NIST Advanced Manufacturing Series 300-5

# Model-Based Approach Towards Integrating Manufacturing Design and Analysis

Anantha Narayanan
Yung-Tsun Tina Lee

This publication is available free of charge from:
https://doi.org/10.6028/NIST.AMS.300-5

National Institute of Standards and Technology
U.S. Department of Commerce

## NIST Advanced Manufacturing Series 300-5

# Model-Based Approach Towards Integrating Manufacturing Design and Analysis

Anantha Narayanan
*Department of Mechanical Engineering,*
*University of Maryland,*
*College Park, MD 20742*

Yung-Tsun Tina Lee
*Systems Integration Division, Engineering Laboratory,*
*National Institute of Standards and Technology (NIST),*
*Gaithersburg, MD, 20899, USA*

This publication is available free of charge from:
https://doi.org/10.6028/NIST.AMS.300-5

July 2018

U.S. Department of Commerce
*Wilbur L. Ross, Jr., Secretary*

National Institute of Standards and Technology
*Walter Copan, NIST Director and Undersecretary of Commerce for Standards and Technology*

**Abstract**

As internet technologies and cloud-based services evolve, a new market structure is emerging across various industries, and particularly in the data-driven-analytics-services industry. This could have a great impact in the smart manufacturing sector, where highly capable and competitive services will be vying for clients. While data analytics promises manufacturers new options for optimizing the capabilities of their systems, it also forebodes challenges integrating with existing and legacy systems across a variety of services and applications. To address these challenges, we propose a modeling framework and a set of software components for connecting independent cloud and third-party services to core manufacturing models. This document describes the framework and its components.

## Table of Contents



## List of Tables



## List of Figures

## 1. Introduction

Integrating business decisions and information technology has long been rated as extremely important by CEOs in various surveys [1]. That importance has grown with today's evolving landscape of internet and cloud-based technologies. Many major players have started providing machine learning and analytics services through the cloud, such as Microsoft Azure [2], Google cloud machine learning engine [3], and machine learning on Amazon Web Services (AWS) [4]. The previous technologies for making decisions related to manufacturing design and analysis have been used to address specific needs in one area or the other only. This has created technology and business silos where 1) in-depth analysis in either area requires significant technical expertise, while 2) the models used and analysis insights gained in that one area cannot be easily transferred to the other. For example, neural networks (NNs) are used in [5] for quality control during autoclave curing, and [6] proposes NNs for monitoring tool conditions in a turning process. Each of these approaches required expertise in understanding NNs, and the devised solutions cannot be easily transferred to other problems in manufacturing. Consequently, it is difficult to optimize and connect business decisions across manufacturing and data analytics without integrating and consolidating multiple models manually. This, of course, is typically an error-prone and time-consuming process.

The profusion of new cloud-based technologies has the potential to either make things worse or make things better. On the one hand, most services address very specific needs, which increases the number of and the types of silos. On the other hand, service providers are striving to reach as many clients as possible by adopting standard protocols and interfaces that facilitate integration across the new silos.

Data analytics techniques have been applied in manufacturing over the past several decades [7]. With improvements in new computing technology and the development of more sophisticated algorithms, the impact of data analytics on manufacturing is expected to increase greatly [8][9]. Some of the more popular, manufacturing-related, cloud-based services provide data analytics capabilities that analyze streams of data to look for patterns and obtain insights into the systems generating the data. The availability of a sophisticated and generic computing infrastructure, along with powerful and efficient services for data analytics, promises great potential. Yet, most applications of data analytics during production are devoted to very specific situations and problems, such as target improvements to process performance, or detecting specific types of faults. For example, they focus on specific needs such as tool condition monitoring, surface roughness prediction, fault detection etc., for specific types of manufacturing processes such as single point turning, face milling etc. Reference [14] presents a survey of various studies addressing these specific areas. The manufacturing industry can benefit greatly if data analytics solutions can be integrated across levels of the factory hierarchy, so that analysis results at the process level can be elevated and used to influence enterprise-level decision making.

In this paper, we present a model-based approach to leverage and integrate the results of analytics services across the entire hierarchy. We propose a multi-level framework for modeling design and analysis operations at various hierarchical levels of granularity and abstraction. The main business goal of the framework is to improve decision-making by making it easier to apply data analysis services across those levels. The main technical goal is to use the framework as a platform to test integration standards and protocols. If successful, the framework will facilitate the integration of analysis tasks across levels of hierarchy by 1) providing intuitive abstractions and interfaces and 2) taking advantage of appropriate standards.

