NIST Advanced Manufacturing Series 100-30

Summary Report: Standards Requirements Gathering Workshop for Natural Language Analysis

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Abstract

The National Institute of Standards and Technology (NIST) hosted the *Standards Requirements Workshop for Natural Language Analysis* on May 21, 2019, on the NIST Gaithersburg, Maryland campus. The purpose of the workshop was to discuss the current trends, successes, challenges, and standards requirements needs with respect to natural language document analysis for decision support in manufacturing. This report documents the event including the summarization of inclusive presentations and brainstorming sessions and identification of key themes. The next steps in this effort are presented towards the end of this document, including planning additional forums and meetings to further engage stakeholders on this important topic.

Key words

Natural Language Processing; Data Analysis; Diagnostics; Manufacturing; Maintenance; Prognostics; Standardization.

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1 Introduction

1.1 Background

Natural language processing (NLP) promotes the analysis, interpretation, and response to human language inputs. With NLP, people can use normal speech and writing patterns to communicate with computer systems instead of relying on programmed or pre-set responses. NLP can be a faster, more user-friendly, and expedient way of communication in machine-human interactions.

There are many applications for NLP in manufacturing, including operations, maintenance, and supply chain logistics. Algorithms parse and interpret human language inputs and recommend the appropriate response(s) or action(s). While NLP has existed since the 1950s, more sophisticated techniques have emerged recently, including deep neural-network based approaches. Applications for NLP are rapidly spreading in many industries given the increasing connectivity between humans and devices.

While NLP is not an emerging field, it is a relatively new concept for manufacturers and maintenance practitioners. Human-machine interactions are prevalent in many aspects of equipment reliability, maintenance, prognostics and diagnostics – making this domain a prime area for application of NLP in manufacturing. To fully take advantage of NLP, a better understanding is needed of the challenges and standards requirements for utilizing NLP as decision support for maintenance in manufacturing.

1.2 Workshop Scope and Objectives

The National Institute of Standards and Technology (NIST) hosted the *Standards Requirements Workshop for Natural Language Analysis* on May 21, 2019 at the NIST Campus in Gaithersburg, Maryland. The focus of the workshop was understanding standards requirements for NLP as it pertains primarily to health monitoring, diagnostics, and prognostics of manufacturing equipment, processes, and products. The workshop was hosted in conjunction with the American Society of Mechanical Engineers (ASME)/NIST Standards Subcommittee Meeting on Advanced Monitoring, Diagnostics, and Prognostics for Manufacturing Operations, held May 22-23, 2019.[1]

The workshop brought experts in the manufacturing, maintenance, and NLP fields together to discuss the current trends, successes, challenges, and needs with respect to natural language document analysis for decision support in manufacturing. Participants included members of the manufacturing, monitoring, diagnostic, and prognostic communities (including both large and small-medium-sized manufacturers), academic researchers, standards developers, and government entities.

The overall focus of the workshop was on leveraging NLP to augment manufacturing decision-support. The workshop included topic areas of: 1) data collection and storage; 2) data cleaning and parsing; and 3) data analysis and visualization. Each topic area was broken up into presentations describing experiences with natural language document analysis, including best practices and lessons learned and breakout brainstorming sessions focused on gaining participant perspectives on the current state (e.g., types of solutions and analysis currently in use), challenges and limitations, and future state for NLP applications.

The full workshop agenda is provided in Appendix A – Natural Language Related links. Acronyms used throughout this report are found in Appendix C and D, respectively.

[1] https://www.nist.gov/news-events/events/2019/05/nist-standards-requirements-workshop-natural-language-analysis-and

This report captures the insights provided by workshop participants. The information presented here is not intended to be all-inclusive of the NLP community and its stakeholders. Rather the information reflects the views of experts in attendance. It does provide a good snapshot perspective of the current state, challenges, and future goals for using NLP in manufacturing operations and maintenance. Note: while the focus was on NLP in manufacturing operations and maintenance, participants often discussed other domains and other non-natural language specific data and analysis. These discussions are also included in the brainstorming portions of the report for completeness.

The rest of the report is structured as follows. Section 2 provides an overview of the data collection and storage needs of maintenance practitioners. Section 3 describes the session on data cleaning and parsing methods for natural language text in maintenance and Section 4 describes the data analysis and visualization session. Sections 2-4 contain figures and summaries from presentations at the workshop. These presentations are available on the event webpage[2]. Each of these sections present

1) a general overview of the topic area,
2) presentation summaries from participants,
3) brainstorming discussions focusing on current state, challenges, and future needs,
4) summary of each topic area.

The report concludes with a summary of the workshop in Section 5.

[2] https://www.nist.gov/news-events/events/2019/05/nist-standards-requirements-workshop-natural-language-analysis-and

2 Data Collection and Storage for Natural Language Analysis

2.1 Overview

Collecting and storing data for use in NLP has its own characteristic challenges. Source materials often involve large quantities of documents from which raw data must be extracted. The raw data is typically unstructured, not designed for easy extraction as natural language, and can contain a variety of fields such as text, dates, and numbers with inconsistencies in format and type. Developing processes for initial extraction of data from a high volume of sources can be complex; implementing the process is often time-consuming and costly. Human input data in historical records, for example, is likely to be entered without a standard process for language, terminology, abbreviations, etc. Extracting data thus requires careful examination of the types of records, repetitive terms, along with colloquial language and jargon. Regardless of the challenges, there is a robust wealth of information available that could be tapped to support automated collection of maintenance records and reliability analysis to yield potential cost reduction and other benefits.

2.2 Presented Topics

Several topics were discussed with implications for data collection and storage in NLP. While some are general NLP topics, most address specific elements of using natural language to improve the efficiency of manufacturing operations and maintenance practices. Each subsubsection heading provides the title and presenter from the presentation.

2.2.1 Human Factors Concerns in Data Collection: Thurston Sexton, NIST

At NIST, the *Knowledge Extraction and Application for Manufacturing Operations Project* is focused on methods of using natural language documents to reduce the cost of equipment and systems maintenance. Advanced, smart manufacturing technologies can potentially reduce the $50 billion spent on maintenance costs annually (2016),[3] but are not yet widely employed. Maintenance work orders (MWOs) represent an untapped source of useful data, but contain non-standard, inconsistent, or even error prone input that is difficult to translate by automated systems. NIST is currently developing methods to extract and make use of data from natural language documents to improve maintenance activities[4]. The MWO data pipeline spans data collection and storage, data cleaning and parsing, and analysis and visualization – all of which are interconnected. An illustrative case study on cutting tool damage typifies the challenges in extracting useful data. In this case study, several different phrases and misspellings were involved in describing several basic cutting issues (described as: cutting too deep, too high a depth of cut, depth of cut too large) and feeding (described as: too high a feed rate, feed too high, tool high of a feed). These differences in descriptions of both the cutting and feeding issues are typical in human language-driven processes and reporting, where a lack of structure is often seen. Additional challenges include non standard formats for dates/times, misspellings, non-matching asset ID numbers (i.e., an asset has one ID number in one system and another ID number in a different system), and domain-specific jargon. Human errors in data collection are a major consideration when improving data quality (Figure 2-1).[5] This figure illustrates error identification based on skill-, knowledge-, and rule-based schema[6]. The mapping of skill-, rule-, knowledge-based behavior onto data collection errors enables an

[3] Thomas, D.S. (2018) The Costs and Benefits of Advanced Maintenance in Manufacturing (Advanced Manufacturing Series (NIST AMS) 100-18.

[4] https://www.nist.gov/services-resources/software/nestor

[5] Reason, J. (1990) **Human Error**. Cambridge University Press.

[6] Brundage MP, Sexton T, Hodkiewicz M, et al. Where Do We Start? Guidance for Technology Implementation in Maintenance Management for Manufacturing. ASME. J. Manuf. Sci. Eng. 2019;141(9):091005-091005-16. doi:10.1115/1.4044105.

examination of activities within maintenance tasks by focusing on events when the system is not performing as desired. NIST is planning to build a roadmap for knowledge extraction of maintenance data based on better understanding of the real-world issues and potential solutions.

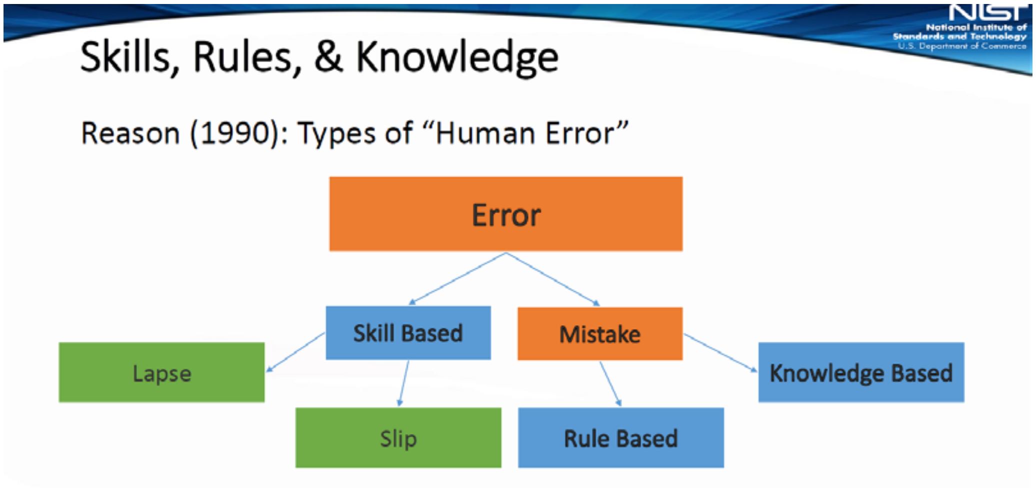

Figure 2-1 Types of Human Language Errors Encountered (Courtesy NIST)

2.2.2 Novel Data Collection Strategies for Maintenance: John Fanneron, BP Group

The equipment intelligence program pursued by the BP Group is addressing some of the growing maintenance skills gaps in the field service industry (Figure 2-2). These include inexperienced technicians, poorly-documented work practices, limited information flow, missed equipment information, and other issues. Skillset deficiencies can lead to fewer jobs completed, higher insurance costs, and slowdown in customer orders. BP group is using the XOi Vision platform[7], which takes advantage of video, customizable workflows, and artificial intelligence to improve maintenance operations. Using a mobile device with the platform, BP Group technicians document job sites, access equipment and training materials, and collaborate with other technicians on a virtual platform. Technicians document work performed and upload content to a computer-based cloud, where the content is then accessible to the organization and its customers, if needed. These process improvements have empowered efficiency increases of up to 35 % in completed service requests. The BP Group is also using Equip ID[8], a mobile application which connects mechanical equipment electronically to the service technician workforce via near field communication (NFC) tags, to deliver equipment-specific data to consistently capture equipment information. Tagging provides data such as make/model, inspection and repair history, along with warranty information, manuals, and other supportive content. Key benefits are improved first-time fix rates, faster maintenance completion times, decreased downtime, and higher revenue, all of which yields a positive return on investment.

[7] http://www.xoi.io/
[8] https://www.equipid.com/

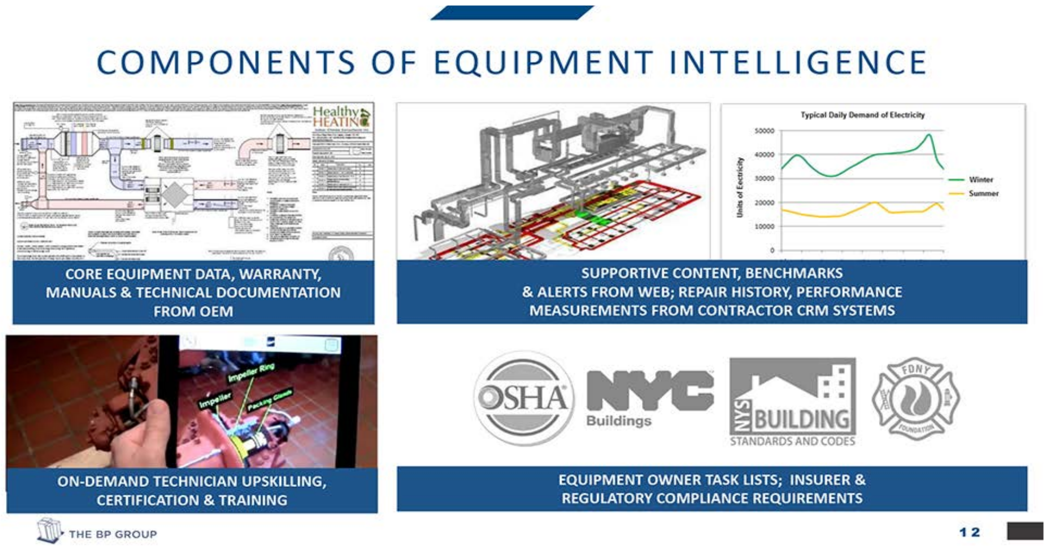

Figure 2-2. Data Sources for Equipment Intelligence (courtesy the BP Company)

2.2.3 Natural Language Document Environment and Challenges: Ken Dunn, British Petroleum

British Petroleum (BP) is a large, complex energy company operating in over 150 countries with assets in oil, gas and alternative energy sources such as wind. Like many large companies, BP has a fragmented data environment with diverse repositories that are geographically spread out. BP is looking at utilizing natural language data for a variety of applications, technologies, and suppliers. Relevant use cases cover expected human interactions, for example, with customers, maintenance personnel, purchasing agents, and other human-driven activities. Functions where NLP could be incorporated include safety, work order creation and equipment maintenance and inspection. The objective is to enable smart, conversational human and machine interactions. Document understanding, classification, and tagging are being pursued as part of the BP NLP effort.

