environment and a variety of other functions. Creating 3D models from the point cloud is a process that, as the technology improves, is becoming a trending standard for creating precise as-built geometry from a scan. This geometry often can then be brought into a native CAD system for additional work to be done.

Workflows in organizations are constantly evolving and changing as processes are added and removed. Point clouds, especially in Architecture, Engineering, Construction and Facility Management (AEC/FM) organizations, are valued for their ability to offer enhanced communication at various stages in a product's lifecycle. Often, CAD/BIM design-based models become a reality. A physical product or structure is made, then over time changes are made and updates need to be applied to newer products or existing structures. Laser

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scanners open the door for capturing a product/structure as it exists today and can allow for advantageous planning for the future or redesign on the fly, which will be discussed in a later section.

DEFINITION OF SCANNER TYPES

Point Clouds are a result of a 3D data capture process of gathering information from the real-world using x, y, z coordinates to make a digital representation of an object or area. Several methods for capturing the 3D data include laser scanning (LIDAR), photogrammetry, structured light scanners, and sonar [6]. While each of these options will be discussed, the primary focus of this paper will be on LIDAR.

Photogrammetry, in short, is software that accumulates photos and generates point clouds and/or 3D models. These photos can include targets for the purpose of more accurately piecing them together, or the software may be capable of identifying similar features between photos for automatic, target less registration. More sophisticated versions of photogrammetry software can create point clouds and models that have similar accuracy created by LIDAR scanners. One of the drawbacks of photogrammetry compared to LIDAR is the requirement of illumination while acquiring the photos. Laser scanning and other projected light solutions generate their own illumination while acquiring data. While photogrammetry shows great cost benefits over laser scanning and the technology is advancing, laser scanning tends to be more accurate and more predictable.

Structured light scanners project patterns or single lines of light onto a target and then use a camera (or multiple) and software to measure how the light is altered. This information is then used to generate either a model or point cloud depending on the product. There are two primary forms of structured light scanners, static and handheld. Static scanners are in fixed positions while the target is placed into the scanning area. In this format, it is possible to arrange the scanners in a 360-degree structure allowing the target to be scanned in 3D at the same time. The second form of structured light scanners are handheld. Handheld structured light scanners can be swept over an object to create the model or point cloud as more of the target is scanned.

Sonar technology generates point clouds by emitting a ping of sound, then recording the return and using software to interpret the distortion. Different configurations of sound emission can then be used for greater accuracy, cover larger areas, or to get live 3D images of underwater objects.

Laser scanning (LIDAR: LIght Detection and Ranging) is the emission of laser pulses and then recording what happens to those pulses. As more lasers are emitted and collected, the resulting point cloud will become denser. The benefit of a denser point cloud is that the result will almost be a photographic representation of object or area. However, more points also mean larger point cloud files which can be difficult to work with if the hardware is not available to support them. Laser scanning can be further broken down into four primary types; time of flight (pulse based), time of flight (airborne), phase based, and close range/handheld.

Time of Flight (“pulse-based”) LIDAR emits “laser pulses and then determines the object location by measuring the amount of time it takes for that pulse to bounce off an object and return to the scanner.” The method of how the return pulse is received and measured differs per scanner manufacturer. While this type of scan is slower, approximately 50,000 points per second, it is able scan objects accurately at greater distances.

Airborne LIDAR often uses a form of time of flight scanning called waveform processing and echo digitization. “This type of time of flight scan can get multiple returns from the same pulse of laser light, which allows for multiple readings from the same laser.” This is useful when there are obstructions between the scanner and the object being scanned. An example could include a busy manufacturing floor where workers often walk through active scans.

In contrast to the time of flight scanners, phase-based scanners emit a continuous laser beam. The scanner can interpret the modulations of the beam’s phase to record the location of anything that interrupts the laser’s path. Because the scanner is continuously emitting the laser beam, it can gather points significantly faster and therefore provide more information per scan. While the information is acquired quicker, as high as one million points per second, the range of the scanner is shorter, as much as 80 meters, and the file size per scan can quickly become difficult to manage.