In this paper, we describe the key components and functionalities of this framework, and illustrate its capabilities for the design and analysis of manufacturing systems. Section 2 provides the motivation for this work. Section 3 gives an overview of our approach. Section 4 presents the details of the proposed framework. Section 5 discusses the benefits of the framework, and the strategies for its implementation. Section 6 describes the usage scenario of the framework. Section 7 presents conclusions and thoughts on future work.

## 2. Motivation

We summarize the motivation for developing this framework by quickly summarizing the current state-of-the-art in data analysis techniques and by describing the gaps and requirements from our perspective. We will address the technical aspects of these topics in greater detail in the following sections.

Data analysis techniques have found application in manufacturing for several years, and the advancement of analysis techniques and tools promises great improvements. However, there are several technical barriers to their general use in manufacturing:

Popular modeling and analysis techniques and tools were developed for general analysis problems, and cannot be easily adapted for use in the manufacturing domain. As stated in the introduction section, most of the data analysis techniques applied in manufacturing are stand-alone because they are designed to address specific manufacturing issues under specific conditions. As a result, they cannot easily be generalized to address other requirements.

Many current techniques require expertise in data analysis, decision optimization, machine learning, and machine sensors. This makes it difficult for manufacturers, who typically lack such expertise, to use them. The most significant impact is the lack of expertise and guidance for new users to apply these techniques to their individual manufacturing problems. There is a need for facilities to represent a wide range of manufacturing problems, connect them to appropriate analytics solutions, and translate analytics results into decisions that impact manufacturing operations across different levels of hierarchy.

To address these technical barriers, we propose a multi-level, model-based modeling framework that will 1) provide an integrated, extensible, easy-to-use environment to serve various types of manufacturing-data-analysis services and 2) minimize the requirements for users to have domain knowledge from multiple disciplines.

## 3. Overview of Multi-Level Modeling Framework for Integrated Manufacturing Design and Analysis

The goal of our proposed software framework is to facilitate the application of data analytics for improving manufacturing decisions, while taking advantage of a variety of third-party cloud services. Our approach to achieving this goal is to provide a model-integration and service-integration framework that will make it easier to connect different levels of the factory architecture to various analysis solutions, with standards as key enablers for integration.

The main features of the framework are

- A multi-level, domain-specific interface to model the different functions of production within each level of the factory hierarchy (processes, machines, cells, factory, enterprise), and across different aspects (resources, production, planning), with libraries of reusable model abstractions
- A service-oriented approach to support various services including data generation, analytics, optimization, simulation
- Standards-based interfaces to discover and realize analysis services and provide model integration and interoperability.
- A foundation for implementing and testing standards to exchange analysis models and to test software compliance with standards.

**Table 1**. Features of the Framework.

| Framework Feature | Description |
|---|---|
| *System specification* | Describe the various hierarchical levels of the system in an integrated model, as a digital representation of the physical system. |
| *Service integration* | Provide a mechanism to integrate analysis services to system requirements through the system specification. |
| *Model interoperability* | Enable the exchange of models and data between the system models and the analysis services by implementing appropriate mappings and transformations. |
| *Standards testbed* | Serve as a testbed for evaluating standards and provide a library of reference scenarios for testing and validating standard implementations. |

To facilitate the application of data analytics for improving manufacturing operations, the Multi-level Modeling Framework provides interfaces and facilities to 1) build digital specifications of manufacturing operations, 2) generate analytical models from those specifications, 3) invoke a variety of analytics services directly from these models, and 4) integrate the results of analysis to support decision making. The framework supports both model integration and service integration across different levels of the hierarchy. The proposed modeling framework provides a graphical interface for specifying manufacturing system models at various hierarchical levels. Through this interface, different services can be implemented; functionalities of these services may include simulation, optimization, inference, and analysis through predictive models. This framework, when complete, will integrate various services through a single modeling interface, and facilitate manufacturing design and analysis workflows that typically require the use of multiple tools and models. The framework will also make it easy to create mock-up scenarios for evaluating standards. This can be used to create reference scenarios for testing standards compliance and evaluating the performance of other standards based tools and services.

**Fig. 1** shows the conceptual approach to building the framework. The framework aims to provide a way for manufacturers to make efficient use of a wide range of cloud-based services for improving manufacturing systems. The manufacturers are most familiar with the physical systems that they work with. Models of these systems must be represented in a digital format to be processed by analysis algorithms. By using standard formats and protocols, the digital specifications can be easily connected to third-party analytics services. The workflow of going from physical systems to digital representations to analytics services is central to achieving our objective.