2.2.4 Thesaurus-Guided Methods for Smart Manufacturing Diagnostics: Farhad Ameri, Texas State University

Artificial intelligence (AI) today is only able to interpret a small portion of human language, to address this, prior domain knowledge needs to be incorporated into AI algorithms. Knowledge, such as relational semantics that represent the spectrum of semantic representations required for a knowledge organization system can include a glossary, dictionary, controlled vocabulary, thesaurus, taxonomy, or ontology. An ontological approach is logic-based (text going to logic-based formulas). A thesaurus-based representation includes relational and lexical semantics (text going to vectors). At Texas State University, researchers are developing a minimalistic knowledge graph (thesaurus) to represent relational and lexical semantics for industrial maintenance (Figure 2-3). The objective is to develop models and tools for text summarization and tagging that can be applied to equipment failure diagnosis and maintenance support. To develop these tools, prior maintenance knowledge is being employed, such as that available in maintenance logs (e.g., “repaired hydraulic hose”). SKOS (Simple Knowledge Organization System)[9], a common data model for knowledge organization, is being adapted for the thesaurus. Relational concept schemes

[9] Ameri, Farhad, et al. "Ontological Conceptualization Based on the Simple Knowledge Organization System (SKOS)." (2014).

in the thesaurus include artifacts, functional and non-functional maintenance problems, maintenance treatments, and property. Relational factors are used, such as ‘part of’, ‘symptom of’, ‘impact of’ and similar. The thesaurus is intended to identify, for example, common artifacts, related artifacts or treatments, inter-related problems, and complementary problems. The thesaurus will summarize and tag maintenance logs and enable decision support in maintenance diagnosis, from symptoms to root causes to treatments[10].

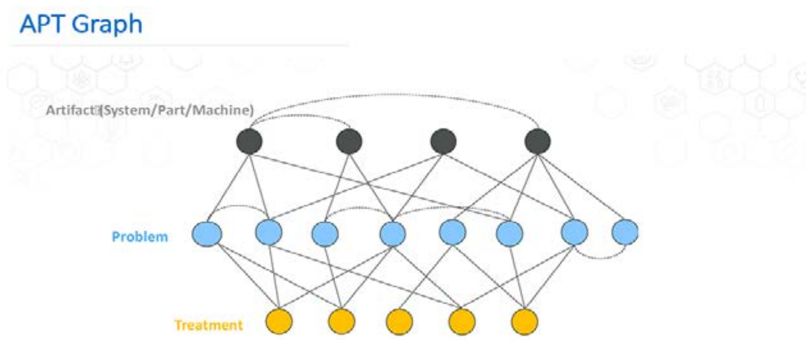

Figure 2-3. Artifact, Problem and Treatment (APT) Knowledge Graph

2.2.5 Standardization of Maintenance Data for Benchmarking and Asset Performance Analytics: Sarah Lukens, GE Digital

GE learned that to deploy NLP algorithms at scale, they had to address many hurdles regarding how maintenance data is collected and stored. Maintenance management work processes are fundamentally similar in every industrial organization. However, the way these processes are implemented and stored in maintenance management systems vary from company to company with respect to data models and storage, coding structures, etc. GE Asset Answers[11] software aggregates work history data from industrial facilities around the world by asset type, manufacturer, and other characteristics. To build a standard data model for aggregate data, GE has developed standardized views of maintenance management processes such as definitions of different event types, dates, and costs. Figure 2-4 illustrates some of the event type definitions being used. Common challenges in analyzing these data fields include inconsistencies in how maintenance data can be recorded across an organization such as variable or inconsistent inputs between various locations and sites. For example, there could be different codes for leaking such as LEAKING, leaks externally, etc., across an organization. The outcome is data in a standardized form which can be used as inputs for asset performance analytics such as benchmarking failures (e.g., ability to calculate/compare Mean Time Between Failures (MTBF)) and consistent application of NLP technologies for utilizing the information found in the structured fields.

[10] Ameri, Farhad, and Reid Yoder. "A Thesaurus-Guided Method for Smart Manufacturing Diagnostics." IFIP International Conference on Advances in Production Management Systems. Springer, Cham, 2019.
[11] https://www.geaviation.com/digital/asset-answers

Event Type Definitions

Event Types	Definition
Repair	**Work required to restore an asset's intended function.**
PM/PdM	Preventive or predictive work • **Preventive: time-based** • **Predictive: condition-based monitoring.**
Miscellaneous	Capital projects and non-maintenance related activities.

Work Types	
Corrective	Equals Repairs
Proactive	PM/PdM and work as a result of PM or PdM
Reactive	Work that causes a break in schedule

Figure 2-4 Workflow Data Flows for GE 'Asset Answers' System

2.3 Stakeholder Perspectives on Data Collection/Storage

During the workshop insights were captured on the current state, challenges and barriers, and desired future state of data collection and storage for maintenance. Three questions were posed during a series of facilitated breakout sessions (Table 2-1); responses to each of the questions are outlined below.

Results show that robust data sources are currently available at the plant site and in the field, with various solutions in play for collection and storage. The quality of this data is variable. Challenges, such as those presented in the following sections, remain that limit the ability to cost-effectively and efficiently extract and utilize interpretable information. This reality creates a strong case to enhance NLP techniques and practices.

Table 2-1 Questions Regarding Data Collection

1. **Current State:** What types of text-based data are your collecting? What solutions are you currently using to collect and store data? Are these working and meeting your requirements, and if not, why?
2. **Challenges:** What are some of the challenges and limitations you are facing for data collection/storage? What kinds of problems are you trying to solve?
3. **Future State:** Given the current state and challenges for data collection/storage, what technologies, research, measurement tools, or standards are needed?

2.3.1 Current State of Data Collection/Storage for NLP

Overview of current state. While this workshop provided an initial pass, more in-depth evaluation of the current state of data collection is needed. The workshop found that some organizations are conducting R&D to understand the best methods to collect and use data. Many different collection resources are available, such as enterprise resource planning systems (ERPs) and manufacturing execution systems (MES). Some companies are evaluating the potential to move toward more product centric data through product data management (PDM) solutions.

Many participants indicated they are at the data collection stage and planning to take the next step to predictive analytics to prevent failures, but are not yet mature at the analytics stage. Some participants indicated that they are using off-the-shelf systems for machine monitoring, often integrated with mobile phone applications (apps). Hardware solutions (e.g., barcodes, sensors, tags, etc.) and related software solutions (e.g., software to store sensor data) also provide an array of automated data collection, which can minimize error. These data collection systems may include analysis capabilities, but often separate systems are used for data analysis.

Another finding during this session indicated that data collection on the factory floor or at the asset is important and common. In some cases, 90 % of data is collected out in the field, and can include information such as identification of operator and machine location details. Data gathering and select analysis is often being done remotely and in real time using a smart phone, with visualization and feedback. After visualizing the data in the application the data is often moved to the cloud for future analysis.

Data sources. As shown in Table 2-2, a variety of both structured and unstructured data sources are potentially available and suitable for use with NLP techniques. In some cases, data is second hand, i.e., manufacturers rely on field engineers to relay data. Unfortunately, not all companies are collecting data, but many plan to in the future. There are still uncertainties on the best data to collect, practical uses for the data, and the cost-benefits. For example, video data of the failure or repair can be collected alongside MWOs, but the organization might be unsure how to best merge this data.

Table 2-2 Types of Data and Sources

- Free text workorders and work requests
- MWO codes
- Video data (in addition to MWOs)
- Operator guides
- Inspection data
- Operator logs
- Reference guides and manuals
- Failure Mode and Effects Analysis (FMEA) templates
- Running machine hours (internal to machine controller)
- Field technician data
- Time and financial data
- Production loss data
- Problem descriptions
- Data for product quality
- Help management software (app collects data and stores in the Cloud)
- Regulatory complaints (data from organizations)
- Compliance data (documents from banks, trading houses)
- Sensor data (average readings to full readings)

Data collection and storage solutions. Table 2-3 illustrates the diversity of solutions currently being employed for data collection, ranging from low technology human driven systems to modern, automated machine monitoring systems. Some solutions (e.g., spreadsheets) have been in use for

over 30 years, while other machine monitoring systems are newer and more sophisticated (e.g., full MES systems).

Table 2-3 Current Data Collection/Storage Solutions

• Spreadsheets (e.g., MS Excel) • Human input to the system (e.g., voice-command, typing) • Databases (e.g., relational, graph databases) • Content management system (CMS) for search and retrieval • Computerized Maintenance Management System (CMMS)/Asset Management System (AMS) Databases • Integrated data stores across plants • Human voice input and transcribe to text • Commercial Solutions – Maximo, other machine-monitoring software – SAP enterprise software – XOi mobile maintenance software – Simplicity advanced asset management and maintenance software	• Application Performance Management (APM) software for data from other sources • On-equipment tags; digital capture via barcodes • Workorder codes • Production loss accounting • External consultants • Domain/company specific standards, e.g. Society for Maintenance and Reliability Professionals (SMRP) • Glossary and dictionaries • Siloed solutions for data analysis vs data collection • Word of mouth (reliance on field engineers to report data) • Artificial intelligence (AI) scribing tools (i.e., tools to automatically take notes)

Properly structured data from equipment and machines (e.g., pressure changes, time stamps, etc.) can be sent directly into software systems for analysis. Conversely, other data may require structuring before analysis, such as including natural language text (e.g., a technician describes the noise of the machine) with traditional sensor data. Maintenance technicians tend to capture data in their own preferred way not always seeing the benefits of following language guidelines.

One organization developed a production monitoring system deployed across multiple plants that works in conjunction with maintenance operations. One system controls the production operations (e.g., MES); another system stores data from maintenance operations (e.g., CMMS). The organization engineered a system, such that information from both the production and maintenance systems is included in their maintenance work orders (e.g., machine state and operator notes). Each plant's data collection and storage may be different, but integrated data can be centrally located in the cloud for ease of analysis.

Data that is time stamped is critical. Some solutions collect data relating to historical/time-stamps for MWO start time, address time (during), and end time (solved). Sometimes hundreds, or even thousands, of time stamps can be recorded from sensors, workers, etc. The challenge is determining which data to record to be useful.

2.3.2 Challenges for Data Collection and Storage

Many challenges were identified that impede effective data collection and storage to support maintenance activities. These challenges are summarized below and in Table 2-4.

Table 2-4 Challenges for Data Collection/Storage Solutions

Data/Text Mining

• Inconsistent data formats:
  – not interoperable between systems, e.g., Enterprise Resource Planning (ERP) → MES Manufacturing Execution System (MES) → ERP, etc.;
  – data formats different among customers
  – Lack of controlled vocabularies (ontologies), fear of complicated ontologies
  – Jargon, abbreviations, use of internal language terms (no standard representations)
  – Combining different sources of data into one central analysis platform (e.g., combining sensor, video, and text data in one database)
  – Dealing with both wired vs. wireless data collection
• Non reproducible solutions
  – Unique data handling requirements for each task
  – Analysis results that are not repeatable
  – Extraction, transformation, and loading (ETL) – unique data transformation needs for each organization[12]
  – Spreadsheets inadequately abstracting data
• Trustworthiness of data
• Differing perspectives on what data is relevant

Data Sharing
• Sharing data without internal Internet access • Sharing data from internal, operation-specific hardware • Confidential data that can't be shared • Lack of standards for data format and sharing, public options for standardizing data inputs (some available for a fee, some confidential) • Getting buy-in and trust for sharing data with service providers
Human Factors
• Operators may have limited understanding of data collection and benefits leading to skepticism of need for new methods (sometimes with good reason) • Different maturity/experience levels of operators/technicians in the workforce (e.g., early career vs end of career) • Communication barriers between technicians/operators and analysts
Institutional
• Matching system design to size of organization (stakeholder needs mismatch); solutions available but difficult to match to organization's needs; companies lack understanding of all available solutions • Inconsistency in work processes • Cost of data collection in general; understanding cost benefits • Up front cost and culture in SMEs; not easy to implement and use, so operator resistance • Security of data and data exchange

Problems stem from both humans and automated systems for data collection, limitations in data and text mining, ability to share and access data for multiple purposes, and institutional issues related to cost and complexity of data collection, relative to company size and goals. Some of the key use cases that organizations are working to solve via better use of data, or with NLP, are shown in Figure 2-5.

[12] ETL – broad process of extracting data from source systems and bringing it into the data warehouse.