Both time of flight and phase-based scanners can be leveraged for mobile laser scanning (MLS). The scanner is partnered with GPS and inertial navigation devices to create a system that is attached to a vehicle. The accuracy of the collected data depends upon the quality of the inertial nav unit, speed of the vehicle that the system is mounted to, and the quality of the software used to process the data. Phase-based scanners tend to be more popular for this application because of their ability to quickly acquire a lot of information which allows the vehicle to move faster during the scan. By partnering with the GPS and inertial nav units, the scanner can generate a continuous point cloud that is georeferenced and registered.

LIDAR is not only for long distance scanners, but short range/handhelds as well. These are primarily used to capture objects about the size of a person or smaller. As manufacturers continue to develop the technology, hand held scanners are becoming more popular for scanning objects as large as cars and small aircraft. "Some close-range scanners can attain very high accuracy, well below 1mm." It is common for hand held scanners to be equipped with both a camera and laser for use in real time scan-to-model workflows. Instead of being hand held, some close-range scanners use a turn table to scan a rotating object or use an arm to sweep over the top of the object. Short range and hand-held scanners are typically used for reverse engineering applications.

DEFINING POINT CLOUD FORM

Once acquired, there are multiple forms of point clouds including Georeferenced vs Non-Georeferenced as well as Structured vs Non-Structured point clouds [6].

Any, single point, location can be defined using an x, y, z coordinate which can be derived from latitude, longitude, and an elevation. Using GPS technology in combination with traditional survey techniques, any real-world point can be established efficiently within a point cloud. By combining the measured, geographic, points with the scanned point clouds, it is possible to know the real-world position, or geo-reference, of all scanned points. It is also possible to scan multiple locations and register them to the same geographical data. This is applicable when compiling a digital mockup of a historic site, for example, and it is desirable to take measurements between two monuments.

When the geographic information is not included in the point cloud, it is considered non-georeferenced. This is a common method to leverage the point cloud as it is a faster process from capture to modeling and collaboration.

Another significant difference to account for with point clouds is whether they are structured. This difference, in some solutions, can affect the processing speed, the functions that can be performed, and the quality of the output. For the purpose of this paper, structured point clouds include relational information from point to point along with the positional information that is always collected [1], [2], [5].

UNDERSTANDING REQUIREMENTS FOR POINT CLOUD UTILIZATION

There are several factors to account for when it comes time to use the point cloud that has been acquired. First, is the hardware able to handle the data? When using point cloud software, always verify the recommended minimums as this step can save a world of headaches and lost time down the road. Good basics to keep in mind; more RAM is a plus and a dedicated graphics card that supports Open Graphics Language is a must. Beyond these two, hard drive space should be considered on a project or team basis.

Second, a shared coordinate system. For example, a building has already been designed and construction is underway, and the next phase of the project calls for 3D scanning to verify that the construction is accurate to the design. In this case, it is beneficial for the point cloud and the model to share the same coordinate system as it would allow for a more efficient incorporation of the model within the point cloud or vice versa.

Third, data formats. This is particularly important when considering structured or non-structured data. Some point cloud point cloud formats can contain multiple properties including XYZ, RGB, intensity, and normal values along with relational information on a point by point basis. Other formats, while lighter, contain significantly less information and therefore is less useful by comparison.

PROCESSING AND UTILIZING A POINT CLOUD

With the dataset in hand and the hardware ready to go, it is finally time to process the data. For the purpose of this paper, there are 5 primary processes to point cloud usage; Registration, De-Noise, Modeling, Analysis/Simulation, and Output. Depending on the software and format of the point cloud data these processes can be completed almost automatically. For example, if the point cloud is structured and has an accompanying geo-reference dataset, registration can be as simple as selecting two or three options and press "go." These options include telling the software to look for targets in the scans to increase registration accuracy, whether to use extracted geometry per scan as a sort of puzzle based on similar shapes between scans, and whether to include geo-reference points. Depending on the data and software, it may also be necessary to perform in interactive work in order to complete the registration process.

Software that allows for automatic de-noise of the point cloud can be a huge time save. For this process, the software may recognize different forms of noise including floating objects caused by steam and dust, front noise caused by objects passing through and active scan, overlapping noise where the same space was in multiple scan shots, etc. By allowing the software to perform this process automatically, users can focus their efforts on a separate task while de-noise is running. It is also a benefit as de-noising a point cloud environment can drastically reduce the number of active points which makes the environment lighter and easier to use/manipulate.