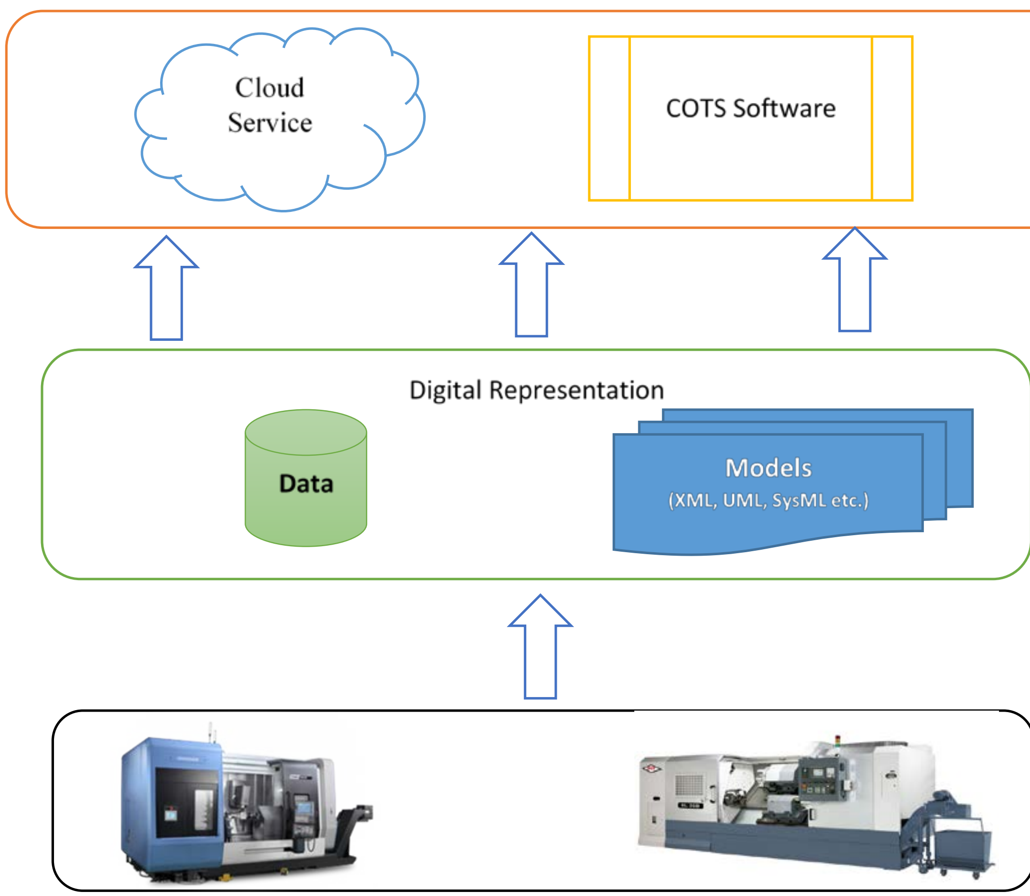


**Fig. 1.** Conceptual approach for manufacturing analysis.

Our strategy for enabling this workflow is to provide an intuitive, domain-specific, modeling environment (DSME) that will allow manufacturers to build digital specifications as accurate representations of their physical systems [10]. A DSME is a visual environment that provides intuitive abstractions of items in a user's domain, which allows domain users to quickly express specifications of their domain models with a very short learning curve. This contrasts with generic specifications, which will require significant learning and work to build specifications of domain models from generic abstractions. Several software tools are built on top of the DSME to process these digital specifications, along with data collected from the physical systems, to generate analysis models for predicting certain targets of interest semi-automatically. For example, a digital representation of a manufacturing process encodes the main parameters and target metrics of the process. Using this digital representation, and data collected from the actual manufacturing process, we can generate an analytical model (such as a neural network [11] or a Gaussian process regression model [12]) that can predict the target metric (such as energy consumption) for this process.

## 4. Framework detail

Here, we will provide a brief description of the components of the framework.

**Fig. 2** shows a detailed view of the proposed framework. There are four main layers. The functionalities of these different layers are described below.

### 4.1. Manufacturing System Layer

The bottom region of **Fig. 2**, the manufacturing system layer, represents the physical system. This includes the physical factory, physical sensors, and other data generators. The physical system may be composed of multiple subsystems, which may overlap with each other. Domain experts study these subsystems using various tools for building models, performing analytics, running simulations, and solving optimizations. One of the big challenges in the evolution toward smart manufacturing systems is the integration of such tools across the different hierarchical levels. The physical elements in this system may have digital representations and associated analytical models in other portions of the framework. These physical and digital elements are connected by a 'digital thread', which is explained later.

