Proceedings of the 2018 Winter Simulation Conference
M. Rabe, A.A. Juan, N. Mustafee, A. Skoogh, S. Jain, and B. Johansson, eds.

DIGITAL MANUFACTURING: REQUIREMENTS AND CHALLENGES FOR IMPLEMENTING DIGITAL SURROGATES

Guodong Shao

Engineering Laboratory
National Institute of Standards and Technology
100 Bureau Drive
Gaithersburg, MD 20899, USA

Deogratias Kibira

Department of Civil Engineering
University of the District of Columbia
4200 Connecticut Ave. NW
Washington DC, 20008, USA

ABSTRACT

A key challenge for manufacturers today is efficiently producing and delivering products on time. Issues include demand for customized products, changes in orders, and equipment status change, complicating the decision-making process. A real-time digital representation of the manufacturing operation would help address these challenges. Recent technology advancements of smart sensors, IoT, and cloud computing make it possible to realize a "digital twin" of a manufacturing system or process. Digital twins or surrogates are data-driven virtual representations that replicate, connect, and synchronize the operation of a manufacturing system or process. They utilize dynamically collected data to track system behaviors, analyze performance, and help make decisions without interrupting production. In this paper, we define digital surrogate, explore their relationships to simulation, digital thread, artificial intelligence, and IoT. We identify the technology and standard requirements and challenges for implementing digital surrogates. A production planning case is used to exemplify the digital surrogate concept.

1 INTRODUCTION

Managing a manufacturing system to meet production objectives in the face of dynamic events and changing priorities is a major challenge. Recent technology advancement of smart sensors, Internet of Things (IoT), cloud computing, artificial intelligence (AI), cyber-physical systems (CPS), and simulation make it possible to realize the "digital twin" of a manufacturing system (Bolton 2016). These technologies enable real-time data collection, computation, communication, integration, modeling and simulation (M&S), optimization, and control. The concept of the digital twin originated by Grieves and Vickers (2016) is to create a digital informational construct of a physical system as an entity on its own. This digital information would be a "twin" of the information that was embedded within the physical system and be linked with that physical system through the entire lifecycle of the system. The digital twin concept was intended to allow manufactures for creating models of the physical production systems and processes using historical and real-time data from smart sensors for near-real-time analysis and system performance improvement.

To promote the digital twin concept, the Digital Manufacturing and Design Innovation Institute (DMDII) has recently supported projects that demonstrate technologies for digital twins (Tobe 2016). On Gartner's 2017 Hype Cycles of Emerging Technologies, digital twin is listed with a time to acceptance of (five to ten) years, i.e., by 2022, one-half of companies will be using digital twins to achieve more efficient system performance analysis and improved productivity (Panetta 2017). Already, major corporations such as Boeing, Siemens, PTC (*Parametric Technology Corporation)*, Dassault Systems, ANSYS, and the Department of Defense (DoD) have started to actively develop digital twins of their products and individual assets. International Data Corporation (IDC) forecasts that companies investing in digital twins will see improvements of 30 % in cycle times of their critical processes in the next five years. By far, the most active company in this drive is General Electric (GE), which is developing digital twins for power stations, clean energy stations (e.g., wind turbines), as well as manufacturing systems.

To date, most implementations of the digital twin concept have been for monitoring and improving product design and performance throughout the product lifecycle (Grieves 2014). Research efforts are underway to advance digital twins to the manufacturing systems or processes that produce the products. Many companies, especially small- and medium-sized enterprises (SMEs), do not have the expertise and resources required to effectively implement the digital twin concept for their manufacturing systems and processes. They lack understanding of the digital twin concept, definition, and associated challenges, and typically have neither sufficient information on the required technologies and standards, nor systematic procedures necessary to implement a digital twin.

There are various definitions of digital twin out there (Grieves and Vickers 2016; Maurer 2017). However, none of them can accurately capture or address the purpose, because the context information is missing and representations are context dependent. “is equivalent to” or “duplication of” makes “digital twin” so abstract and almost impossible to implement. In this paper, we explain the digital twin concept and provide our own definition of “digital surrogate” as an alternative to “digital twin.” We also identify (1) the role of simulation within digital surrogates and the relationships among IoT, AI, digital thread, and digital surrogates; (2) the challenges for realizing digital surrogates, (3) the standards needed to perform modeling, data collection, data analytics, modeling and simulation, and system integration, (4) an illustrative example of production planning applications to demonstrate the concept of digital surrogate, and (5) future areas of research to fully realize digital surrogates for manufacturing systems. We believe that with enabling standards and technologies, companies, including SMEs, will be able to develop digital surrogates for their specific objectives much more easily, cheaply, and faster.

