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INFRASTRUCTURE FOR MODEL BASED ANALYTICS FOR MANUFACTURING

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ABSTRACT

Multi-resolution simulation models of manufacturing system, such as the virtual factory, coupled with analytics offer exciting opportunities to manufacturers to exploit the increasing availability of data from their corresponding real factory at different hierarchical levels. A virtual factory model can be maintained as a live representation of the real factory and used to highly accelerate learning from data using analytics applications. These applications may range from machine level to manufacturing operations management level. While large corporations are already embarking on model based analytics initiatives, small and medium enterprises (SMEs) may find it challenging to set up a virtual factory model and analytics applications due to barriers of expertise and investments in hardware and software. This paper proposes a shared infrastructure for virtual factory model based analytics that can be employed by SMEs. A demonstration prototype of the proposed shared infrastructure is presented.

1 INTRODUCTION

Multiple trends are coming together to create exciting opportunities across all aspects of human lives. These trends include increasing computing power with accompanying reduction in its cost, increasing connectivity and speed across internet, increasing capabilities for data collection through sensors, and increasing access to data and applications via cloud and fog computing technologies. These trends have largely relaxed the constraints of computing power and data availability and enabled rapid growth in application and further development of technologies such as Internet of Things (IoT), artificial intelligence (AI) and analytics. The application of simulations and mathematical optimization techniques are rapidly growing too, taking advantage of the same trends. A number of these technologies have been around for years but were constrained in their applications due to lack of infrastructure of computing power, data access, and connectivity. For example, artificial intelligence attracted a lot of attention in 1980s building on special purpose languages such as PROLOG and LISP, special purpose hardware such as Texas Instruments Explorer workstation, and deployment of expert system applications for such varied fields as medical advice (Shortliffe 1986) and manufacturing scheduling (Jain et al. 1989). However, such developments plateaued with their growth constrained by the infrastructure limitations.

The ongoing rapid growth in infrastructure has not only provided an opportunity for development of earlier developed technologies, it has also spurred further developments across most of them. AI in particular has gained from a shift from mimicking human intelligence and rule based approaches of 1980s to now building on machine learning based analytics. Analytics applications employ increasingly rigorous and advanced applications involving large amount of computations. For example, Neural Networks are getting stacked for deep learning applications. Mathematical optimization and simulation applications have seen new developments based on the advancements in infrastructure. Simulations software today allow quick executions of large models that integrate multiple paradigms such as system dynamics and discrete event representations, compared to a couple of decades ago where applications of even single paradigm models were limited in size due to execution speed limitations.

There are multitude of efforts for developing and deploying standalone applications based on the four technologies listed above, namely AI, analytics, mathematical optimization, and simulation. Efforts are also beginning to be reported that synergistically employ these technologies together. This paper proposes an infrastructure for an application that brings together simulation and analytics technologies for supporting manufacturing operations management and machine level decisions. Majority of recent and under development analytics applications analyze real data to identify patterns and develop insights to support decision making. However, the knowledgebase of such applications is restricted to analyzing scenarios that occur in real life and thus their predictions are credible within that envelope only. Simulation applications on the other hand can generate credible outputs for a range of what if scenarios. Using the simulation as a data-generator for a range of scenarios and using that data to train analytics application can increase the prediction envelope of the analytics application by several fold. Such use of simulation models to generate data, which is then analyzed by data driven analytics applications, has been referred to as model based analytics.

This paper reports on the next step in bringing model based analytics closer to actual implementation. The progression of the work has been reported in successive years at this conference. Jain et al. (2017) presented initial work for model based analytics by linking a virtual factory prototype to a Neural Network (NN) for developing a meta model for manufacturing order promising. Jain et al. (2018) took the model based analytics further by linking virtual factory prototype to a Gaussian Process Regression (GPR) application and using the capability to compare NN and GPR for the order promising function. This paper proposes infrastructure for deploying the model based analytics capability to facilitate its eventual application by small and medium enterprises (SMEs). The emphasis is on SMEs since they generally lack the resources to develop and implement advanced technologies.

The next section briefly reviews recent literature for similar efforts. Section 3 presents a modeling and analysis framework that has been developed with a focus on machine learning based analytics applications for manufacturing. The framework is enhanced in Section 4 to include simulation models and to link them with analytics applications to enable (simulation) model based analytics. A prototype implementation of the proposed infrastructure is described in Section 5. Section 6 concludes the paper with discussion of future directions.