### 4.2. Model Ecosystem Layer

Above the manufacturing system layer in **Fig. 2** is the model-ecosystem layer. This layer houses the technical foundations for connecting a variety of tools and services. An initial attempt at developing such a model ecosystem for data analytics was described in [13]. The model ecosystem comprises several components and functionalities, which are essential for the framework to fulfill its objective. The two major components in this layer are the DSME and the Meta-Library.

*Domain Specific Modeling Environment:* For our purposes, a model is a digital representation, which can be computer processed, of the critical features of a physical component or phenomenon. Traditionally, such representations are based on modeling formalisms tailored for the task at hand. These formalisms provide abstractions suitable for both the task and the specified analytical objectives. Using these formalisms to build the required models can be quite difficult, especially for general practitioners who are not trained in using these formalisms. To address this problem, we take a domain-specific modeling approach, where the modeling abstractions are closely related to the manufacturing domain. On the one hand, this makes it easier for the practitioners to build more accurate digital representations their manufacturing systems. On the other hand, however, the resulting representations are frequently inadequate for using data analytics services. We address this difficulty by using model transformations, which automate much of the work necessary to convert these manufacturing-domain models into analytical-domain models.

*Meta-Library***:** A meta-model is a collection of domain-specific concepts and relationships, which defines the essential elements and rules of the domain. These concepts and relationships are "instantiated" to allow building models that represent physical systems in that domain. Meta-models provide 1) a standardized way to represent physical-system models, which facilitates the exchange of these models, and 2) the foundations needed for developing tools to analyze and interpret these models. The meta-library is a collection of meta-models describing various aspects of manufacturing systems.