Data/text mining. One of the top challenges is that data formats can be different and not interoperable among different systems. This makes performance measurement and benchmarking difficult. Other issues that arise include missing data, inconsistent equipment hierarchy and taxonomy (e.g., an asset has one ID in one system and another ID in a different system), and an inability to compare data across dissimilar assets (e.g., pipes versus turbines).

Data sharing. Confidentiality and security of data is a challenge for sharing and exchange. Service providers don't own the data so they cannot share data records (unless codes/identifiers are removed). OEMs and manufacturers often won't release their data because it contains proprietary information. In other cases might be released only to selected vendors who have a "need to know". Levels of trust need to be established before data can be shared. Few companies are willing to invest time scrubbing and then posting their datasets for specific purposes (e.g., data science competitions, benchmarking).

- Automated fault causation (CNC)
- Extracting value out of free text data
- Deriving insights from unstructured data
- Understanding data and data quality before analyzing it
- Work process for extracting data
- Defining quick wins for data analysis
- Customizing analytics
- Identifying operator skills gaps

Figure 2-5 Types of Maintenance Problems to be Solved

Human factors. One of the major challenges of data management is that equipment operators may be skeptical of improved data collection techniques because these collection techniques may require additional effort and any benefits are not well-documented or understood. Operators, as well as analysts, often lack the domain knowledge needed to understand the data and the context, why it's important to collect the data, how the data will be used, the impact on the plant and maintenance, and so forth. Anomalies in human driven data (e.g., jargon, misspellings, abbreviations) are a significant challenge in the accurate extraction of interpretable data from maintenance documents. Operators may need assistance and training to implement data collection protocols. Intelligence augmentation is an emerging concept to aid with this issue. Instead of trying to replace or automate human driven tasks, augment and aid humans during these tasks in a positive way. Ease of use is also important for the mobile-savvy generation. Workers are often more familiar with smartphone/tablet apps than manuals. The differing cultures/views and type/maturity of workers needs to be considered in order to best facilitate improvements in the maintenance world.

Institutional issues. Companies are not aware of all available solutions and/or are not always sure what is most appropriate for their needs and predominately seek custom solutions. For small and medium size enterprises (SMEs) the primary challenges are mostly related to cost. They are willing to invest but first seek to understand the benefits, particularly the expected return on investment. Company culture also impacts decisions; a SME could have anywhere from 6-50 people and prefer their own methods for maintenance decision making. They often don't want or see the need to do something different. Getting smaller companies to understand savings can be challenging. Knowing when machines could fail, or transparency in scheduling, when to postpone maintenance and save money – these are benefits SMEs can readily understand. Explaining benefits to operators versus management (e.g., how to make your job easier and better) may be the best approach. Building buy-in and trust through success with small test cases may be another solution. Another consideration is that any minor inaccuracies, such as false positive and false negatives from a system can build distrust for users. However, it is important to recognize that in the case of some SMEs, investment into new technology might not be worth it.

Security. Security is yet another a challenge when working in the manufacturing domain, especially in defense manufacturing. Due to security risks, data cannot always be processed in the cloud because it is often not secure enough. Companies also have similar concerns over trade secrets and proprietary data, such that they often monitor and require that it cannot leave the plant. These security concerns make performing analysis and servicing equipment a significant issue.

2.3.3 Future Requirements for Data Collection/Storage

Discussions of future requirements covered a range of ideal, advanced methods for effective data collection and storage. Important to all methods is some form of data standardization; ability for information exchange and interoperability of data between systems; reliable reusable methods and guidelines; and accounting for human factors. Future needs and requirements are summarized in Table 2-5 and below.

Table 2-5 Future Needs and Requirements for Data Collection/Storage Solutions

Overarching Goals
• Health Management, from factory to cloud • Intelligence Augmentation (IA) techniques for data collection • Common, integrated framework for downstream processing of data • Dynamic translation (e.g., chat-bot) to verify NL data entry of maintenance logs • Reliable abstractions, data security (e.g., innovative data security methods, such as blockchain, which uses decentralized databases to encrypt/store data), and traceability (addresses challenge of matching systems to organization needs)
Natural Language Processing
• NLP guidelines to define needed inputs and achievable outputs • Methods to remove dropdown menu options • Techniques for automated ETL • Methods for collecting the correct data
Data Standards and Formats
• Industrial standard for data formats • Alignment of data standards with more proprietary data solutions • Collection of standards that adapt to newly introduced assets, solutions • Methods to differentiate between structured and unstructured data
Preparation for Data Analytics
• Analysis methods to analyze data at database, instead of moving around data to various systems • Data with time stamps so it can be associated with the correct problem(s) • Algorithms and methods for fault identification built into machines (given a fault what are potential causes), with organizational maturity and capability matching (guidebooks)(addresses challenge of matching systems to organization needs) • Integration of data across databases through ontology • Common, shared databases between different systems • Single secure enterprise-wide server co-located with cloud
Human Factors
• Reward system for culture change management (addresses key challenge of operator resistance and poor understanding of data); incentives for improved data collection • Implementation guides for incorporating data collection with human factors techniques

Goals. While this workshop focused on NLP solutions, participants noted that their overarching was achieving proper health management with continuous systems from the factory to the cloud. This goal requires a common, integrated framework for downstream processing of data, data

security, and traceability. Participants noted that NLP is a key technology to help achieve this goal. Understanding how to communicate data that is generated by people in many different ways is a huge step. NLP standards for data treatments and solutions are identified as both a grand challenge and ultimate goal. Creating these standards would allow the manufacturing and PHM community to standardize, share, and use data in improved ways.

Dynamic translation is an important goal for NLP, i.e., the ability to translate human text inputs in real time into computable, consistent data, ask and answer queries from humans, etc. It is essential to separately deal with automatic machine data and human-generated data.

Data standards and formats. An industrial data interoperability standard including natural language data between all enterprise systems is an important future goal. This type of standard would allow for similar analysis to be applied to different data and systems. This could take the form of the MTConnect[13] type of standard for machine condition monitoring (e.g., a communication standard for reliability data). This would include data integration standards between different levels of data (e.g., ISA95 Level 1 to Level 2 to Level 3 to Level 4).[14] Data integration should be bidirectional between levels (e.g., ERP, MES, OPC/UA, etc.),[15] for ease of data access (Figure 2-6). Applications should also interface with the standard data format. Data collection standards should also be dynamic and adapt to newly introduced assets, systems, and solutions.

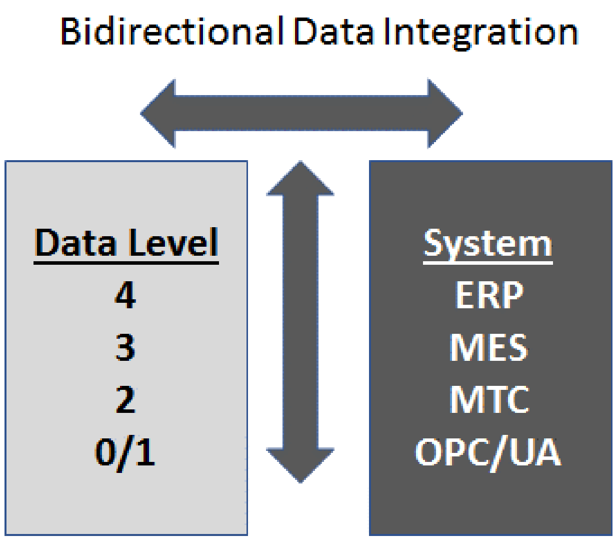

Figure 2-6 Desired Approach for Standard Data Integration

Preparation for data analytics. Currently, different systems cannot make use of similar methods of analysis; standards would create more options for robust analytics. The data should be stationary (e.g., not passing excel sheets between analysts locally) and linked directly with analysis through automatic time-synchronization. Another want is building and maintaining a physical, secure server(s) for an entire enterprise that can be accessed via the cloud in a distributed manner. This would allow an operator, for example, to view information that is relevant to their plant at other physical facilities, via a single digital location. Some of the considerations that arise include how to relate local databases at one plant to the enterprise cloud, e.g., should they have compatible and consistent formats for data exchange.

[13] MTConnect – manufacturing technical standard to retrieve process information from numerically controlled machine tools.

[14] International Society of Automation standard for developing an automated interface between enterprise and control systems.

[15] OPC Unified Architecture (OPC/UA), a machine-to-machine communication protocol for industrial automation.

2.4 Summary

The general themes for data collection and storage are highlighted in Figure 2-7, including key challenges and needs. This provides a snapshot of stakeholder discussions and provides some insights on a potential path forward.

Figure 2-7 Summary of Results for Data Collection and Storage for Natural Language Analysis

3 Data Cleaning and Parsing for Natural Language Analysis

3.1 Overview

In NLP, the process starts with a corpus (digital collection or written text) of documents, which goes through text wrangling (gathering text from many sources, rewriting/consolidating text into a unified content repository), then cleaning and parsing. NLP data cleaning involves detecting and correcting or removing inconsequential or inaccurate terms to improve quality. This cleaning might include removing punctuation or special characters and cleaning up numbers, misspellings, abbreviations, and contractions. Data parsing in NLP involves determining the syntactic structure of text by analyzing its constituent words based on underlying grammar. The result is typically a 'parse tree' describing the sentence root, nodes (e.g., noun phrase, verb phrase, etc.). Parsing approaches in use today are mostly statistical, probabilistic, and machine learning-based. Data cleaning and parsing techniques, as well as the complexity and challenges associated with each, depend on the type of data and intended application or analysis.

3.2 Presented Topics

Presented here are topics that cover some of the current systems and tools being used for data cleaning and parsing, as well as research that is underway regarding various techniques for NLP. Additionally, some of the challenges encountered with using NLP in maintenance and related applications are addressed. Finally, some broad perspectives on NLP were presented, as well as those specifically related to maintenance and operations systems. Each subsubsection heading provides the title and presenter from the presentation.

3.2.1 Small Data Tagging using NESTOR: Michael P. Brundage, NIST

Research and development efforts at NIST are using the NESTOR tagging tool[16] to assist with parsing of natural language data for cleaning and parsing data related to equipment maintenance. Nestor is an NLP toolkit developed by NIST to aid in performing structured data extraction with minimized annotation time. It was designed to help manufacturers "tag" maintenance work order data based on methods developed via the *Knowledge Extraction and Applications for Manufacturing Operations*[17] project within NIST's Engineering Laboratory. The goal is understanding data sets that are too unstructured or filled with jargon in such a way that they can be readily analyzed.[18] Cleaning data is a first step in extracting useful information from MWOs, i.e., identifying anomalies in data such as different spellings,

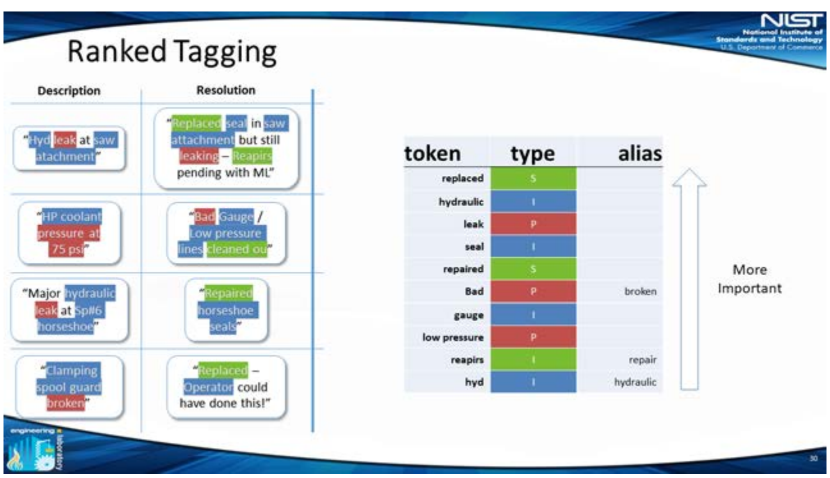

Figure 3-1 Tagging Strategy for Data Cleaning/Parsing

[16] https://www.nist.gov/services-resources/software/nestor
[17] https://www.nist.gov/programs-projects/knowledge-extraction-and-application-manufacturing-operations
[18] https://www.nist.gov/blogs/taking-measure/when-manufacturer-asks-how-do-we-get-smart

abbreviations, phrases or formats for the same type of maintenance issue or term, and resolving them into consistent terms. For example, a leak issue could be written by the technician as 'hydraulic leak, hyd leak, hyd leaking, coolant leak' or other abbreviations/terms – but when resolved should appear as a standard 'hydraulic leak.' Different ways of cleaning and transforming maintenance work order (MWO) data are possible, but range widely in time and cost required, as well as effectiveness. Often, thousands and up to millions of terms and records need to be screened. Ranked tagging (Figure 3-1), such as that possible with NESTOR, was found to be a fast and efficient process compared to other annotation methods. Going forward, NIST plans to refine the NESTOR model, explore visualization techniques, and pursue development of standard guidelines through the ASME Prognostics and Health Monitoring Subcommittee.