2 RELATED WORK

2.1 Virtual Factory

This paper uses the definition of a virtual factory as a multi-resolution simulation model of a manufacturing system capable of supporting analysis at different levels of hierarchy with interfaces to real factory and analytics applications. The definition largely overlaps with those of digital twin of factory, shop floor digital twin, and digital factory used by some authors (for example, see Garetti et al. 2012). Reported work over the last 2 years relevant to this definition of virtual factory are briefly reviewed in this section. The work focusing on virtual reality aspects or collaboration across manufacturers to make a “virtual factory” is not included here. Readers are referred to Jain et al. (2017) for relevant literature prior to 2017.

A number of efforts report development and implementation of virtual factory models with increasingly diverse applications and identify challenges. Hwang et al. (2017) use a virtual factory model to demonstrate and validate the use of an IoT based performance measurement system. Brenner and Hummel (2017) describe a prototype implementation of a digital twin in a learning factory setting. Modoni et al. (2018) present the digital twin of a factory as a digital factory and also as a virtual factory and highlight its benefits and technical challenges including the lack of interoperability of supporting software systems. Caggiano and Teti (2018) present a digital factory model that allows machine level modeling using a 3D simulation and cell level flow using a discrete event simulation. These efforts indicate continued development of the virtual factory concept with varied applications.

2.2 Model Based Analytics for Manufacturing

There appears to be little work reported that employs model based analytics for manufacturing applications. Giri et al. (2012) propose use of model based analytics for management of power grid and point to its capability for what-if analysis and coming up with corrective actions as a major benefit over measurement based analytics. Kajmakovic et al. (2018) propose to use model based analytics for predictive fail safe systems in industrial operations. Some authors identify the approach as simulation based analytics. Biller et al. (2017) modified simulation models of Silicon Carbide manufacturing operations and analyzed the outputs to address the challenge of limited data from a real facility. Ji and AbouRizk (2018) utilize simulation based analytics for decision support for pipe welding quality management in industrial construction. The opportunities offered by combination of simulation and data driven analytics models are being recognized and its increasing use is anticipated.

2.3 Model Based Analytics Infrastructure

The infrastructure for model based analytics and virtual factory has recently drawn attention of researchers. Chen and Lin (2017) support use of Factory Simulation as a Cloud Service (FSaaCS) for SMEs and identify two major issues, the need to convert models for different simulation systems available on different clouds and estimating the simulation time. They focus on load balancing approaches for FSaaCS. Coronado et al. (2018) describe a Manufacturing Execution System (MES) based on MTConnect protocol and cloud based technologies suitable for SMEs that can be used to develop a shop floor digital twin, an overlapping concept to virtual factory discussed above. The proposed MES could be one building block that SMEs can employ for developing the model. Further development can bring in analytical tools for model based analytics.

A few efforts have been reported outside the manufacturing domain. Lee et al. (2013) present a model based analytics service available via cloud for building energy consumption. He et al. (2018) describe a multi-tier fog computing structure for model based analytics of large scale IoT for smart cities. Gausemeier et al. (2011) discuss integration of manufacturing with control engineering and information services and describe a general procedure model for integrative development of mechatronic products. Lee et al. (2014) propose a framework for self-aware and self-maintained machines for Industry 4.0, which includes cyber physical systems and decision support systems, and address the trends of manufacturing service transformation in big data environment. To our knowledge, there is no framework that integrates simulation into the design and analytics aspects, thus expanding the data driven capabilities beyond the status quo.

Overall, this brief review indicates that there is recognition that the advancements in simulation and data analytics are offering exciting potential for their combined application as model based analytics. Integration frameworks need to be developed or extended to incorporate such combinations. There is also recognition of an emerging need to facilitate the application of model based analytics through development of infrastructure particularly for SMEs.

3 FRAMEWORK FOR DATA DRIVEN MODELS

Data analytics (DA) allows identifying performance improvements across multiple levels of manufacturing system functionality. DA techniques have been applied in manufacturing for many years (Harding et al.

2006). Most of these DA applications, however, are addressed to very specific issues under specific conditions (Sharp et al. 2018). Furthermore, DA applications are prohibitively complex and expensive, especially to SMEs. This is because DA techniques often require expertise in data collection, data analysis, machine learning, and decision optimization. A typical SME cannot afford to have a DA expert on staff. Thus, manufacturers need an enhanced decision-support facility so that analysis results at the process level can be elevated and used to influence enterprise-level decision making faster and better. The manufacturing industry can benefit greatly if such facility can 1) represent a wide range of manufacturing problems, 2) connect them to appropriate DA solutions, and 3) translate DA results into decisions that impact manufacturing operations across different levels of hierarchy. To address the need, a model-based analytics framework for manufacturing has been developed (Narayanan and Lee 2018) and is shown in Figure 1.