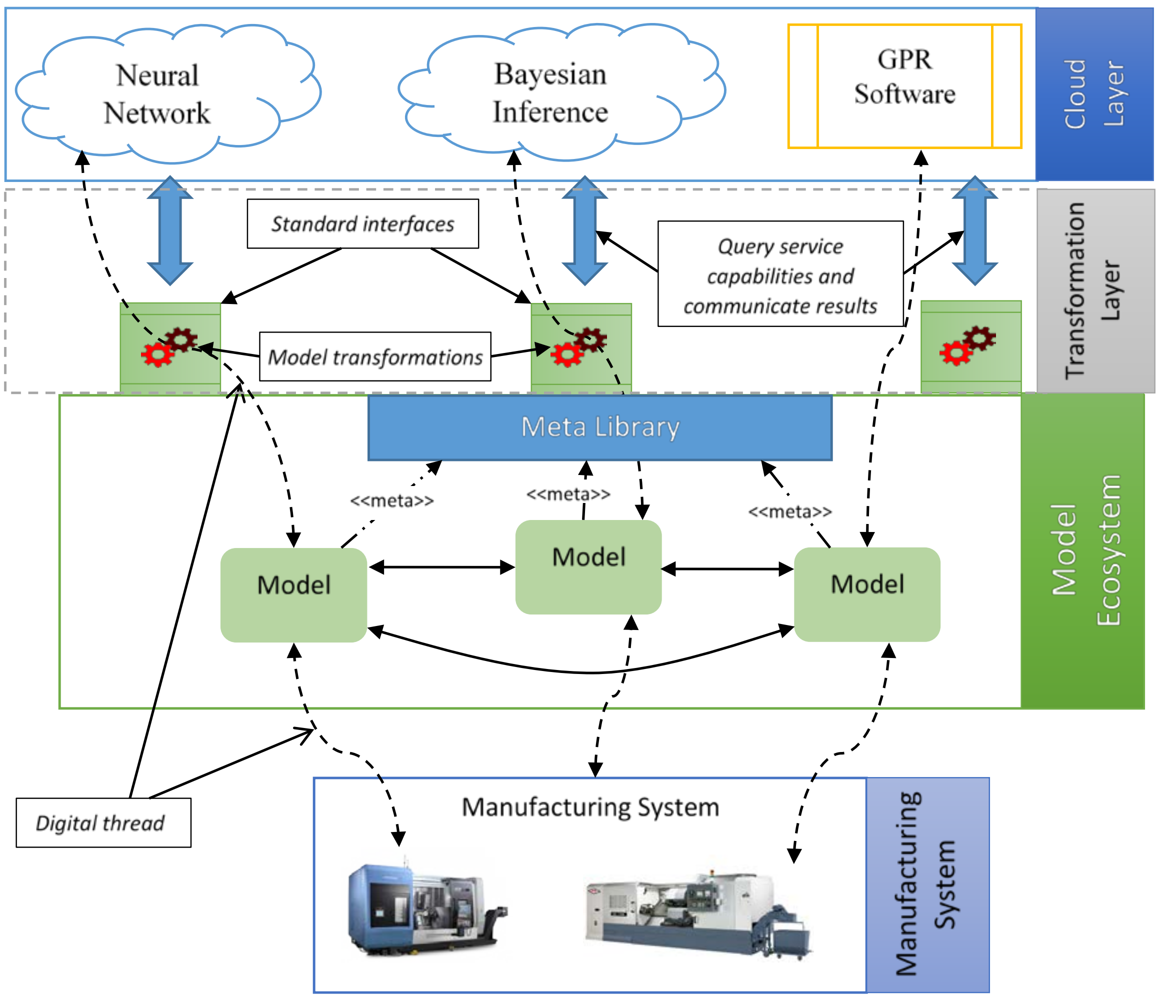


**Fig. 2.** Modeling and analysis framework for manufacturing.

### 4.3. Transformation Layer

The model ecosystem must be connected to the cloud layer to allow various third-party tools to be used to perform analyses based on the system models. In the transformation layer, we build several software tools that process those system models to generate analysis models. These software tools are called model transformations, since they transform one type of model into another. The transformation process is based on a mapping algorithm that identifies specific entities in the manufacturing-system domain, and produces a corresponding entity in the analysis domain. When all the required entities have been appropriately represented in this way, a solution to the analysis model will be a solution to the manufacturing problem. Automating the model-transformation process requires encoding the expertise involved in building the analysis model as a software program. We have demonstrated that this is feasible for generating neural networks for predicting energy use in manufacturing processes [14]. When possible, the analysis model can be generated in a standard format, such as the Predictive Model Markup Language (PMML) [15], which can then be used with a variety of off-the-shelf analysis tools.

### 4.4. Cloud Layer

The cloud layer includes various third-party services addressing various analytics needs. While we generally think of third party services as cloud services invoked through online protocols, the notion also encompasses standalone third-party applications. In the traditional silo model mentioned earlier, a manufacturer would have to understand how to use each of these third-party services, and represent their manufacturing problem in a format accepted by these tools. In the absence of standards, a lot of system information critical for analysis may be omitted from the analysis, rendering it ineffective. Using third party analysis tools also requires the manufacturer to have analytics expertise, and usually ties the users to a single propriety tool platform that they have been trained in. This is a major hindrance to the widespread use of advanced analytics in the manufacturing industry, especially for small and medium manufacturers. Our framework will help manufacturers address this issue, by providing standards-based interfaces and automated or guided model transformations, making it easier for manufacturers to use a range of analytics services on their system models.

### 4.5. Other Framework Components

In addition to the four layers described above, the framework includes components, described below, that support the interactions between the layers. While they play a crucial role in the functioning of the framework, we expect that these components will be developed through a collaborative effort by the community of researchers and practitioners.

**Model Library**: The framework will support the use of a variety of model libraries for various purposes. These can include libraries of 1) pre-built system models to accelerate system specification, 2) analysis models for various analysis objectives, 3) reference data sets for specific scenarios, and 4) extensions based on custom scenarios and data by individual organizations.

**Standard Interfaces**: Standards will play a significant role in the success of this framework. For example, the PMML standard is very important for building predictive models to be used with third-party tools. Standard interfaces based on standardized protocols will be crucial in connecting the framework to a variety of third-party services.

**Digital Thread**: A digital thread [16] is a mechanism that connects distinct types of models and their corresponding physical entities to provide traceability across the system. The digital thread allows manufacturers to trace analysis results back to actual physical components. This traceability is necessary and plays a key role in decision making.

**Analysis Discovery Service**: The framework will include an analysis discovery service (ADS) that will guide manufacturers to the appropriate analysis services based on their needs. The ADS is a very important component of the framework, since it is crucial to fulfilling the objective of bringing advanced analytics capabilities closer to manufacturing users who are not experts in analytics. The implementation of the ADS will require a high level of expertise in both the manufacturing and the analytics domains 1) to identify the most common manufacturing analysis challenges and 2) to match them with the best analysis techniques. Standards and protocols for publishing and searching analysis services will also play a significant role in the implementation of the ADS. The ADS will greatly simplify and expand the use of advanced analysis services in manufacturing. It can be used in combination with the 1) DSME layer for specifying domain models, 2) the transformation layer for processing the domain models, and 3) standard interfaces for calling analysis services.

## 5. Discussion

In this section, we discuss the features, implementation, and use of the framework. Many of the technologies required to implement this framework are available and being used in other research, as will be shown in Section 6. This paper suggests a way to use those technologies to facilitate a broad manufacturing community to take advantage of a variety of important analytics tools and services.