3.2.2 Semi-Automatic Processing of Unstructured Short Text in Maintenance Records: Melinda Hodkiewicz, University of Western Australia

At the University of Western Australia, researchers on the Siri for Maintenance Project[19] are working on transformative changes to maintenance activities using data science tools. Recording information on the thousands of maintenance tasks performed every year in asset-intensive industries is vital to improving maintenance efficiency and asset reliability. This data provides a historical record and knowledge to enable better preventive and predictive maintenance, information about equipment life, and process productivity. Currently, maintenance records are mostly captured as short, unstructured text using time-consuming and often inconsistent processes. The objective of this project is exploring transformation of unstructured maintenance records into structured, machine readable information that can support automated recording of events. As a test case, researchers looked at approximately 700 000 historical maintenance records for heavy mobile equipment and devised a proposed pipeline for record transformation. In the first step (pre-processing module), records go through tokenization, then semantic transformation, normalization, abbreviation, and lemmatization to become a structured, pre-processed and concise maintenance records (Figure 3-2). Methods were also devised for symptom/state detection and maintenance item detection to create the final base pipeline of maintenance activities for performance evaluation (Figure 3-3). The result – a concise method for more accurately automating and capturing maintenance activity through consistent processing of natural language inputs.

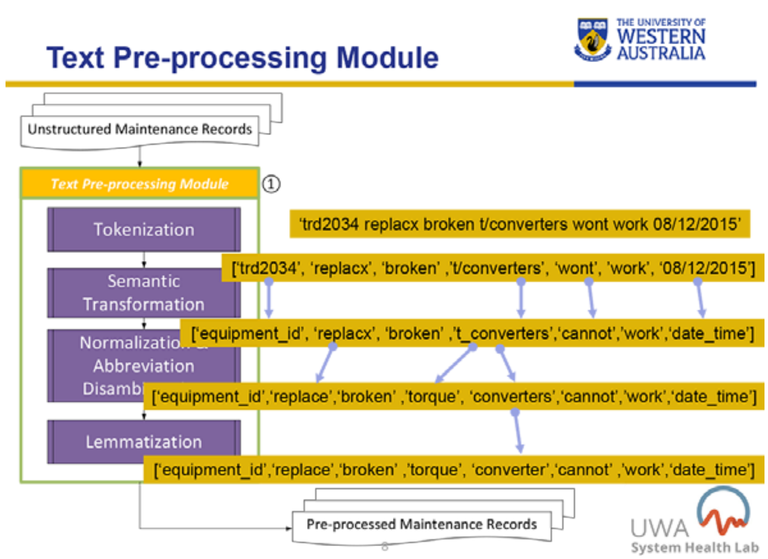

Figure 3-2 First Steps in Pre-processing MWO Data

[19] Siri for Maintenance project, University of Western Australia. https://systemhealthlab.com/shl-projects/current-shl-projects/siri-for-maintenance/

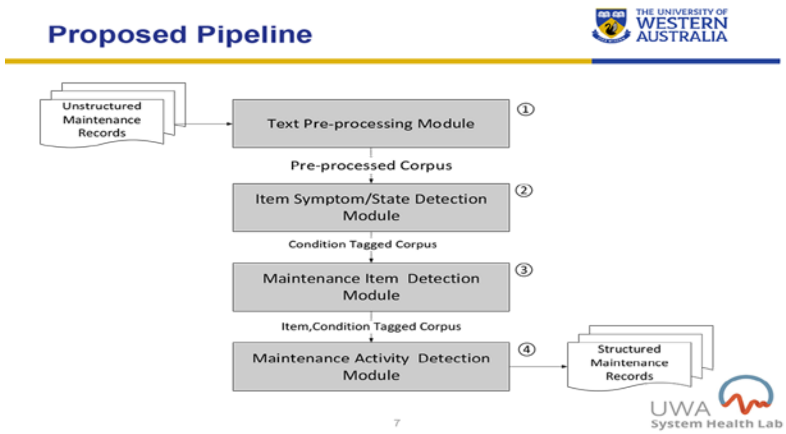

Figure 3-3 Pipeline for Processing and Analyzing MWO Data

3.2.3 Natural Language Processing for Regulatory Compliance: Aaron Massey, University of Maryland, Baltimore County (UMBC), Alden Dima, NIST

Legal texts, such as regulations, policies and legislation, play an important role in software and requirements engineering. Automated text mining for requirements analysis of policy documents with respect to privacy is being explored at UMBC. There is a large volume of relevant privacy policy documents that require searching, which is costly and time-consuming. The UMBC project seeks to determine whether automated text mining can help identify whether a policy document contains requirements expressed as either privacy protections or vulnerabilities. Researchers are mining a large corpus of privacy policy documents containing over 2000 privacy policies, terms of use, terms and conditions, and terms of service, etc. The basic approach (Figure 3-4) uses a Latent Dirichlet Allocation (LDA) model,[20] a NLP generative statistical model that allows sets of observations to be explained by unobserved groups that identify similarities in data. LDA is a type

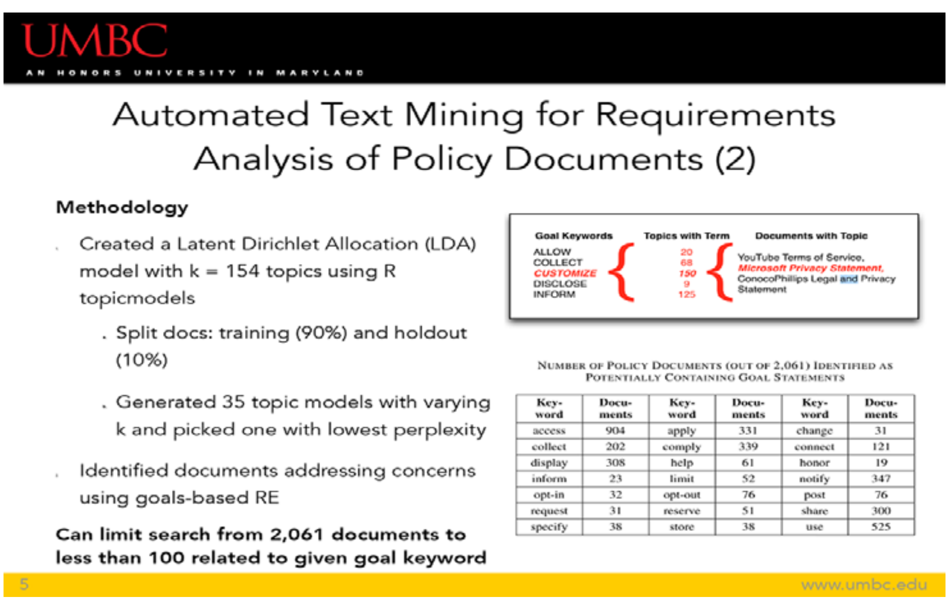

Figure 3-4 Regulatory Privacy Use of NLP

[20] https://en.wikipedia.org/wiki/Latent_Dirichlet_allocation Accessed 10/18/2019.

of topic model that assumes each document is a mixture of a small number of topics where each word can be attributed to a document topic. The enormous number of documents and terms to be extracted make automated text mining challenging and complex. Keyword searches, for example, can return many false positives requiring re-analysis, which creates new concerns. Additionally, the lack of labeled training data and requirements for large training sets represent a barrier. While NLP can play an important role in Requirements Engineering, the benefits and challenges of this approach remain mostly a topic for academic research.

3.2.4 Composite Learning Algorithm for Records Evaluation: Maria Seale, U.S. Army Engineer Research and Development Center

Manual maintenance logbook labeling has been a long-time challenge for aviation equipment maintenance. Logbook labels, which include maintenance causes, types, and component information, can be used to inform engineering reliability, but only about 10% are scored for this purpose using manual methods. The U.S. Army Engineer Research and Development Center (ERDC) has been working on a project using automated methods to convert over 40 million aviation maintenance records to more useful, scored engineering reliability data. The automated Composite Learning Algorithm for Records Evaluation (CLARE)[21] method enables improved usage of logbook data for analysis, reducing burdens on technicians and improving reliability engineering (Figure 3-5). With CLARE, natural language text fields are translated to predictive labels that identify the cause and type of maintenance, as well as any components involved. The Distributed Random Forest (DRF) method[22] is used for label predictions. DRF handles large complex data sets well, is computationally simple, and results in average predictions over all classifications. CLARE, and its enabling technologies, will allow U.S. Army maintenance data to be a more reliable and significant factor in the reliability of equipment platforms. Future efforts are planned to correlate logs with sensor data, develop cross-service capabilities, and generalize CLARE for multiple platforms.

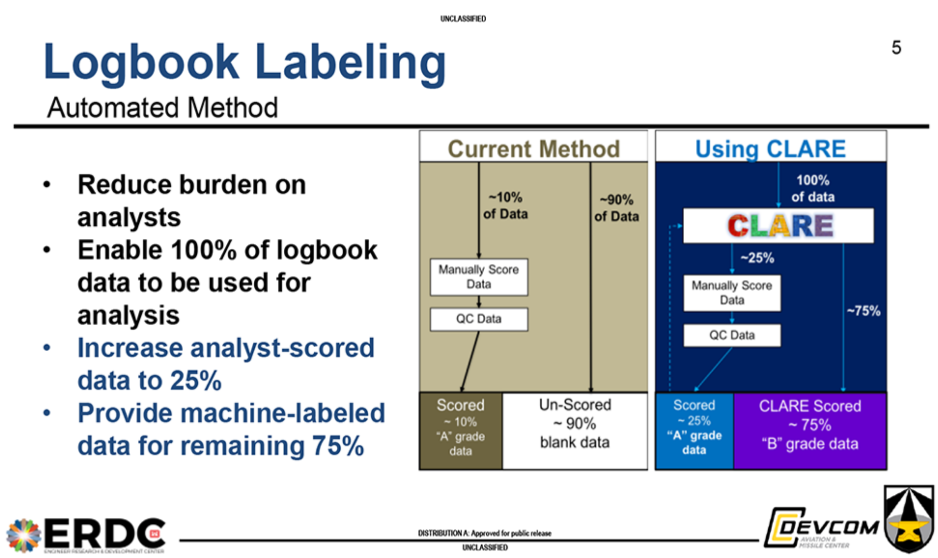

Figure 3-5 CLARE for Aviation Maintenance

[21] Ruvinsky, Alicia, et al. "Integrated Data Engineering for Automated Labeling (IDEAL) and Future Design of Aircraft." 2019 IEEE Aerospace Conference. IEEE, 2019.
[22] https://en.wikipedia.org/wiki/Random_forest Accessed 10/18/2019.

3.2.5 Using NLP Challenge Problems to Drive Technology: Ellen Voorhees, NIST

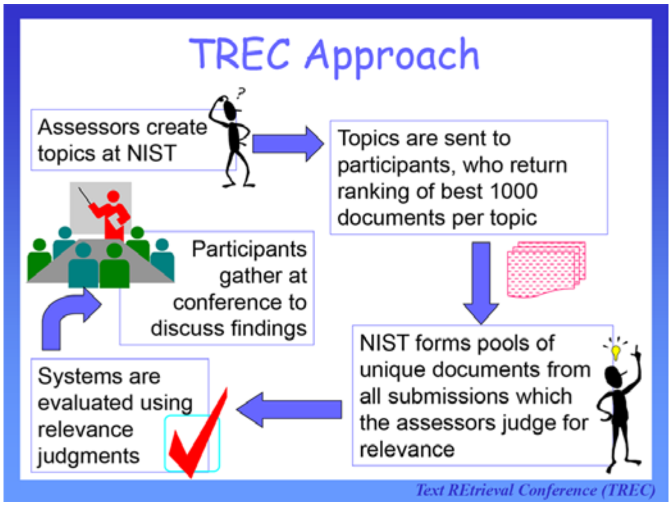

Figure 3-6 TREC Tracks and Benefits

The NIST Information Technology Laboratory supports the Text Retrieval Conference (TREC)[23], a workshop series designed to provide infrastructure for large-scale testing of text retrieval technology and a forum for the exchange of research ideas. The TREC approach (Figure 3-6) supports realistic test collections and uniform, appropriate scoring procedures. One of TREC's objectives is to provide content-based access to documents not especially structured for computer access, such as blog posts, journal articles, voice mails, video, medical records, and tweets. The many TREC tracks cover a wide range of topics of interest to many information retrieval (IR) researchers and companies, from the law to physical sciences, IT, and medical fields. TREC tasks have launched research areas leading to new products such as cross-language retrieval, video retrieval, and e-discovery. NIST provides a technology-neutral site and unique technical expertise for operationalizing tasks and developing/validating evaluation methods for IR. Through TREC, collaborators hope to form a strong research community and methodologies, improve the state of the art, and facilitate technology transfer. TREC also amortizes the costs of infrastructure across the community by leveraging a relatively small government investment to provide accessible research and methods. An economic impact assessment of the program suggested significant benefits from TREC – at least $3.35 accruing to IR researchers for every dollar invested by NIST and partners.[24]

3.3 Stakeholder Perspectives

In this section, perspectives on the current state, challenges, and desired future state of data cleaning and parsing for NLP are presented. Three questions were posed during a series of facilitated breakout sessions (Table 3-1) and responses to each of the questions are outlined below.