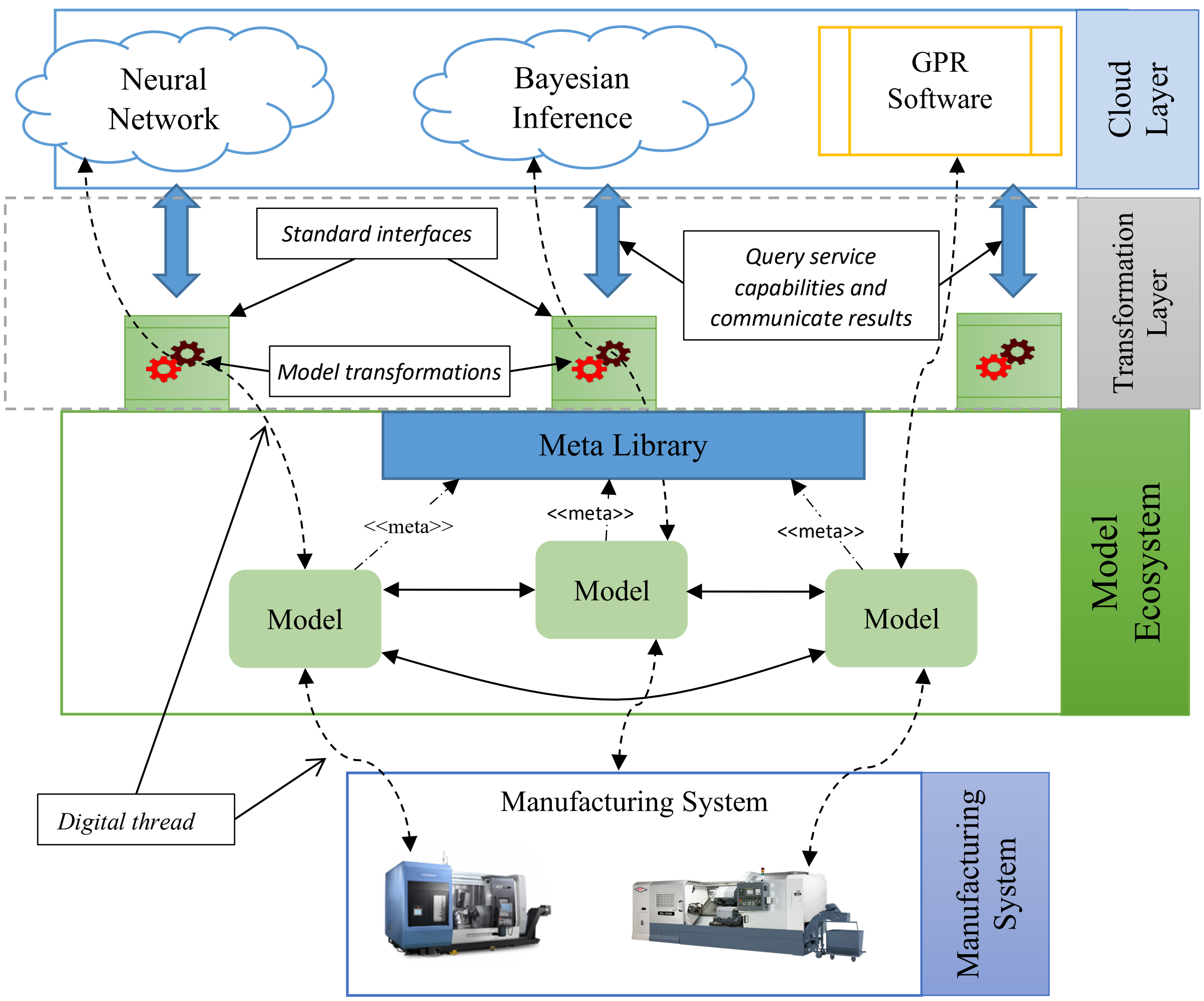

Figure 1: Model-based analytics framework for manufacturing.

The framework consists of a set of software to connect independent cloud and third-party DA applications or services to core manufacturing models. The framework supports both model integration and service integration across the entire hierarchy. The goal of the framework is to help the manufacturing industry to match their requirements to appropriate analysis services. The framework consists of four major layers described below.