### 5.1. What are the advantages of this approach?

The approach we present here is tailored for the manufacturing domain. It presents several advantages over the traditional approach of working with multiple generic tools, and reframing manufacturing problems using generic abstractions.

- The domain-specific environment can better represent the constraints in the manufacturing domain, resulting in more accurate system models
- The service-discovery component can match analysis services that are more appropriate for manufacturing related requirements
- The integrated environment makes it easier to convert analysis results to decisions that impact specific parts of the manufacturing system. Changes to the system description can be better traced to the reasons for those changes.

### 5.2. How will the industry use it?

The framework will help the manufacturing industry to match their requirements to appropriate analysis services. The modeling environment will simplify system specification for manufacturing operations across different levels of hierarchy. The problem statement and service discovery interface will make it easy to find implementations that will provide the analytics service appropriate for solving the relevant analysis problem.

### 5.3. How will research enable it?

The core parts of the framework are the modeling techniques and the communication interface. Advanced modeling techniques will be used to define intuitive and robust abstractions and interfaces for system specification and problem formulation. This will provide a robust basis for manufacturing users to specify their systems, and invoke a variety of analysis services using standardized interfaces.

### 5.4. How will developers build it?

The framework will be built using a service-oriented approach. The core modeling abstractions are built in a standardized way to facilitate the specification of complex manufacturing systems. Standard interfaces will be provided to communicate with third-party services for various analysis tasks. The analysis services may be implemented independently, relying on the accurate transfer of relevant information through the standard interfaces.

## 6. Usage Scenario

In this section, we present a hypothetical scenario illustrating the use of the framework. Components described in Section 4 that have not been implemented yet will not be explained in detail. We provide an overview of how those components would be used when implemented fully. This will illustrate the way in which the components will be used, and the ways in which different analytics steps will interact and function in an integrated environment. The focus here is to illustrate the procedure and benefits of using this framework, not on the technical issues related to implementation.

In the hypothetical scenario, a manufacturing factory performs discrete production processing of certain parts. We will represent the production process as a domain model using the DSME, use the analysis-discovery service to find appropriate analysis tools, and integrate the results back into the system model for decision making.

### 6.1. System Specification

The DSME is used to build a hierarchical model of the factory. This hierarchical model serves as a digital specification of the physical system and can be processed by software algorithms to perform various tasks. **Fig. 3** shows an example of such a specification. The figure shows a hierarchical model representing the system in three levels of detail. The *Plant Level* shows different manufacturing cells and transport structures. Each cell can be specified in greater detail, which is depicted in the next lower level, the *Cell Level.* The figure shows such a specification for one such cell including its processes, resources, inputs, and outputs. The processes can be specified in further detail at an even lower hierarchical level. The *Process Level* model shows an example, where a process may be specified in greater detail by identifying process parameters, graphs, and physical equations. The notations used in **Fig. 3** are only provided as examples of how the visual model might appear, and do not represent well defined semantics. When the DSME is fully developed, each of the symbols used will have well defined semantic and syntactic rules to construct a sound system model.

### 6.2. Analysis Discovery Service

The analysis discovery service (ADS) will function as an interactive guide to select and execute analysis tools for using the developed models and specifications described above. The activities of constructing the system model and executing analytics tools can happen in parallel, since each analytics service is only concerned with one portion of the system at a time. Services may include building prediction models for specific metrics, identifying optimum process parameters to attain a certain objective, running a simulation of a portion of the system model, among others. Prediction models may include a variety of different machine-learning techniques offered by different tools and cloud services.