Results of the breakout sessions highlight that cleaning and parsing tools do exist, but are not necessarily ideal for maintenance applications, thus require customization. A disconnect also exists between data science and domain knowledge, and how to best integrate these skills to achieve data cleaning objectives.

[23] https://trec.nist.gov/
[24] Economic Impact Assessment of the NIST's TREC Program. 2010. RTI International.

Table 3-1 Questions for Data Cleaning and Parsing

1. **Current State:** What solutions are you currently using for cleaning and parsing data? Are these working and meeting your requirements, and If not, why?
2. **Challenges:** What are some of the challenges and limitations you are facing for data cleaning/parsing, and what kinds of problems are you trying to solve?
3. **Future State:** Given the current state and challenges for data cleaning/parsing, what technologies, research, measurement tools, or standards are needed?

3.3.1 Current State of Data Cleaning and Parsing for NLP

Many of the tools currently used for data cleaning and parsing are domain-specific customized solutions utilizing historical data sets. Popular programming tools, such as Python[25] or Matlab[26], are used to develop in-house vocabulary, ontologies, etc. Some off the shelf software applications also incorporate data cleaning tools, such as Tableau[27]; examples of data cleaning/parsing solutions are shown in Table 3-2. Some of the key problems that organizations are working to solve via use of cleaned and parsed data are shown in Figure 3-7.

Several factors must be considered in deciding what tools to use for cleaning/parsing data:

- An open source tool will require customization if analysis/ applications are not routine. After significant customization, even open source tools become more company specific.
- The availability of and need for customer service and support is another consideration, especially for open source tools.
- A secure environment will also likely be required; security requirements add more layers of customization.

There is also a trade off in parsing and collecting data. For example: *What is more important? Quality of data or volume of data*? If you are using commercial software, quantity of data may be more important. With millions of data points, even if the data is of relatively low quality, information could still be extracted because of the large size of the data. One promising method of extracting information involves annotating the data with a structured language.

Table 3-2 Examples of Current Data Cleaning/Parsing Solutions

- Manual, isolated tools, in-house cleaning solutions (i.e., manually annotating data)
- Outsourced solutions, requiring outside data scientists
- Classification tools/algorithms: graph-based (Word2vec), rules-based, tagging tools (e.g., Nestor), random forests, LSTM
- Open-source tools (e.g., Open Refine[28], Data Wrangler[29], etc.)
- Custom scripts (Python, MatLab, R)
- Redaction/Anonymization software
- Domain-specific, segmented solutions (e.g., EEG medical data)

[25] https://www.python.org/
[26] https://www.mathworks.com/products/matlab.html
[27] https://www.tableau.com/
[28] http://openrefine.org/
[29] http://vis.stanford.edu/wrangler/

Several annotation tools are available using different approaches (e.g., graph-based, rule-based, tagging, etc.). The Nestor tool developed by NIST has had success capturing domain knowledge through "tagging". Tagging methods have been successfully used to create robust dictionaries across a range of data sets. Some tools are more sophisticated, such as those used for deep learning.[30] Random forests (ensemble learning method for classification, regression and other tasks) and long short-term memory (LSTM) are examples.[31] LSTM networks are suitable for classifying, processing and making predictions based on time series data. An R package for semantic analysis captures features in the text.

- Reducing noise and extracting features in the data
- Improving data quality
- Generalization, i.e., can a generic language model solve problems
- Language modeling algorithms (e.g., Bidirectional Encoder Representations from Transformer/BERT)
- Identifying chain of causality
- Retaining topography of problem (Eric)
- MWO traceability
- Retaining topography of problem space

Figure 3-7 Types of Problems being Solved by Data Collection/Parsing Solutions

3.3.2 Challenges for Data Cleaning and Parsing for NLP

A variety of challenges limiting the ability to effectively conduct data cleaning and parsing were identified and summarized below and in Table 3-3.

Infrastructure/Methods. Data cleaning, by itself, is a problem – defining the purpose of cleaning, identifying the right data to clean, and having the most effective tools are some of the issues encountered. Data cleaning is expensive as there are many variables that go into data cleaning, and costs can be wide-ranging depending on the size, complexity, and anonymization requirements of the dataset. Many manual, isolated processes are currently in use for data cleaning and often lack integration of results between maintenance and operation systems. Scaling methods for both large and small datasets and across domains can also present a challenge.

Standardization. A lack of standardization and guidance for data cleaning was identified as a major. Many existing standards were not written with natural language data in mind. Natural language data is also collected in many ways, making cleaning difficult to standardize. Access to standardized data for testing and validation of cleaning/parsing tools is also lacking; A reference standard for natural language maintenance data is not available

Data inputs. The lack of ontologies and consensus on ontologies for maintenance was noted as a major challenge for data cleaning and parsing in this field. Ontologies would help to demonstrate the relationships and properties of concepts to aid in all aspects of translating data. Another challenge for input data relates to dealing with the sheer size of datasets, especially when combined with the wide variety of inconsistencies that must be addressed. Low quality data is yet another problem. One solution to this problem might be to focus on better data collection rather than better data cleaning. However, unstructured data will often require some level of cleaning. The performance of available tools and algorithms that can deal with unstructured, low quality data is uncertain. A gap exists between academic research and industry in defining what is the necessary data for validation (i.e., what is a good representative dataset of natural language produced in industry?). Semantics might also be lost by using different cleaning strategies resulting in the loss

[30] Subfield of machine learning concerned with algorithms based on the structure and function of the brain called artificial neural networks.
[31] LSTM – an artificial recurrent neural network architecture used in deep learning.

of useful data. **Integration of data and domain knowledge.** Integrating data science with domain-specific knowledge and requirements is a challenge for cleaning and parsing, as well as other aspects of NLP. An experienced equipment maintenance professional may know little about being a data scientist, and vice versa. Data scientists might impose a certain data structure that doesn't exist in the practical manufacturing environment, resulting in a loss of context and usefulness. For example, if word order is important in the process, you might lose that if a data scientist without domain knowledge imposes non sequential data structure. The challenge is to effectively combine the different sources of knowledge and expertise (data science, database technicians, domain, etc.) to minimize the loss of context and usefulness.

One of the key challenges to integrate data and domain knowledge lies with the data, itself. Extracting the data, parsing the data, etc. can become very complex and success will be based on the technology-level knowledge of those handling the data. Useful information could be lost in the process, simply because people that own/operate the machines are not data scientists. Outsourcing can be problematic – it may not be feasible to bring people in who have the needed technology/company knowledge and expect them to parse data properly. There may be underlying data/text that is not included in the data, requiring an expert to interpret. The key risks for outsourcing are misunderstanding the domain data, and lack of tacit domain knowledge. Further, in large companies, hiring data scientists might make sense, but smaller companies might not be able to afford personnel dedicated to this function. Data scientists may be excited initially to come in and solve problems, but without some timely 'wins' they may experience burnout causing employee retention or focus problems.

Table 3-3 Challenges for Data Cleaning/Parsing

Infrastructure/Methods
• Knowing how to clean data with specific purpose in mind • Growing cost of cleaning (e.g., Cloud, initial and continuing cost) • Manual, isolated processes lacking integration between database technologies, data science, engineers, etc. • Scaling of ambiguity methods to large datasets/databases
Standardization
• Lack of standardization, in part because of open source community • Limited standards for domain knowledge representation • Lack of data packages for testing and validation • Limited COTS tools to understand data bias; limited understanding of validation biases
Data Inputs
• Lack of ontologies; organizations that are hesitant to make specific ontologies public • Sheer volume of data and storage of data; low quality data • Ability to curate data; limited guidelines for data elimination • Input inconsistencies, lack of human factors cleaning – Technicians not paid for "good data" – Systems that require humans to verify correctness – Lack of human factors requirements in cleaning data • Dealing with n-gram (multiple word) representations • Topic modeling application and slang

Integration of Data Science and Domain Knowledge
• Lack of integration of data analysis/models with domain experts • Lack of understanding of data science specifics leading to poor assumptions when creating analysis pipeline • Lack of effective training/training approaches – training domains experts in tools vs. training data scientists in domain knowledge • Lack of actionable information for domain experts

3.3.3 Future Needs for Data Cleaning and Parsing for NLP

Future needs for data cleaning and parsing revolve primarily around the need for better tools, standards and guidelines. Improvements to data inputs on the front end, as well as domain-relevant ontologies and classification techniques are important. Future needs and requirements are summarized in Table 3.3 and below.

Goals: The primary goal is to further software's ability to clean data purposefully, i.e. begin with the end in mind. This includes understanding the context and purpose for cleaning up front, then identifying and curating the right data. The assumption that "any data is good data" is not always valid. Curation requires not only identifying good data, but also removing the sources of bad data.

Standards and guidelines. Creating guidelines for how to fill in unstructured fields is an important future task. These guidelines should be constructed with the ultimate operational goals for end use in mind. With so many different scenarios possible, standardizing the process to get there will ensure consistency between the actual unstructured information and the results of analysis.

Table 3-4 Future Needs and Requirements for Data Cleaning and Parsing

Overarching Goals
• Ability to clean data for a specific purpose (begin with the end in mind) • Identifying and curating the right data • FMEA for data-driven decision making
Methods and Tools

• COTS tools for all functions
• Improved algorithms and coding practices
• Upfront model training to reduce time to implementation
• Tools that are easy to deploy and disseminate
  – Standardized data pipeline and documented process
  – Parsing/cleaning tools that require less programming expertise
  – Standard metrics to compare results, based on providing actionable information

Standards and Guidelines

• Requirements engineering and regulatory requirements
• Guidelines for generating, capturing, and using unstructured data
• Platform/ecosystem or framework
  – Enable plug-and-play
  – Enable ability to apply similar analytics on different data
  – Documented past analyses for quick reference

Data Inputs

• Use of formal, consensus-based, domain-specific ontologies
• Classifications for redaction (e.g., what's proprietary, public, etc.)
• Agreement on contextualization and abstraction
• Multi-modal data leveraging (photos, video feed, etc.)
• Human-centered metrics to improve maintenance operation (i.e., for human safety)
• Improved sensing for data inputs (also discussed in data collection)
  – Best practices for sensor selection and correction actions, with enough granularity of sensing
  – On-board sensors (e.g., body vest) to improve MWO data
  – Knowledge base/graph for sensing and fault tree analysis

Methods and tools. The future presents growing needs for tools that are easy to deploy and disseminate. Participants indicated the need for more plug and play technologies (including analytics). A standardized data pipeline and process with parsing and cleaning tools that require less programming expertise could be used in the future. Workshop participants indicated the need for standard metrics and publicly available datasets to compare results. Ease of deployment of tools should be considered at the same time as ease of usability of tools. Improved interfaces between these tools and automated processes, where possible so operators do not have to annotate manually, could ease deployment. Upfront training can also lessen the time needed to use models in practice.

Data inputs. An important future requirement is that reference domain ontologies should be open, free and publicly available. Ontologies should be developed with the data and the types of analysis in mind. Understanding the correct level of abstraction is important to determine how to present information to a maintenance practitioner for decision making (e.g., a maintenance technician needs different information than a maintenance scheduler). New data input should consider other data sources and the interoperability concerns when being designed (e.g., discussing requirements for a new text input system that requires photographs of maintenance as well). Human factors concerns are also important to discuss when determining data input mechanisms in the future.

3.4 Summary

The general themes for data cleaning and parsing are highlighted in Figure 3-8, including key challenges and needs. This provides a snapshot of stakeholder discussions and provides some insights on potential paths forward.

Figure 3-8 General Themes for Data Cleaning and Parsing for Natural Language Analysis

4 Data Visualization and Analysis for Natural Language Analysis

4.1 Overview

The purpose of pursuing natural language data collection, cleaning and parsing is to generate data that is computable and can be utilized for analysis. In maintenance, common topics for analysis include key performance indicators (KPIs), cost, reliability (e.g., to support reliability centered maintenance), failure analysis, and keeping equipment online and running productively. Once data is collected, stored, cleaned and parsed, it can be compiled into text-based and visual reports to promote analysis. For example, data on condition monitoring will help to inform decisions about dispatching and scheduling.

Data visualization describes how data is presented for interpretation and review by human agents. Various kinds of data visualization software allow users to create graphs, dashboards, tables, or other visual representations. Data visualization software has become increasingly sophisticated, enabling presentation of data geographically, spatially, and temporally, as well as through video and animation. Visualization can help kickstart change by demonstrating benefits in ways that are readily understood.

4.2 Presented Topics

There are many examples of systems, tools, and new techniques for data visualization being effectively used for analysis in manufacturing maintenance. Information, and challenges regarding information, and analytical systems used to inform decisions in manufacturing and maintenance are presented in the following subsections. As with the above subsections, each subsubsection heading provides the title and presenter from the presentation.