- The manufacturing system layer, representing the physical system, includes the physical factory, physical sensors, and other data generators. The physical system may be composed of multiple subsystems organized as different lines, departments, cells, etc. At lower levels of the hierarchy, various machine tools and equipment are used to performs steps in the process plan for different products.
- The model ecosystem layer includes two major components: the domain-specific modeling environment and the library of meta-models. This layer provides the technical foundations for connecting a variety of analysis tools and services. The modeling environment will simplify system specification for manufacturing operations across different levels of hierarchy. It takes the domain-specific modeling approach to model abstracts in digital representations for manufacturing systems. The digital, manufacturing-domain models are then converted into analytical-domain models using model transformation to facilitate DA applications. Meta models are used to describe various aspects of manufacturing systems, based on the essential elements and rules of the domain of the individual physical systems; they are presented in a standardized way to facilitate model exchange and integration (OMG 2016).
- The transformation layer includes a set of model transformations or software tools that transfer system models into analysis models. It utilizes mapping algorithms that identify specific entities in the manufacturing-system domain and produce a corresponding entity in the analysis domain. The analysis model will be used to provide a solution to the manufacturing problem. When possible, the analysis model can be generated in a standard format, such as the Predictive Model Markup Language (PMML) (Guazzelli 2019), which can then be used with a variety of off-the-shelf analysis tools.
- The cloud layer includes various third-party services addressing various analytics needs. The third-party services can be standalone or cloud-based applications. The model ecosystem is connected to the cloud layer to allow various third-party tools to be used to perform analyses based on the system models.

To support the interaction among the layers, the framework provides additional components such as model library, standard interfaces, digital thread, and analysis discovery services. The model library includes pre-built system models to accelerate system specification, analysis models for various analysis objectives, reference data sets for specific scenarios, and possibly, extensions based on custom scenarios and data by individual organizations. Standard interfaces, based on standardized protocols and guidelines, are provided to make it easier for manufacturers to use available analytics services on their system models. The framework uses digital thread (Society of Manufacturing Engineers 2011) mechanism to connect digital representations and their corresponding physical entities. The digital thread allows manufacturers to trace analysis results back to actual physical components of the system. This traceability is necessary and plays a key role in decision making. The analytics discovery service guides manufacturers to the appropriate analysis services based on their needs. The discovery service is a very important component of the framework since the manufacturing users often are not experts in analytics. The service discovery interface will make it easy for manufacturers to find implementations that will provide the analytics service appropriate for solving the relevant analysis problem. The implementation of such service will require a high level of expertise in both the manufacturing and the analytics domains.

The core parts of the framework are the modeling techniques and the communication interface. Advanced modeling techniques are used to define intuitive and robust abstractions and interfaces for system specification and problem formulation. The framework is being developed using a service-oriented approach. The core modeling abstractions are being developed in a standardized way, e.g., the Core Manufacturing Simulation Model standard (Lee et al. 2011) has been used to facilitate the specification of complex manufacturing systems. Standard interfaces, e.g., PMML, are provided to communicate with third-party services for various analysis tasks. The analysis services are being built relying on the accurate transfer of relevant information through the standard interfaces. In the initial implementation, the framework is envisaged to carry only the basic items in each component. It is expected more component items will be developed through a collaborative effort by the community of researchers and practitioners.

4 PROPOSED INFRASTRUCTURE

In this section, we propose enhancements to the framework described in Section 3 to include simulation models in the framework and have their results be analyzed by data driven models.

4.1 Enhanced Framework for Model Based Analytics

Section 3 described the framework for data driven models for advanced manufacturing. Two of the essential components of the framework are the model ecosystem, which holds the digital representations of the manufacturing system, and the transformation layer, which enables the creation of data driven models from the digital representations. We extend these components to support simulation models. We extend the transformation layer to be able to automatically generate simulation models from the system representations in the model ecosystem. The implementation details are described in Section 5. Figure 2 shows the extended framework to support simulation models.