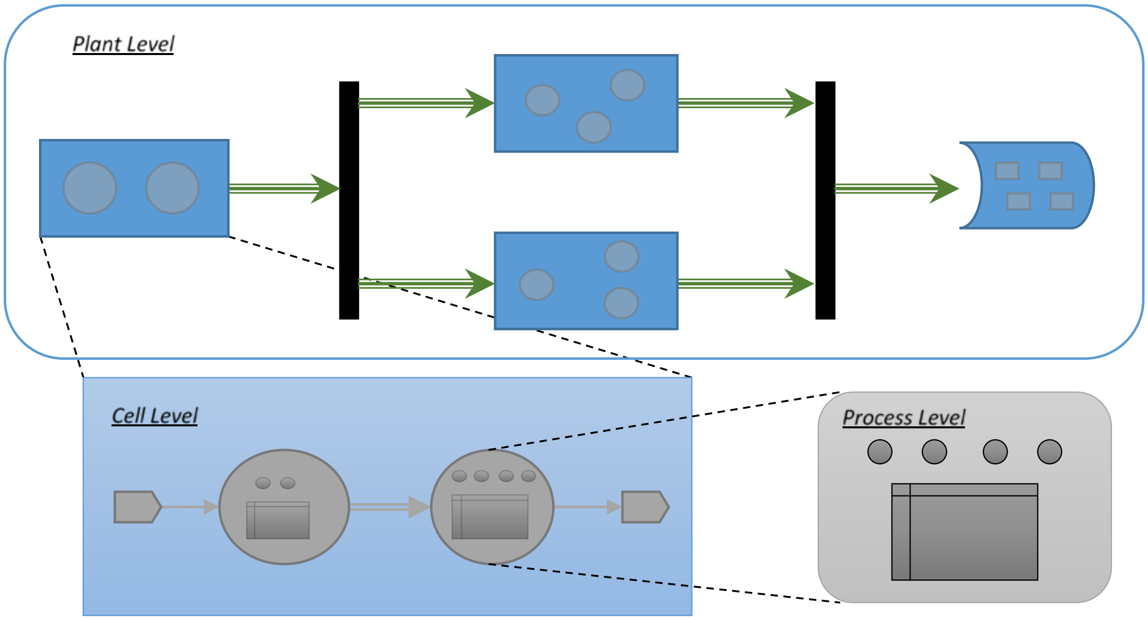


**Fig. 3.** Example of hierarchical system model in a DSME.

The user will be able to invoke the ADS, by launching a visual interface that shows specific analysis tools and services. The user will be able to select from a library of tasks, and identify portions of the system model where the analysis is to be performed. For example, the user may select a certain process specification, and identify one of the process metrics as the target for building a predictive model. The ADS will suggest appropriate machine learning models to accomplish this objective, based on expert recommendations. The user will be able to browse tools and services for building their selected prediction model. The following subsection describes how the selected tool can be invoked on the system model to complete the analysis task.

### 6.3. Analysis Integration

Once an analysis tool or service is identified, it must be invoked with the appropriate inputs to achieve the analysis objective. The transformation layer of the framework will process the system model to generate the necessary input files in the appropriate format. The input files are generated by algorithms that process the system model in the DSME, extract the information necessary for the analysis tools, and compile them into the specific information format required by the tools. Each type of analysis task will require a different transformation algorithm, but once a library of transformation algorithms is built, many model transformation tasks can be easily invoked at the press of a button. Developing standards and protocols for exchanging information with analysis tools and services will help in making these transformation algorithms simple and robust.

**Fig. 4** conceptually illustrates how a portion of the system model may be extracted by a model transformation algorithm, to produce a specification file that will serve as an input to an analysis tool. The model transformation encodes expert knowledge from the manufacturing and analytics domains, to process a manufacturing specification and generate an analytics model. The analytics model may be generated in a standard format such as PMML, and used with third part analysis services. Data collected from the manufacturing operations may then be used with this model for analysis to obtain prediction results.

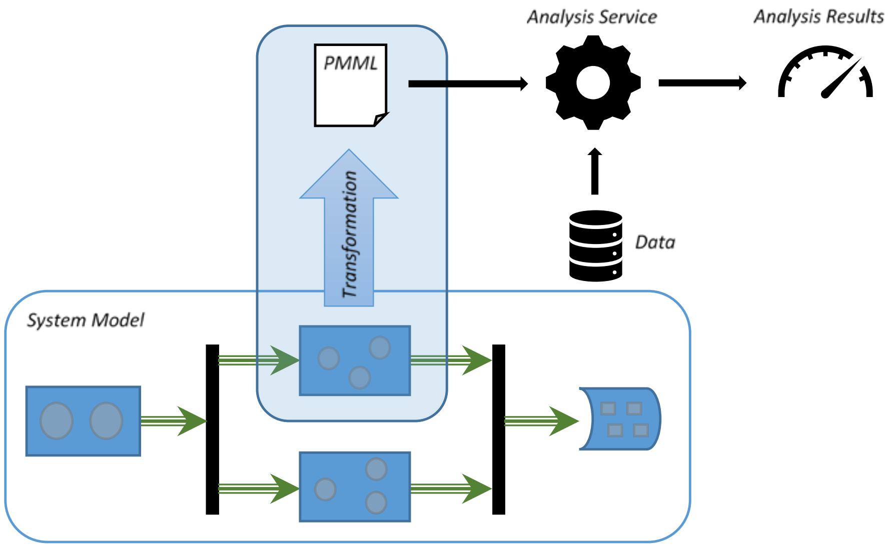


**Fig. 4.** Conceptual illustration of invoking analysis using model.

The domain specific modeling layer, transformation layer, and the analytics discovery service together make it easier for manufacturers to apply a variety of analysis solutions to their manufacturing problems. The integrated framework allows analysis results to be fed back into the system model, making it easier to chain successive analysis tasks on overlapping portions of the system model. This also facilitates decision making based on a consolidation of different analysis tasks.