With the preparation of the point cloud environment now complete, the next steps depend on the project requirements. A brief overview of the remaining three processes for point cloud usage are provided here:

Modeling from the point cloud can be broken down into multiple processes: point isolation, mesh creation, utilization of the mesh and export to CAD or BIM software. During point isolation, the user designates points from the point cloud to generate a mesh from. The purpose of isolating individual points or a section of the point cloud is to reduce processing time and to get a model of only the object desired. Next, a mesh is typically generated from the points chosen, and an object is created in the point cloud environment to represent the new mesh. Finally, the created mesh can be used for a variety of processes that will be discussed in the analysis/simulation section or exported in a variety of formats for utilization in external CAD systems or BIM software.

Point clouds can be used for analysis of as-built vs. as-designed, gathering an accurate layout of an existing building or facility, simulation of introducing new equipment to a facility or performing a layout change, large changes or updates to an existing product or facility and many other functions. The functions available for utilization of the point cloud depend on the software in which the point cloud is being processed/utilized. For the purposes of this paper and the next section, InfiPoints will be the software discussed.

The meshes generated from the point cloud can be exported to CAD modeling systems for advanced processing of the mesh/creation of a solid model for use in design. Similarly, the point cloud or meshes can be exported to BIM software for the purposes of planning, arrangement, design and other functions. The outputs available depend on the software being used, but typical outputs are neutral CAD formats such as Parasolid, STEP, IGES and neutral BIM formats such as IFC while mesh models can be output to STL.

INFIPOINTS POINT CLOUD MANAGEMENT

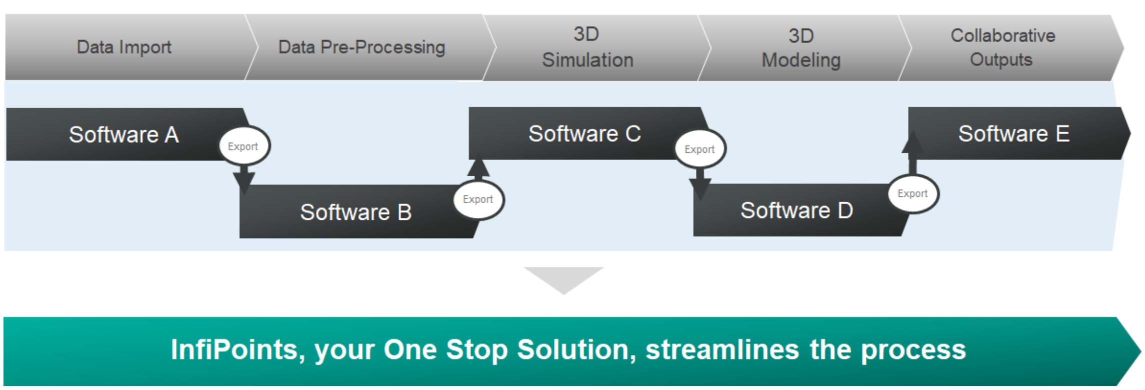

Figure 1: InfiPoints Concept

As mentioned in the previous section, the software in reference to the processes utilized is InfiPoints. While other software packages exist, Figure 1 (above) shows the concept that InfiPoints streamlines the process from importation of data to the export of multiple output forms. The software used to manipulate a point cloud is important to consider, as your end-goals may rely on a specific output or quality not supported by all software. One benefit of InfiPoints is that it eliminates the need for multiple software packages and allows the import, pre-processing, modeling, analyzing/simulating and exporting of data all in one package. This next section will explain how taking data from import to export looks with InfiPoints and describe some of the outputs unique to the software.

By maintaining the whole process of point cloud utilization to a single software, the quality of the data is protected as it will not need to be exported from one software to the next through multiple formats. By capturing point cloud utilization in one software, data size is kept to a minimum as duplicate data is prevented. For example, a single point cloud may be needed to produce 3D models of a manufacturing facility in one software and then in a second software, the same point cloud will have to be imported to simulate collision detection. Instead, InfiPoints imports the point cloud once and can then perform both tasks. InfiPoints is also advantageous because it keeps the organization of the overall project simpler. As seen in Figure 2 (below), the InfiPoints interface organizes the typical point cloud workflow in concise tabs to help the user focus on the necessary operations from importing the raw scans, to providing a variety of outputs.