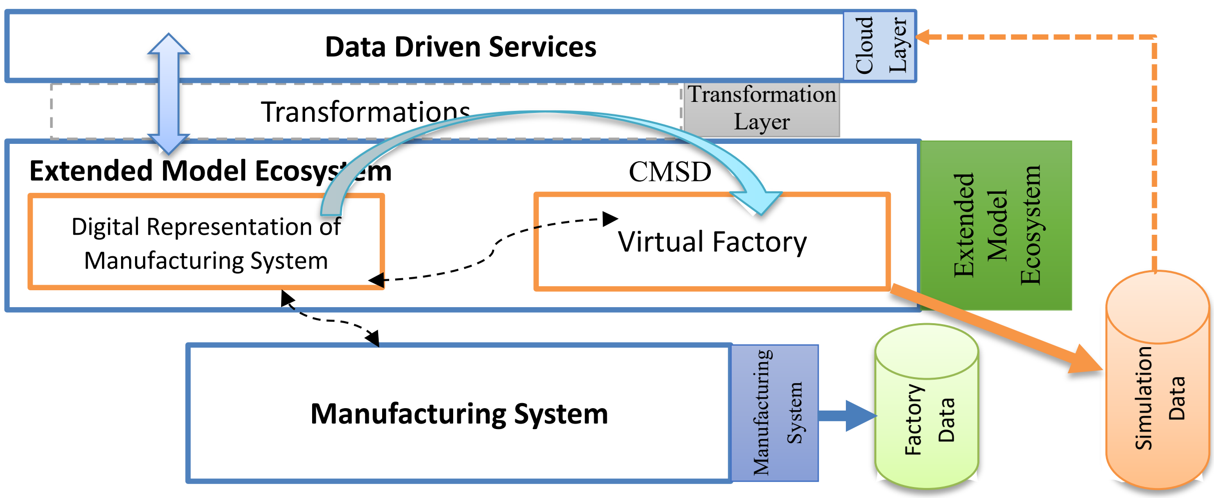

Figure 2: Extended framework for simulation model based analytics.

The goal of the extended framework is to provide the ability to easily configure simulations of a manufacturing system. The extended framework will allow users to make arbitrary changes to the digital representation of the system to easily create new configurations of the system. A model transformation component will automatically generate a simulation model from the digital representation in a standard CMSD (Riddick and Lee 2010) format. This allows users to rapidly generate multiple simulation models for various configurations. The standard simulation model may then be imported into a variety of simulation tools to run simulations. These simulations can be used for various purposes, such as generating synthetic data for new data driven models, or for performing other types of optimizations. In the subsections below, we discuss these applications in more detail.

4.2 Virtual Factory Model

The "model" employed for model based analytics is a virtual factory in the context of manufacturing. The virtual factory is envisaged as a multi-resolution model that allows representation and analysis of the corresponding real factory at different levels of hierarchy. In a real factory, the performance can be analyzed at various levels such as machines, cells, departments, and the entire factory including their interactions with supporting system using the data streams from various sensors and data collection systems. The virtual factory would allow analysis at the desired level of resolution similar to the real factory except it would have the advantage to create and analyze a range of future potential scenarios. The virtual factory will need to be closely linked to the real factory to be its high fidelity representation. The virtual factory will also need to be interfaced with data analytics applications similar to the real factory for this purpose. The virtual factory is proposed to reside in the extended model ecosystem to gain from defined interfaces to the real manufacturing system and the data driven models in the framework.

The virtual factory will have a synergistic relationship with data driven applications. The primary intent is of course to have the virtual factory generate data for model based analysis. However, the analytics applications will help the virtual factory in return by improving the data used for simulations. For example, the data for machine failures can be continuously tracked and periodically analyzed to improve the distributions used to represent them in the virtual factory.

4.3 Support for Model Development

The framework provides an intuitive domain specific modeling environment that makes it easy for practitioners to develop digital models that closely and accurately represent their manufacturing systems. The modeling environment enforces rules that ensure that the models are sound, and allows for error checking. Digital threads trace relationships between model elements and the physical component that they represent. This allows us to develop rule based transformations that can automatically create other types of models from these models. One example of such a model transformation allowed us to generate neural networks for predicting energy consumption from milling machine models (Lechevalier et al. 2014).

In the extended framework, we implemented such a model transformation to generate a CMSD file as a standard representation of a simulation model. This transformation is completely automated, and allows users to make changes in the factory model and quickly generate simulation models. The CMSD file may be imported into a simulation tool such as AnyLogic to execute the simulation. More details of the implementation are presented in Section 5.

4.4 Support for Analytics

As stated before, the transformation layer of the framework implements various model transformations to generate analytic models from the system model. Data from the factory is used to train the analytic models. However, in many cases data from the factory is not available. For example, if the factory is newly set up, there may not be sufficient historic data. Also, the user may want to experiment with various factory configurations, and data may not be available for all of these new configurations. In such cases, it is beneficial to have this data generated synthetically through simulations. Figure 2 shows how simulations can be executed to generate simulated data, which can then be used to train the analytic models.

5 INFRASTRUCTURE PROTOTYPE

In this section, we present our preliminary implementation of the framework, and describe its use through an example.

5.1 Implemented User Modeling Environment

The model ecosystem shown in Figures 1 and 2 was implemented using the Generic Modeling Environment (GME) (Ledezci et. al. 2001). GME is an open source tool for creating configurable modeling environments. We developed a meta-model (abstract model) in GME that describes the main concepts and modeling rules of the model ecosystem. The meta-model defines the rules based on which models can be built. The concepts and relationships in the meta-model are “instantiated” to build models. The models represent actual items in the physical systems in that domain. Figure 3 shows a screenshot of the domain specific modeling environment in GME. It shows an instantiated model of a manufacturing process, showing the process parameters, metrics and variables. The tree structure on the right of Figure 3 represents the hierarchical structure of the entire system model. The environment we implemented for this framework allows the user to model the factory layout, parts manufactured, the process plans, and the resources used.