This hypothetical scenario described the usage of the framework in practice when fully implemented. Portions of the scenario described above have proof-of-concept implementations [14], and in future work we will provide more detailed descriptions of these components with more complete implementations.

## 7. Conclusion and Future Work

Data analytics presents many new possibilities for analyzing and improving the performance of manufacturing systems. Cloud services now include several different analytical tools that are becoming increasingly popular. These services are being developed by independent providers; using them, however, requires expertise in diverse areas. Additionally, overall success in improving manufacturing operations relies heavily on proper interaction and integration of different analysis tasks. This is generally difficult to achieve, especially for small companies with limited workforce and limited access to expertise.

In this paper, we presented a framework that includes an environment that facilitates both the integration of those analysis tasks and the creation of domain- specific models. That environment includes 1) an intuitive interface to specify manufacturing operations, 2) features to guide users to use appropriate tools for their analyses, and 3) methods to integrate the results of different analysis tasks back into the domain model. We believe that such a framework will greatly increase the access to advanced analysis options for many companies including small and medium-sized enterprises. It will also make it easier for service providers to reach a wider range customers, and reduce the cost of educating customers in specific analysis systems.

## Disclaimer

Certain commercial software products or services may be identified in this paper. These products or services were used only for demonstration purposes. This use does not imply approval or endorsement by NIST, nor does it imply that these products are necessarily the best for the purpose.

## References


[1] V. Srinivasan, An integration framework for product lifecycle management, *Computer-Aided Design*, 43 (5) (2011), pp. 464-478

[2] Microsoft Azure. https://azure.microsoft.com/en-us/services/machine-learning-studio/

[3] Google Cloud. https://cloud.google.com/ml-engine/

[4] Amazon Web Services. https://aws.amazon.com/machine-learning/

[5] B. Joseph, F. W. Hanratty, Predictive control of quality in a batch manufacturing process using artificial neural network models, *Industrial & engineering chemistry research*, *32*(9), 1951-1961.

[6] D. A. Dornfeld, M.F. DeVries, Neural network sensor fusion for tool condition monitoring, *CIRP Annals-Manufacturing Technology* 39, no. 1 (1990): 101-105.

[7] J. A. Harding, M. Shahbaz, and A. Kusiak. Data mining in manufacturing: a review. *Journal of Manufacturing Science and Engineering* 128, no. 4 (2006): 969-976.

[8] J. Manyika, M. Chui, B. Brown, J. Bughin, R. Dobbs, C. Roxburgh, and A. H. Byers. Big data: The next frontier for innovation, competition, and productivity. (2011).

[9] Young, M., and D. Pollard. What businesses can learn from big data and high-performance analytics in the manufacturing industry. *Big Data Insight Group* (2012).

[10] Ledeczi A, Bakay A, Maroti M, Volgyesi P, Nordstrom G, Sprinkle J, Karsai G. Composing domain-specific design environments, *Computer*, 2001;34(11): 44–51.

[11] Haykin, Simon. 2004. NEURAL NETWORKS: A Comprehensive Foundation. Prentice Hall 2 (2004).

[12] Rasmussen, C. E., 2004, Gaussian Processes in Machine Learning, *Advanced Lectures on Machine Learning*, Springer Berlin Heidelberg, New York, 2004, pp. 63–71.

[13] Lechevalier, David, Anantha Narayanan, and Sudarsan Rachuri. 2014. Towards a Domain-Specific Framework for Predictive Analytics in Manufacturing, In *2014 IEEE International Conference on Big Data (Big Data)*, 987–995. IEEE.

[14] Lechevalier, David, Anantha Narayanan, Sudarsan Rachuri, and Sebti Foufou. A methodology for the semi-automatic generation of analytical models in manufacturing. *Computers in Industry* 95 (2018): 54-67.

[15] Guazzelli, A., Zeller, M., Lin, W.C. and Williams, G., 2009, PMML: An open standard for sharing models, *The R Journal*, 1(1), pp.60-65.

[16] Society of Manufacturing Engineers, Connecting the Digital Threads, *Manufacturing Engineering*, vol. 146, no. 6, pp. 33-36, 2011.