One of the most powerful tools available with point clouds is the capability to collaborate on a full 3D environment throughout a project. To make this possibility as smooth as possible, InfiPoints can produce a light weight environment that is captured by a viewer file which can more easily be shared with project members, suppliers, or customers. With the viewer file, the point cloud can be visualized in 3D along with any models or drawings within the environment without. Notes and dimensions can also be applied in order to share instructions back to the primary point cloud utilizer all while keeping the data inside of the viewer file secure.

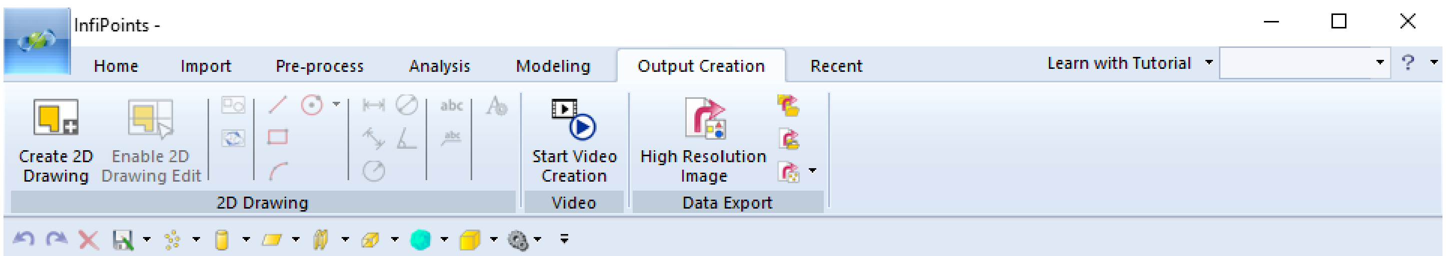

Figure 2: InfiPoints Tab-Based Navigation

CONCLUSION

Laser scanning technology advances have made it possible for quick and easy gathering and pre-processing of point cloud data. As software continues to evolve, new methods for utilization of point cloud data will surely emerge. Recall that when gathering point cloud data, the hardware/software used matters the most. Fidelity of LIDAR point cloud data is dependent on the scanner used and the software utilized for registration and pre-processing of the data. While several methods exist for capturing point cloud, this paper provided an overview of LIDAR scanning and provided an in-depth look at the importation, manipulation and exportation of point clouds. When gathering and using point cloud data, remember to maintain your end-goal and utilize hardware/software that makes sense to your operation. Whether your point cloud is of a paper clip, or an entire factory/building, it is important to understand how to process, manipulate and share the data gathered. InfiPoints makes this process simple by consolidating multiple software packages into one suite of tools while providing unique collaborative outputs for the user. A major gap being addressed by point cloud data is the process of as-built vs. as-designed validation and layout planning. As this gap and many others are slowly closed, communication of information inside of a products lifecycle becomes easier and easier. With time, point clouds will continue to contribute increasingly powerful results and processes to ever-growing industries.

REFERENCES

[1] AutoDesk. How to identify difference between a "Structured Scan" and a "Non-Structured Scan" point cloud data for ReCap Pro project?

[2] AutoDesk User Group International. (2017, April 11). Cool, a Point Cloud... Now What?

[3] Furukawa, Y., Curless, B., Seitz, S.M., et al., Reconstructing building interiors from images, Proceedings of the International Conference on Computer Vision (ICCV), October, 2009, pp. 80–87.

[4] GSA, "GSA BIM Guide For 3D Imaging, version 1.0." vol. 3 http://www.gsa.gov/bim: U.S. General Services Administration (GSA), 2009.

[5] Madsen, R., Nica, V., Barbulescu, A., Kehl, C., & Tsesmelis, T. (2011, May 30). 3D Scanning and Reconstruction of Large-Scale Environments.

[6] Pfeifle, S. (Ed.). (n.d.). WHAT IS 3D DATA CAPTURE?

[7] Tang, P., Huber, D., Akinci, B., Lipman, R., & Lytle, A. (2010). Automatic reconstruction of as-built building information models from laser-scanned point clouds: A review of related techniques. *Automation in Construction*, *19*(7), 829–843. http://doi.org/10.1016/j.autcon.2010.06.007

[8] Van Gool, L. (2011). Real-time Rendering of Massive Unstructured Raw Point Clouds using Screen-space Operators (M. Dellepiane, F. Niccolucci, S. Pena Serna, & H. Rushmeier, Eds.).

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