We implemented a model transformation that takes the factory representation shown in Figure 3, and generates a CMSD file. The CMSD file is an XML file that represents all the elements of the factory model necessary to create a simulation of the factory. We implemented a plug-in for the AnyLogic simulation tool, to read the standard CMSD file and generate an AnyLogic simulation model. We executed the simulation in AnyLogic, and generated data from the simulation. The generated data was then used to train machine learning models for cycle time predictions for the purpose of order promising. We generated a Neural Network (NN) and a Gaussian Process Regression (GPR) model. These models are described in Section 5.3.

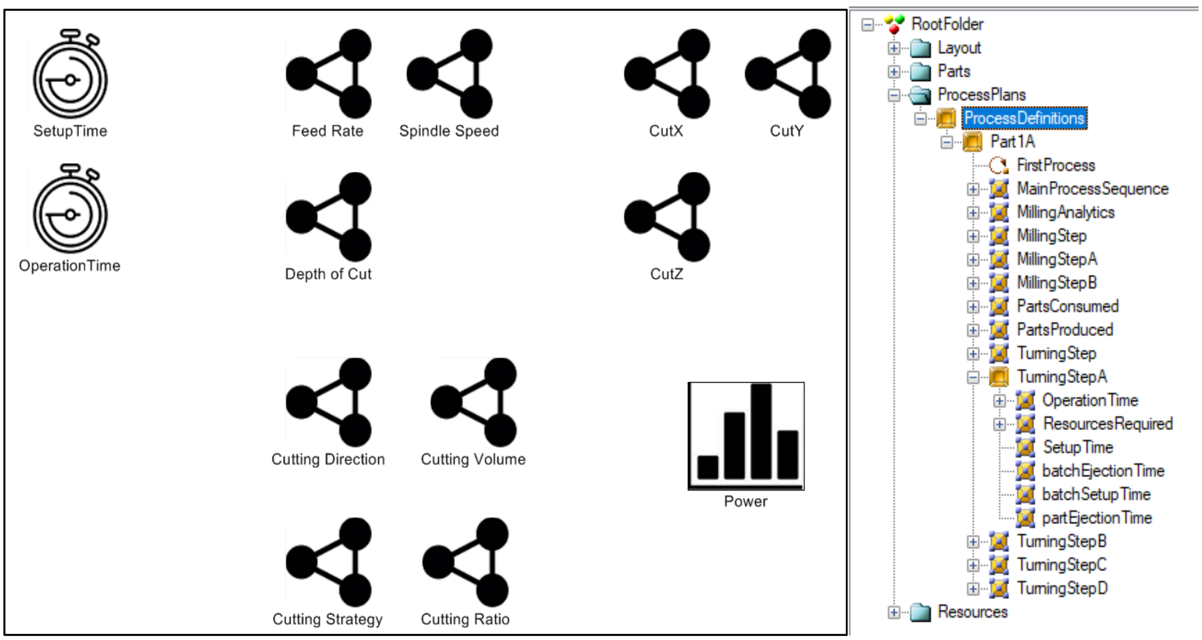

Figure 3: Model representation of a manufacturing process.

5.2 Implemented Virtual Factory Model

The virtual factory model is based on the scenario described in Jain et al. (2017) and Jain et al. (2018). The use case is based on order promising for a small job shop and hence the corresponding model may be referred to as a virtual job shop. The job shop produces parts from three different material types. The goal is to predict a shipment date at the time of the order, based on the material type chosen for the part, and the current load on the shop.

The job shop model was built in GME, in the domain specific modeling environment (DSME) described above. The DSME allows us to visually construct a hierarchical model of the job shop, and specify all the machine parameters within the model itself. The job shop model consists of a turning cell with four turning machines, and a milling cell with two milling machines. A process model is built in the DSME to describe the process flow. The model elements can be seen in the tree hierarchy on the right side of Figure 3. MillingStep and TurningStep specify the machine cells, and MainProcessSequence specifies the overall process sequence.

We implemented a translator tool that automatically generates a standard CMSD file from the shop floor model specified in the DSME. This CMSD file was then imported into the AnyLogic simulation tool (using another plugin that we implemented), to execute the simulation. The virtual factory prototype does have the capability to utilize multi-resolution models with the most detailed level capable of modeling machine dynamics. However, with the focus on analyzing job shop cycle times for this study, only the discrete event model of material flow across the shop was used. We generated synthetic data for the scenario from the simulation, which was then used to train a prediction model for order promising.