4.2.1 Predictive Asset Management and Applications to Manufacturing: James Waltner, Lockheed Martin

Lockheed Martin produces a wide spectrum of sophisticated land, sea, and air equipment, and collects a large variety and amount of data to sustain these fleets. The information collected covers many aspects of equipment, including operations and maintenance, supply chain and logistics, safety, engineering, and testing. Merging multiple data sources (e.g., traditional sensor data and natural language input) provides a basis for total systems health management which can reduce costs, improve reliability, and enable condition-based maintenance – with a focus on high equipment availability. Ad hoc analyses look for patterns to identify what happened, e.g., is it something different, is there a difference between what operator tells us and what actually happened? These analyses can improve reliability and even predict when customers need parts around the globe. Each operator has their own way of writing maintenance logs, so they collect the data, adjust as needed, store, and make it available for analysis in a consistent format (Figure 4-1).

Operations data, when married with maintenance data, enables technicians to see problems before they occur. NLP maintenance data with embeddings can be passed through a recurrent neural network to produce a result predicting the most likely maintenance outcome. FRACAS[32] – Failure Reporting, Analysis, and Corrective Action System model is used for failure reporting, analysis, and corrections for work unit codes, with 96.2 % model confidence (actual vs. modeled), allowing for better predictive asset management. The key takeaways are that sustainment analytics require relevant data, informed application of tools and engineering expertise. The frontiers of data analytics must be pushed; GPUs (graphical processing units) are a critical enabling technology that

[32] https://en.wikipedia.org/wiki/Failure_reporting,_analysis,_and_corrective_action_system

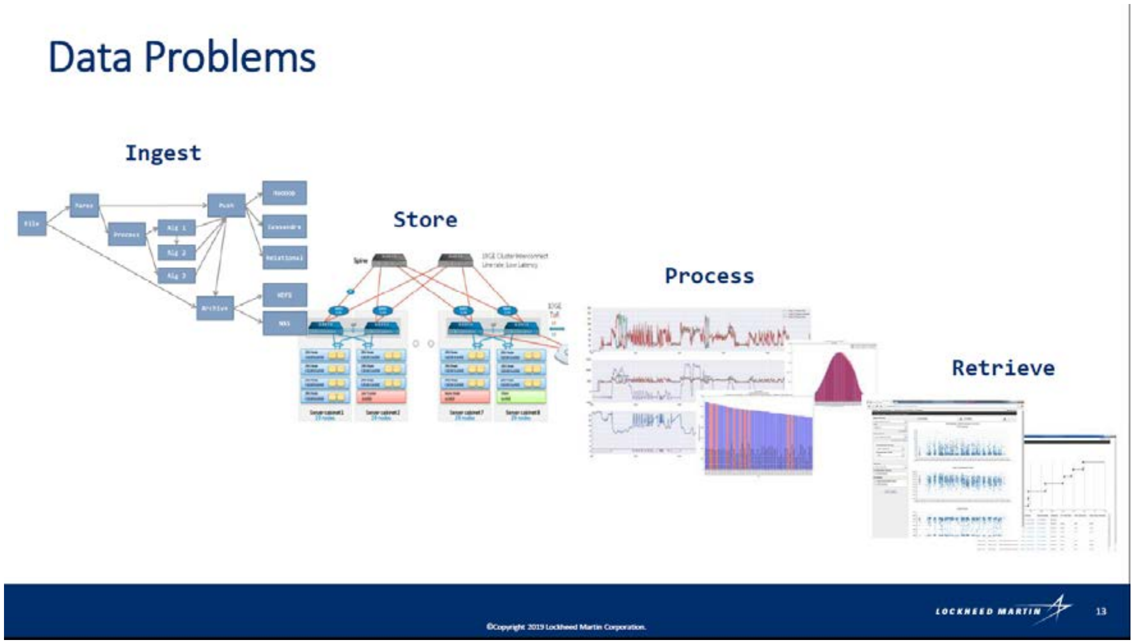

Figure 4-1. Data Flows and Problems for Lockheed's Predictive Asset Management

has allowed Lockheed Martin to pioneer technologies in this field. Designing in high-quality, contextualized data is a path for providing a high value predictive asset management solution.

4.2.2 Challenges of using NLP in Large Manufacturing Environments: Al Salour, Ph.D., Boeing Research & Technology

Mission critical equipment and processes in aircraft manufacturing include composite fabrication, metal fabrication, drill and fill systems, and support systems. Boeing's aircraft have some unique characteristics and performance challenges, such as composite materials that must be lined up with no overlaps or heat-compacted, non-standard engineering configurations, aluminum and titanium fabrication, high-volume drilling systems susceptible to vibration, etc. The Boeing Model for equipment data flow (Figure 4-2) illustrates the multiple sources where maintenance tickets can be created. Almost every qualified employee can write maintenance tickets which results in different naming conventions, language, and reporting methods. This creates non-standard work order tracking, which presents a significant challenge. Natural language standards for maintenance systems, data collection, and performance evaluation would help reduce maintenance costs by controlling the type and flow of data. Just cleaning and controlling the natural language used daily in maintenance tickets would also help significantly. Many challenges exist for NLP in large manufacturing organizations. With so many different machines and work centers, it is hard to agree on priorities for standardization, and difficult to enforce standards across multiple sites. New technology for NLP and their benefits are not well-understood and need to be explored. A unified plan and software are needed to fully develop and adopt NLP across the organization. Boeing believes NLP is a good tool for improving maintenance and operations. This perspective is leading to hiring data scientists to help build the manufacturing knowledge base.

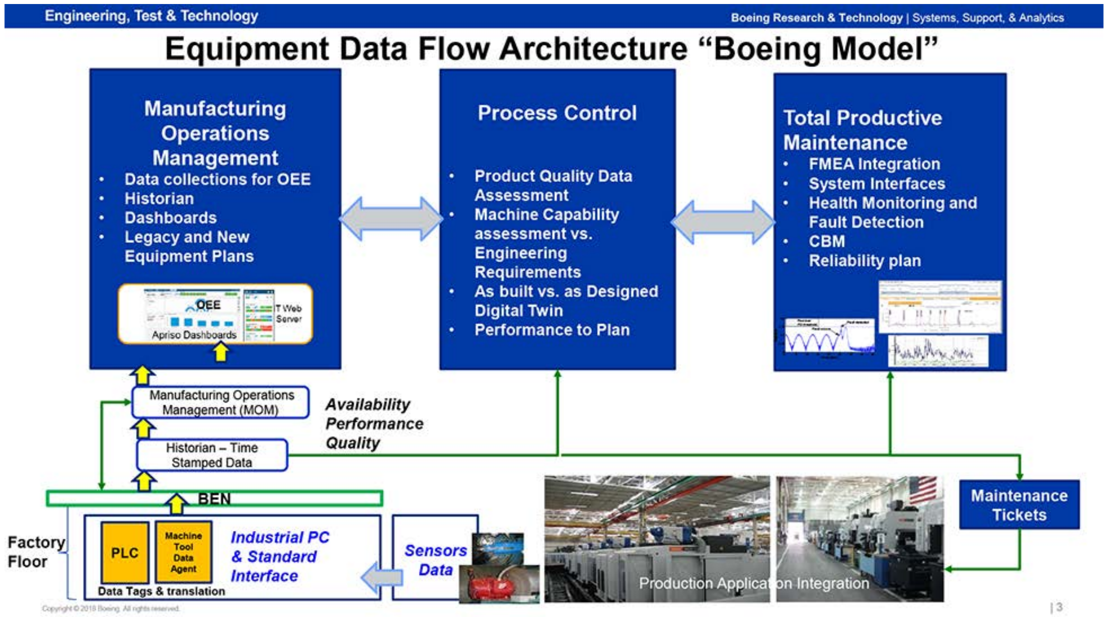

Figure 4-2 The Boeing Model for Equipment Data Flow

4.2.3 *Visual Analysis of Unstructured Text Data: Senthil Chandrasegaran, University of California-Davis*

This project at University of California-Davis is focused on visualizing machine maintenance work order data. The goal is to figure out a way to efficiently visualize data that is most beneficial to the analysis. Speech data from technicians can be thought of as unstructured and similarly maintenance work orders are comparable to unstructured human-driven text from speech. Visual analysis is important for the human in the loop, as it makes use of the analyst's tacit knowledge, such as pattern identification, and allows for anomaly detection. Three aspects of importing text logs into NLP and leveraging text visualization are being investigated in this project: contextual information for visualizing text; visualizing intrinsic and extraneous measures to help identify patterns and anomalies; and integrating machine learning and visualization for monitoring and analysis. VIZ Scribe[33] is a technique to visualize text and context at the same time. An actual sketch can be pulled up to see how the design technique has progressed over time. An activity log can be created to track how things happen, visualizing and exploiting both actions and context (Figure 4-3). Visualizing intrinsic and extraneous measures is analogous to looking at a body of work by a writer, identifying concepts of interest in qualitative data, and naming and tagging them. Open coding or Axial coding[34] can be applied, where you identify the relationship between concepts through inductive reasoning. To do this, researchers produced user-defined categorizations and word clouds to identify concepts and pull out word clouds and assess frequency of use. Maintenance logs could be processed similarly by identifying critical or often-used words and highlight parts of speech that happen often, creating heat maps of words, and conducting qualitative analysis.

[33] Chandrasegaran, Senthil, et al. "VizScribe: A visual analytics approach to understand designer behavior." International Journal of Human-Computer Studies 100 (2017): 66-80.
[34] https://en.wikipedia.org/wiki/Axial_coding

Talk Traces[35] is a concept for monitoring meetings, e.g., like a meeting transcript for maintenance logs. Each concept could be represented as a vector and used to identify differences and similarities produced word embedding. Tagging data through visualization can help assign meaning and patterns and make ML results more interpretable.

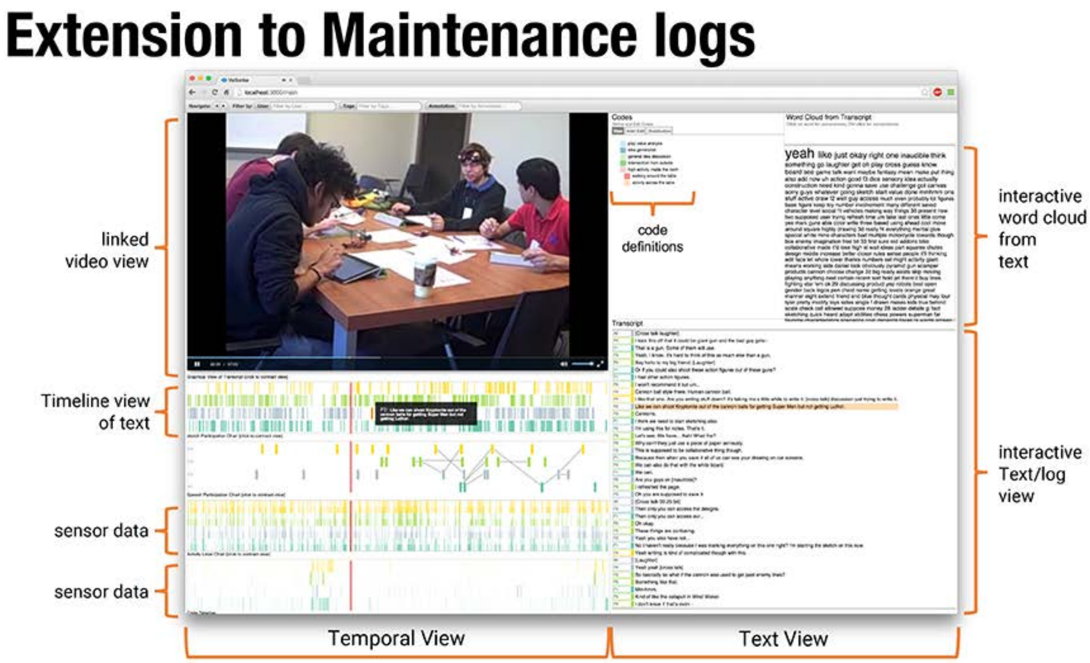

Figure 4-3 Visualization of Maintenance Log Data

4.2.4 Assessment of Text Analytics Technology for Maintenance of Manufacturing Equipment in Small-Medium Enterprises: Radu Pavel, Ph.D., TechSolve

TechSolve, Inc. provides machining process solutions, Industrial Internet of Things (IIoT) products and services, operates a fully-instrumented machining laboratory, and is a State and Federal Manufacturing Extension Partnership (MEP) Center. TechSolve also has PHM test beds to help understand the behavior of machines under various degradation or failure-prone conditions. TechSolve is currently applying the NESTOR[36] tagging software to industry data for small and medium enterprises (SMEs). They are looking at SMEs to determine their practices relative to logging maintenance work orders and understand what guidance and best practices would be useful to improve daily and long-term maintenance and analysis. An exercise was undertaken with several companies to understand the kinds of data being used to determine maintenance strategies and problems (Figure 4-4). Companies are collecting a wide spectrum of data using a variety of platforms. Findings show that companies may store data in MS Access or Excel or use sophisticated software; some with over 400 columns; and all with different techniques. While some were confident in data and analytics, others were uncertain about what to use and whether it was