The advantage of building the model in the DSME and generating the simulation model, as opposed to building the simulation model directly in the simulation tool, is twofold. First, The DSME is designed to be used by a manufacturing domain expert, and uses concepts and visual representations that are easy to understand for a domain user. This can greatly accelerate model development, reduce model errors, and ease maintenance of models. Second, The DSME allows us to implement many different algorithms for various tasks in a more powerful and elegant way than does a simulation tool (which is restricted to simulation tasks). In particular, we can implement several model translators to generate other types of models from the specification in the DSME. For example, we implemented a Neural Network (NN) generator that can automatically generate a NN for a machine from its specification in the DSME (Lechevalier et al. 2014). This neural network can then be trained on data (real or synthetic) for that machine. Thus, from a single model in the DSME, we are able to generate and run a simulation, generate an NN model, and use the data from the simulation to train the NN. Figure 4 provides an overview of the infrastructure prototype.

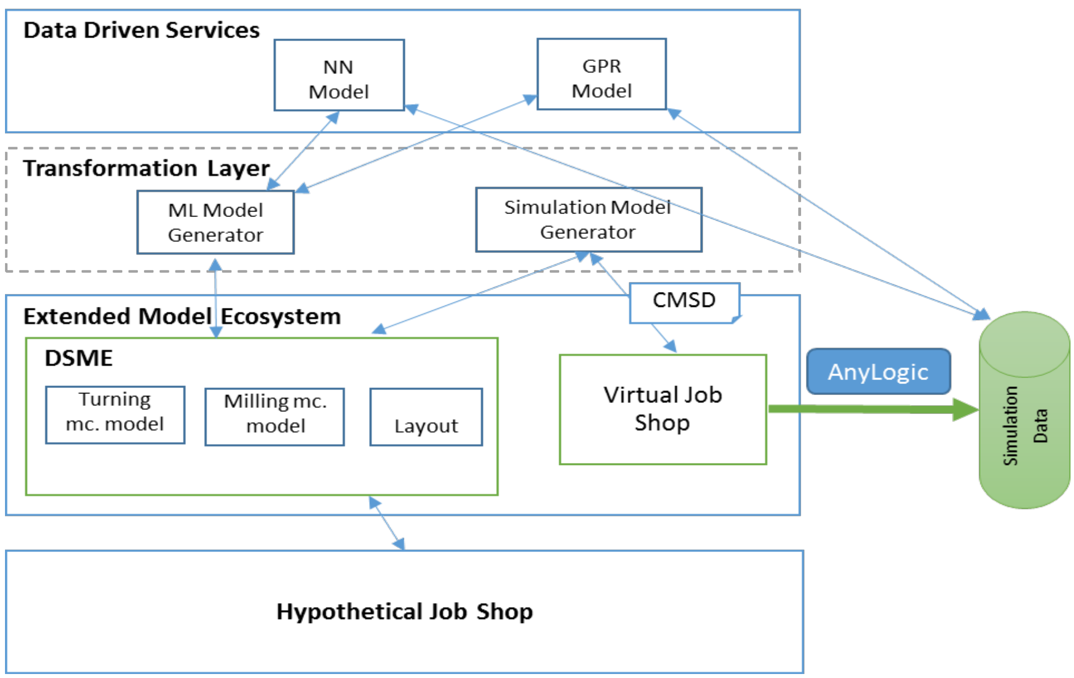

Figure 4. Overview of the implemented infrastructure prototype.

5.3 Implemented Analytics Applications

Based on the simulation model described above, we implemented two different machine learning models to predict throughput. We first trained a Neural Network (NN) model (Jain et al. 2017) for throughput prediction. We then generated a Gaussian Process Regression (GPR) model (Jain et al. 2018) for the same purpose, and compared it to the prediction accuracy of the NN model. We summarize these models here. For theoretical background on NNs and GPR, we refer the reader to Haykin (2004) and Rasmussen (2004).

The NN model takes a set of input variables and makes a prediction on a desired target variable. In our case, the target was "cycle time", which was needed to estimate the expected time for order completion. The input variables included the material type, the number of parts in the order, and the current load on the system. The material type is one of aluminum, steel or titanium, and is represented using one-hot encoding, i.e., it is represented by three variables (one for each material), with a zero or one depending on the material chosen. The load on the system is modeled by a triplet (n_A, n_S, n_T), which denotes the parts of material type aluminum, steel, and titanium currently being processed in the system. For a new job shop, there is not sufficient real data to train a reliable model for predicting duration under many varying conditions. Our simulation model described previously overcomes this problem, by generating simulated data for a variety of shop conditions. The data generated by the simulation model is then used to train the NN model. The resulting NN model is capable of predicting an estimated duration for new orders, and can be used to give an estimated ship date when the shop is operational.