[35] Chandrasegaran, Senthil, et al. "TalkTraces: Real-Time Capture and Visualization of Verbal Content in Meetings." Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems. ACM, 2019.
[36] https://www.nist.gov/services-resources/software/nestor

effective. Companies that want to be compliant with ISO 9001[37] and AS9100[38] are more likely to have MWO data. Companies with maintenance records typically use a management system, but not necessarily the best system, to log work orders into a database. All participating organizations

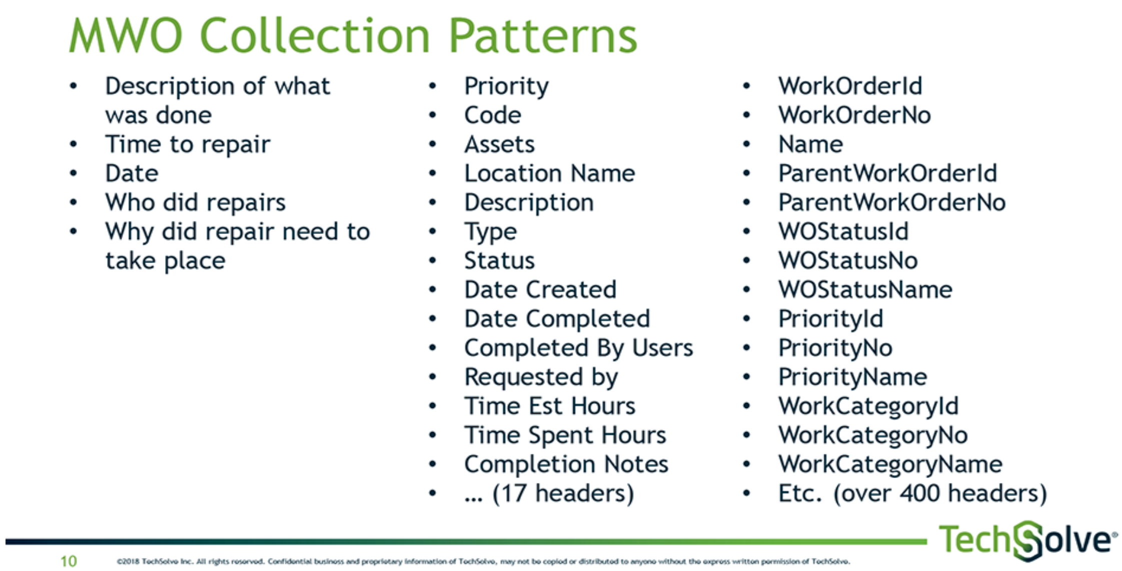

Figure 4-4 Maintenance Text Analytics

expressed the desire to have improved analytics and visualization methods that would allow them to better understand and to address their problems and extract actionable data.

4.3 Stakeholder Perspectives

Perspectives on the current state, challenges, and desired future state of data visualization and analysis were discussed at the workshop. Three questions were posed during a series of facilitated breakout sessions (Table 4-1); responses to each of the questions are outlined below.

Results show that a variety of tools are available for maintenance analysis, including in-house solutions, standard COTS, and products customized for organizations. Challenges presented focused on those that limit the effectiveness of these tools in utilizing natural language inputs.

Table 4-1 Questions for Data Visualization and Analysis

1. **Current State:** What solutions are you currently using for data visualization and analysis? Are these working and meeting your requirements, and If not, why? What types of analysis are you doing?
2. **Challenges:** What are some of the challenges and limitations you are facing for data visualization/ analysis, and what kinds of problems are you trying to solve?
3. **Future State:** Given the current state and challenges for data visualization/analysis, what technologies, research, measurement tools, or standards are needed?

[37] https://www.iso.org/iso-9001-quality-management.html
[38] https://www.sae.org/standards/content/as9100/

4.3.1 Current State of Data Visualization and Analysis for NLP

A variety of tools with varying levels of effectiveness are in use for analysis of maintenance text-based data (Table 4-2). Most require customization; how well they perform depends on the quality of the data and the fit for the organization. Figure 4-5 illustrates the types of analysis organizations are conducting or would like to conduct.

Table 4-2 Examples of Current Data Visualization and Analysis Solutions

• Apache Hadoop and Spark™ • Home-built script (e.g., Python, Open Cascade, community tools/libraries, R (visualization and analysis), Julia Programming Language) • Docker Data • SMRP solutions (15 KPIs) metric evaluation • MS Office Excel • Third-party analysis tools • COTS tools (black box) • NLP libraries, e.g., – spaCY – Natural Language Toolkit (NLTK) – Gensim	• Commercial Tools – ShopViz Asset Management Software – Asset Answers (GE Aviation benchmarking for maintenance providers) – Upkeep® Maintenance Software – HIPPO Computerized Maintenance Management System (CMMS) – FIIX® Maintenance Management Software – Worx Hub – One-off solutions (SAP, ORACLE) not related to traditional systems

Software utilities/platforms. General purpose software for big data and programming problems are being applied to maintenance data. Apache Hadoop™ is a collection of open-source software utilities used for massive data computations and visualization. Julia is a general-purpose programming language designed for high-performance numerical analysis and computational science. Other programming languages such as Python and R are used for data and science visualization as well as analysis. These are used to make home-grown solutions that rely on open data and platforms.

There are both advantages and disadvantages to containerization, such as with Docker[39] or Snappy[40] (snap packages) for both deployment and collaboration. The more data is containerized, the less you know about what it contains. Conversely, an advantage to using containerization is both in consistency in how the data is viewed if sent to someone and consistency for versioning of libraries in applications. This allows programs to remain in working condition even if a dependent library (or even the language itself (e.g., Python)) is updated. For example, an application developed using Python 2.7 might not work with an update to Python 3.0. However, a containerized solution would maintain those dependencies and would allow the application to still run correctly since the container would include Python 2.7. If a reliability engineer in the field is still using MS Excel or SQL type queries might not be compatible with something like Docker.

Maintenance solutions. NLP COTS solutions for maintenance are available, but often cannot be scaled and customized, or they work as a 'black box' with limited user understanding. Sometimes these software tools are just dashboards to which the user feeds data from other databases. Spreadsheets are still a favorite database in many organizations for text-based maintenance information.

[39] https://www.docker.com/
[40] https://en.wikipedia.org/wiki/Snappy_(package_manager)

More tailored solutions have advantages, but are limited in their applicability. For example, Maximo[41] and Upkeep[42] are both more suited for large companies, but may be inappropriate for many SMEs because they have irrelevant features to smaller manufacturers. Many propriety solutions are not easily customizable, while some solutions are limited in the type of input data they can process.

4.3.2 Challenges for Data Visualization and Analysis

Many of the challenges for data visualization and analysis center around the capabilities of existing tools and solutions, data management, and cultural issues. The challenges identified are summarized in Table 4-3 and below.

Solutions: While solutions for analysis and visualization are available, they are sometimes difficult to use, deploy, customize, and scale. Some solutions work well in smaller applications but fail to achieve the desired results during scale-up. Additional difficulty in consistently reproducing results can lead to a lack of user confidence. The challenge with COTS solutions is training operators to use it effectively.

- Pattern recognition/discovery
- Text analytics as a standard plugin for tools
- Casual analysis (absent of automation)
- Standard code mapping (classification, semi-automated)
- Finding uptime and downtime capabilities
- XSB – logic-based programming platforms for analysis
- Multiple language issues (AI)
- Pattern recognition/discovery
- Text analytics as a standard plugin for tools
- Casual analysis (absent of automation)
- Standard code mapping (classification, semi-automated)
- Finding uptime and downtime capabilities
- XSB – logic-based programming platforms for analysis
- Multiple language issues (AI)

Figure 4-5 Analysis of Interest to Participants

Data management: The enormous size and complexity of available data is a challenge for achieving meaningful analysis that can be interpreted and acted upon. There can be many different data types coming from a variety of sources, signals, sensors, and text input, which can be overwhelming when attempting to analyze. When determining appropriate data analysis and visualization solutions, the strengths and weaknesses of different data collection and storage solutions need to be considered.

Human factors. Some companies do not perform maintenance analysis as they do not understand the benefit of the tools available. Another reason maintenance analysis is not performed is many companies have data but are not sure what to do with it. In general, there are cultural issues that need to be overcome within organizations to increase awareness of the benefits of text-based analysis and build trust and confidence in the results. The same issues discussed in previous sections related to whether a data scientist or domain expert should be involved apply here as well.

[41] https://www.ibm.com/products/maximo
[42] https://www.onupkeep.com/

Table 4-3 Challenges for Data Visualization and Analysis

Solutions

• Solutions that are not easy to use and/or deploy
  – Scalability challenges
  – Lack of robustness and reliability; small failures can have a large effect
  – Isolated analytics that are not transferable to each other
• Un-explainable solutions; 'black box' approaches in software reduces trust
• Difficulty reproducing results; inconsistency of results which leads to lack of user confidence
• Lack of software interoperability
• Lack of relationship to Manufacturing Execution System (MES), e.g., time, asset, job
• Transferability to other languages
• In-house solutions that are not portable

Data Management
• Managing complexity of data and results; analyzing many signals from many different sources • Quality of data effects, depending on type of analysis; unbalanced data despite cleaning • Data stored across many different systems, without one overarching solution
Standards and Guidelines
• Perspective that each plant's problems are unique, and standards may not apply • Inability to model and reason on conflict between what happens in practice compared to specification, regulations, or standards
Human Factors
• Building trust, confidence and understanding of results • Lack of understanding benefits, resistance to date collection • Ambiguity in intent or meaning when people enter data • Limited training for data tools; new hires must learn models from scratch

4.3.3 Future Needs for Data Visualization and Analysis for NLP

The future needs and requirements identified for data visualization and analysis are summarized in the remainder of this section and in Table 4-4. In the future, it is hoped that solutions for analysis will have increased functionality, be automated, flexible and user-friendly, as well as handle a diversity of analytical tasks.

- Deep queries using logic programming
- Good language translators
- Advanced logic query/discovery
- Recommender systems (probabilistic)
- Upstream to downstream view of data and vice versa; digital threads
- Advanced, effective visualization techniques
- Intelligence-augmented workflows
- Automated pipelines, flows, and processes
- Secure, trusted, traceable
- Ability for data sharing and dissemination
- Flexible, dynamic, and modular infrastructure
- Ability to compare historical to current state
- Easy analysis applications, user-friendly
- Web-based data upload and analysis

Figure 4-6 Desired Future Solution Capabilities and Characteristics from Participants

Solutions. Some of the ideal characteristics and desired capabilities identified for data visualization and analysis are shown in Figure 4-6. User-friendly, easy to use solutions will be critical to facilitate widespread adoption of tools for maintenance text analysis. Web-based solutions will ease use and

portability. This would include the ability to upload data, run tests, compare results, and return optimal parameter settings.

Combining collection and analysis is a desired trait of future tools and could be especially useful for large datasets. In some cases, analytics need to be 'close' to the data (e.g., proprietary, very large datasets), and analysis must be conducted locally (i.e., can't be on a network or server). Datasets can be so large that analysis and visualization slows down the network (e.g., bandwidth issues). Better solutions are needed to enable local analysis as well across the enterprise.

In the future, containerized solutions promote greater collaboration and teamwork, as they provide a means to 'contain' the data in its original state, from solution to solution. This is one approach to enable transfer of data between different facilities or organizations in the future.

Table 4-4 Future Needs for Data Visualization and Analysis

Future Solutions and Strategies
• Combining collection and analysis rather than separated; bring analytics to the data, not vice versa • Containerized solutions • Web-based solutions for ease of use • Local options; ability to pick the best tools (i.e., edge vs. cloud, etc. chosen on a case-by-case.) • systems/processes/data sets • Python/MatLab for data analytics • Ability to readily apply similar analytics on various data, i.e., documented past analyses for quick reference (e.g., reusable analysis vs. reusable data) • Plug and play analytics (e.g., plugging Nestor into existing solutions) • Cost model impact analysis for decision making • Intelligent machines – "Fix me" • Self-healing robotics/machines • New equipment must have digitization built in to link with natural language (e.g., MTConnect; PC vs. PLC)
Standards and Guidelines
• Guides for re-usable analysis (modular, composable) • Defined guidelines/data standards within the context of failure modes • Consistent data, equipment labels, etc. • Consistent model for compliance, frameworks, architectures • Standard for best practices/guidelines for analysis (e.g., VIZShop) • Standard datasets for maintenance best practices • Better coding practices for cleaning to improve portability and reusability • Verification and validation functions – less black box, more semantic; contextualized data to increase trust • Standard addressing what not to do (key sources of error/confusion); first step could be data fusion and dissemination • Standardized data input to MWOs
Institutional Factors
• Data sharing and dissemination • Workflows intelligence-augmented to achieve superior performance • Ways to demonstrate value and benefits of analysis to operators

Intelligence augmentation (IA) techniques, also referred to as intelligence amplification, machine augmented intelligence, etc. describes using information to augment human intelligence. Good analytical maintenance tools in the future will allow humans to operate at a higher level and potentially better even than automation (e.g., inexperienced engineer operating at level of an experienced engineer).