We also created a Gaussian Process Regression (GPR) model for duration prediction from the same simulated data. GPR is a probabilistic method of interpolation to determine the target value from the inputs. GPR produces a distribution of the expected target value, allowing us to account for uncertainty in the prediction. The GPR model uses the same inputs and outputs but provides a prediction window for the target based on the uncertainty. In input regions where sufficient training data was available to provide a reliable prediction, the uncertainty is small. Figure 5 shows a comparison of the NN and GPR models on simulated test data. The grey color bands around the GPR predictions represent the confidence bounds generated by GPR. More details of the comparison between these prediction models can be found in Jain et al. (2018).

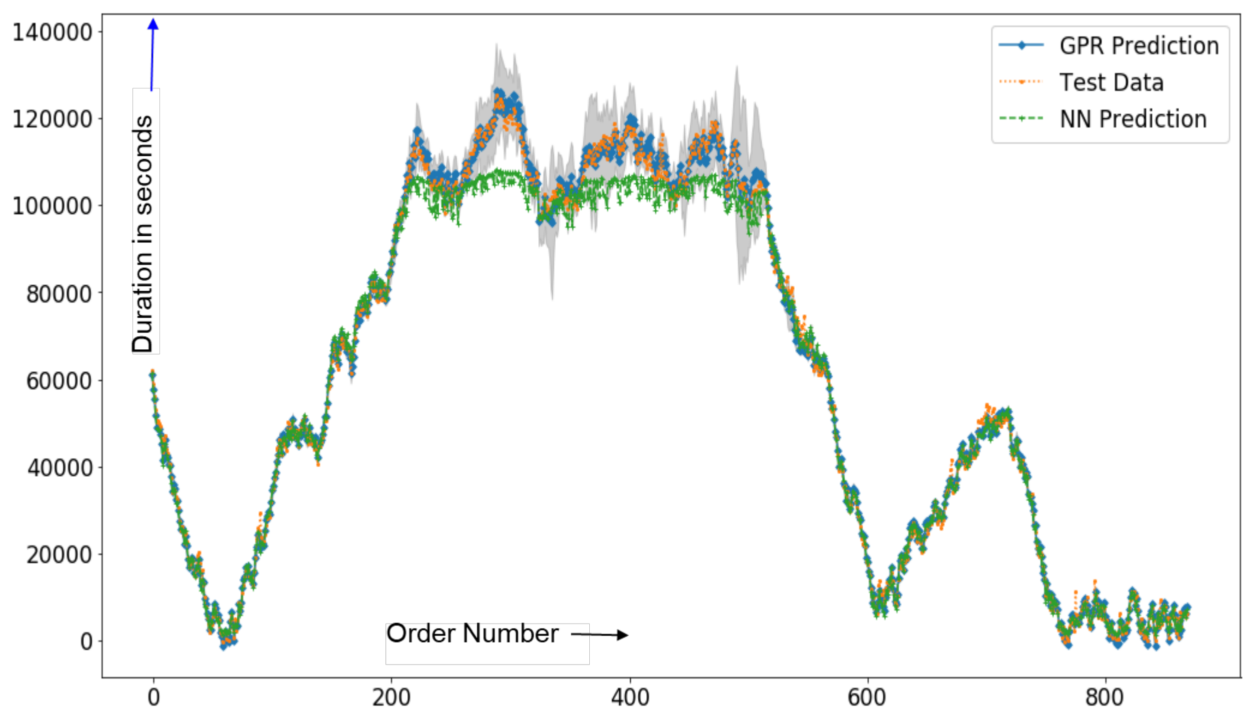

Figure 5: Comparing NN and GPR for cycle time predictions (Jain et al. 2018).

6 CONCLUSION

This paper proposed an infrastructure for model based analytics with emphasis on orienting the capability for SMEs. A prototype implementation for the infrastructure has been described that uses a small virtual factory to generate cycle time performance data that is then analyzed by NN and GPR applications to develop a predictive model for order promising. The next proposed step is to use data from a larger real manufacturing system to set up the model based analytics capability and exercise it for addressing issues of interest to the decision makers. Future work may focus on successive iterations of enhancements in all the components of the framework including the interactions with manufacturing personnel, increasingly automated generations of virtual factory models, interfaces of virtual factory with real factory data systems, and interfaces of virtual factory for guided analytics driven by decision makers.

DISCLAIMER

No approval or endorsement of any commercial product by the National Institute of Standards and Technology (NIST) is intended or implied. Certain commercial software systems are identified in this paper to facilitate understanding. Such identification does not imply that these software systems are necessarily the best available for the purpose.

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