Solutions are needed with good Application Programming Interfaces (APIs), user interfaces, wrappers, and ontology, plus capabilities for verification and validation (V&V) and interpretable visualizations. The impacts of good visualization can be powerful with the right context.

Standards and guidelines. Participants identified the need for future methods to ensure consistency in data formats, equipment labels, and other maintenance data sources. There is also a need for guidelines and data standards in the context of failure modes in different domains – this is the common, universal language for reliability (e.g., the oil and gas industry's usage of ISO14224 through Offshore and REliability DAta (OREDA)[43]). Failure modes can be an anchor point for maintenance, i.e., recognition of common failure modes can connect to operational as well as revenue impacts resulting from failures. For example, guidelines could cover the failure mode of a specific component, on a specific application, for equipment failures that are the same and recognized across domains. Guidelines written in the language in which many engineers already converse (e.g., sensor patterns, maintenance best practices, equipment, etc.) can provide a common ground for good analysis. Human reliability analysis language from the nuclear industry[44] is a good example of established engineering language.

Institutional. Participants strive to be self-sufficient and conduct analysis without handing over data. Data sharing and dissemination of datasets is a challenge requiring better solutions. One approach is to come up with a reference data set exemplifying maintenance best-practices in the future (e.g., test cases, what works in each, patterns tending to work). Small, demonstrated test cases could justify the value of maintenance and automated systems.

4.4 Summary

The general themes for data analysis and visualization are highlighted in Figure 4-7, including key challenges and needs. This provides a snapshot of stakeholder discussions and some insight on a potential path forward.

[43] https://www.oreda.com/

[44] Swain, Alan D., and Henry E. Guttmann. Handbook of human-reliability analysis with emphasis on nuclear power plant applications. Final report. No. NUREG/CR--1278. Sandia National Labs., 1983.

Data Analysis and Visualization

CHALLENGES

Limits of Solutions
Solutions that are difficult to use/deploy
Lack of COTS solutions
Blackbox (less trusted) solutions
Reproducibility of results
Software interoperability
Transferability to other languages

Data Management
Complexity of data and results (multiple signals/sources)
Quality of data effects, unbalanced cleaning

Standards and Guidelines
Perspective that each plan has unique problems (non-standard)
Inability to model and reason differences between actual practice and specification

Human Factors
Building trust, confidence in results
Limited understanding of benefits of data
Human bias in data inputs

FUTURE NEEDS

Strategies and Solutions
Combined data analysis and collection
Containerized solutions
Local analysis options; ability to readily pick the best tools
Plug and play analytics
Reference-able, reusable analytics
Self-healing, intelligent machines

Standards and Guidelines
Guides for reusable analysis (modular, composable)
Guidelines/data standards for failure modes
Consistent data/equipment labels
Standard datasets for maintenance best practices
Verification and validation functions

Institutional Factors
Ease of data sharing/dissemination
Operator resistance to data/analysis
Intelligence-augmented workflows

GOALS

Automated pipelines, flows, and processes (secure, traceable)
Ability for data sharing and dissemination
Flexible, dynamic, and modular infrastructure for analysis
Ability to compare historical to current state

Figure 4-7 General Themes for Data Analysis and Visualization for Natural Language Analysis

5 Summary and Next Steps

The *Standards Requirements Workshop for Natural Language Analysis* explored a diversity of stakeholder perspectives on the current state, challenges, and future needs for using NLP to advance maintenance decision-making. The derived insight is expected to prove instrumental for NIST researchers, manufacturers, and members of the NLP community to advance the capability, assessment, and adoption of NLP technologies to enhance maintenance activities throughout industry. Key takeaways from the workshop include:

- NLP is an effective tool for improving the collection and analysis of text-based maintenance data in manufacturing. NLP is currently at a nascent stage in most maintenance data collection and analysis programs. There are still significant challenges to address to effectively collect, clean, and parse human language inputs from a wide range of maintenance records and enable accurate decision-making.
- Solutions exists for many aspects of data management and interpretation of maintenance data. Some solutions are developed in-house or use open source software or programming languages; others are off the shelf software designed for maintenance of equipment, with varying degrees of success in practice. Many solutions require customization, i.e., do not necessarily fit the diverse range of manufacturing organizations, and could be expensive to operate and maintain. NLP is incorporated in only a few solutions.
- Standards and guidelines are needed to attain consistency in maintenance data and support widespread use of NLP. Improved systems are needed for analysis of equipment maintenance, performance and reliability using data produced using NLP.
- NLP, along with good analytical systems, requires collaboration between data scientists and domain specialists. Larger organizations are more readily able to maintain staff with data science knowledge; small and medium size companies may find this cost-prohibitive, so instead must train operators with domain knowledge to analyze maintenance data. There are trade-offs in both scenarios.
- Ideal future solutions will be flexible, user-friendly, incorporate some form of NLP techniques to improve data, accommodate both scaled and local analysis, be web-based, allow for a wide range of analysis and visualization methods, and allow for transference between solutions.

NIST is continuing to conduct research to support NLP for maintenance and operations as well as development of standards in this area. The results of this workshop and future planned activities will serve to inform, guide research directions, and contribute to the ASME PHM Subcommittee on Monitoring, Diagnostics, and Prognostics for Manufacturing Operations[45].

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

Acknowledgements

Many thanks to the NIST staff who served as lead facilitators and recorded discussions during brainstorming activities. Their support helped to make this event a great success. In addition, thanks to NIST Conference Services staff for providing seamless support for logistics.

Brainstorming Leads
William Bernstein
Thomas Hedberg
Thurston Sexton

Brainstorming Notetakers
Michael Hoffman
Madhusudanan Navinchandran

Appendix A – Natural Language Processing Workshop Agenda

Start Time	Presenter/Organization	Presentation Topic
7:30 AM	Registration	
8:00 AM	Mike Brundage, NIST Systems Integration Division	Opening Remarks
8:10 AM	Brian Weiss, NIST Intelligent Systems Division	Opening Remarks about ASME Standards
8:15 AM	Howard Harary, NIST Engineering Lab Director	Welcome to NIST
8:30 AM	Introductions (All)	
Data Collection/Storage Session		
8:45 AM	Mike Brundage, NIST	Introduction to Data Collection/Storage
8:50 AM	Thurston Sexton, NIST Systems Integration Division	Human Factors Concerns in Data Collection
9:05 AM	Jack Fanneron, The BP Group	Novel Data Collection Strategies for Maintenance
9:20 AM	Ken Dunn, British Petroleum (BP)	BP's Natural Language Document Environment and Challenges
9:35 AM	Farhad Ameri, Texas State University	A Thesaurus-guided Method for Smart Manufacturing Diagnostics
9:50 AM	Sarah Lukens, GE Digital	Maintenance Data Collection Challenges
10:05 AM	*Brainstorming Session: Current State, Challenges and Future Needs*	
10:50 AM	Break	
Data Cleaning/Parsing Session		
11:10 AM	Thurston Sexton, NIST	Introduction to Data Cleaning/Parsing
11:15 AM	Mike Brundage, NIST Systems Integration Division	Small Data Tagging using the Nestor Tagging Tool
11:30 AM	Melinda Hodkiewicz, University of Western Australia	Semi-Automatic Processing of Unstructured Short Text in Maintenance Records
11:45 AM	Aaron Massey, University of Maryland Baltimore County (UMBC)	Natural Language Processing (NLP) for Regulatory Compliance Requirements
12:00 PM	Maria Seale, U.S. Army Engineer Research and Development Center	Composite Learning Algorithm for Records Evaluation (CLARE)
12:15 PM	Ellen Vorhees, NIST Information Technology Lab	Using Challenge Problems to Drive Technology
12:30 PM	Lunch	
1:15 PM	*Brainstorming Session: Current State, Challenges and Future Needs*	
Data Analysis/Visualization Session		
2:30 PM	Mike Brundage, NIST	Introduction to Data Analysis/Visualization
2:50 PM	James Waltner, Lockheed Martin	Merging NLP Documents with Operations Data
3:05 PM	Al Salour, Boeing	Challenges of using NLP in Large Manufacturing
3:20 PM	Senthil Chandrasegaran, U. of California, Davis	Visualizing Maintenance Work Order data
3:35 PM	Radu Pavel, TechSolve	NLP and Decision Needs for SMEs
3:50 PM	Break	
4:10 PM	*Brainstorming Session: Current State, Challenges and Future Needs*	
4:55 PM	Brainstorming Leads	Summary of Brainstorming Sessions
5:15 PM	Brian Weiss, NIST	Discussion on Prognostics/Health Management Group
5:18 PM	Mike Brundage, NIST	Closing

Appendix B – Participant List

Donnie Alonzo, American Society of Mechanical Engineers (ASME)

Farhad Ameri, Texas State University

Shelly Bagchi, National Institute of Standards and Technology

Christopher Baldino, The BP Group

Hasan Bank, Craftnetics Inc.

Eric Belski, Aerotech, Inc.

William Bernstein, National Institute of Standards and Technology

Ning Bi, Itamco

Michael Brundage, National Institute of Standards and Technology

Senthil Chandrasegaran, University of California, Davis

Qing Chang, University of Virginia

Alden Dima, National Institute of Standards and Technology

Kirk Dohne, National Institute of Standards and Technology

Ken Dunn, BP

Terril Falls, Institute for Systems Engineering Research, Mississippi State University

John Fanneron, The BP Group

Justin Fessler, Salesforce

Sara Fuller, Center for Advanced Vehicular Systems Extension, Mississippi State University

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Saideep Nannapaneni, Wichita State University

Anantha Narayanan, National Institute of Standards and Technology
Madhusudanan Navinchandran, National Institute of Standards and Technology
Radu Pavel, TechSolve, Inc.
Helen Qiao, National Institute of Standards and Technology
Al Salour, The Boeing Company
Maria Seale, U.S. Army Engineer Research and Development Center
Thurston Sexton, National Institute of Standards and Technology
Michael Stewart, University of Western Australia
Douglas Thomas, National Institute of Standards and Technology
Ellen Voorhees, National Institute of Standards and Technology
Mark Walker, D2K Technologies LLC
Evan Wallace, National Institute of Standards and Technology
Peter (James) Waltner, Lockheed Martin
Brian Weiss, National Institute of Standards and Technology
Dazhong Wu, University of Central Florida
Guoxian Xiao, General Motors Company

Appendix C – Useful Links

Presentations and Workshop Details

https://www.nist.gov/news-events/events/2019/05/nist-standards-requirements-workshop-natural-language-analysis-and

Report: Industry Forum on Monitoring, Diagnostics and Prognostics

https://www.nist.gov/publications/summary-report-industry-forum-monitoring-diagnostics-and-prognostics-manufacturing

Standards Requirements Gathering Workshop Report

https://www.nist.gov/publications/summary-report-workshop-advanced-monitoring-diagnostics-and-prognostics-manufacturing

Measurement Science Roadmapping for Prognostics and Health Management Workshop – Report and conference paper

https://www.nist.gov/publications/measurement-science-roadmap-prognostics-and-health-management-smart-manufacturing
https://www.nist.gov/publications/measurement-science-prognostics-and-health-management-smart-manufacturing-systems-key

Standards Needs for Maintenance Work Orders

https://www.nist.gov/publications/standards-needs-maintenance-work-order-analysis-manufacturing

Standards for PHM Reports – Report and conference paper

https://www.nist.gov/publications/standards-prognostics-and-health-management-phm-techniques-within-manufacturing
https://www.nist.gov/publications/standards-related-prognostics-and-health-management-phm-manufacturing

Nestor
https://www.nist.gov/services-resources/software/nestor

Appendix D – Acronyms

AI	Artificial Intelligence
AMS	Asset Management System
API	Application Programming Interface
APM	Application Performance Management
BP	British Petroleum (note: BP Group is independent of British Petroleum)
CMMS	Cloud-based Maintenance Management System
CMS	Content Management System
COTS	Commercial Off the Shelf
ERP	Enterprise Resource Planning
ERPs	Enterprise Resource Planning Systems
ETL	Extraction, Transformation and Loading
FMEA	Failure Modes and Effects Analysis
FRACAS	Failure Reporting, Analysis, and Corrective Action System
GPU	Graphical Processing Unit
HMI	Human Machine Interface
IA	Intelligence Augmentation
IIoT	Industrial Internet of Things
IoT	Internet of Things
ISO	The International Organization for Standardization
KPI	Key Performance Indicator
MES	Manufacturing Execution System
MEP	Manufacturing Extension Partnership
ML	Machine Learning
MS	Microsoft
MTBF	Mean Time Between Failure
MWO	Maintenance Work Order
NIST	National Institute of Standards and Technology
NLP	Natural Language Processing
NLTK	Natural Language Toolkit
OEM	Original Equipment Manufacturer
OPC-UA	Open Platform Communications – Unified Architecture
PDM	Product Data Management

PHM	Prognostics and Health Management
SDO	Standards Development Organization
SKOS	Simple Knowledge Organization System
SME	Small and Medium-sized Enterprise
SMRP	Society for Maintenance and Reliability Professionals
V&V	Verification and Validation