Showcasing the digital surrogate concept for supporting production planning and control in the case example is motivated by a survey carried out by the Supply Chain Management (SCM) World. The survey reveals that the most pressing challenges facing manufacturers today are response time to unforeseen events, meeting delivery dates, new product introduction cycle times, and a flexible product mix (Manenti 2015). Kibira et al. (2016) developed inceptive methodologies for integrating heterogeneous methods and tools including data analytics and simulation-based optimizations, which can help address these challenges when incorporated within the digital surrogates.

The rest of the paper is organized as follows. Section 2 gives the definition of the digital surrogate within the CPS environment and discusses the relationships of digital surrogates with simulation, IoT, data analytics (AI and machine learning), and digital thread. Section 3 summarizes general challenges of implementing digital surrogates. Section 4 identifies relevant standards that support the digital surrogate implementation. Section 5 describes an illustrative example. Section 6 presents the final discussion and conclusion.

2 DEFINITION AND SCOPE

In this paper, we propose “digital surrogate” as an alternative to “digital twin”, which is appropriate for a specific context, especially for modeling and simulation. We define digital surrogate as “An integrated model that represents, connects, and synchronizes a part of or the whole physical manufacturing system or process, enabled by historical and real-time data from the physical system or process.” With the capabilities of data analytics, simulation, and optimization, the digital surrogate describes the physical system with desired knowledge, capabilities, behaviors, and characteristics. Multiple digital surrogates may be required for some situations such as a distributed manufacturing system.

Figure 1 shows the digital surrogates in a CPS environment. The digital surrogates and the physical systems are connected through IoT or smart sensors and actuators, i.e., the digital surrogates are fed with real-time data from their physical systems, and control and action commands are sent back to the physical systems. Synchronization between digital surrogates and the physical systems, either online or offline, ensures that the production systems are constantly optimized as the digital surrogates receives real-time performance information from the physical system. The integration between model components within a digital surrogate is enabled through application of relevant interoperability standards.

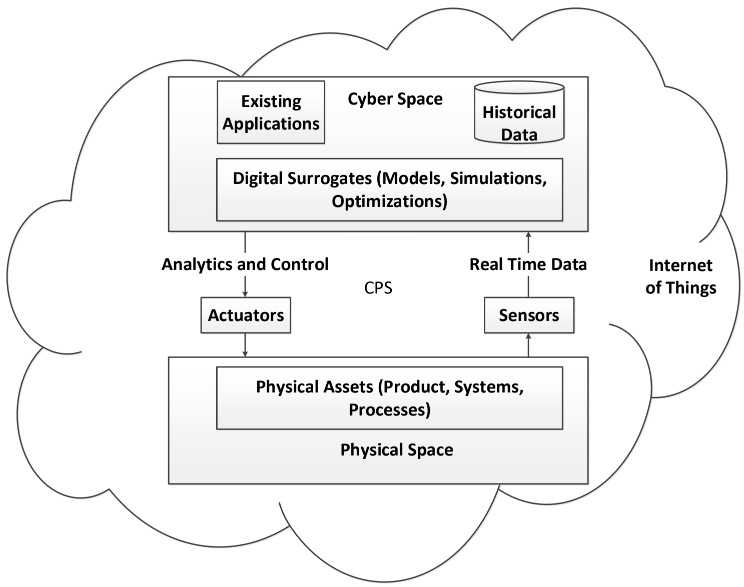

Figure 1: Relationship among Digital Surrogates, CPS, and IoT.

The main goal of digital surrogates is to analyze and optimize a manufacturing system or a process in the cyber-space. The digital surrogates can monitor the status of production systems or processes, predict system performance, and prescribe system behavior or control actions without interrupting production operations in the physical space. By integrating data from both the cyber-space and the physical space, digital surrogates can help evaluate alternative plans and schedules, schedule maintenance, optimize operations in real-time, and prescribe future operations. Specifically, the digital surrogates utilize historical and real-time data to perform data analytics; interact with other manufacturing applications; simulate the factory floor, systems, and processes; track manufacturing operations; detect system performance deficiencies; and derive actionable recommendations for better designs, validated and optimized processes, and optimal maintenance cycles.

A typical digital surrogate has three basic conditions: (1) physical systems connected through IoT, (2) a digital thread that collects, processes, and manages data, and (3) the capabilities to use the collected data to derive actionable recommendations through modeling and simulation, data analytics, and optimization. Digital thread is an information flow that shares and connects the product's data throughout its lifecycle (Hedberg et al. 2016). The following subsections discuss the relationships of digital surrogates with manufacturing simulation, IoT, data analytics (machine learning and AI), and digital thread in more details.

2.1 The Simulation Aspect of Digital Surrogates

The lifecycle of a product or a system includes design, manufacturing, services and operations, and end of life. Simulation, as a major component in the digital surrogates, can be used and integrated in any of these phases throughout multiple layers of operation and decision-making (AIChE 2012). Depending on the lifecycle phase and type of analysis, the type, role, and required level of simulation resolution can vary. Our focus is on the manufacturing system where simulation plays important roles, before, during, and after production. These are briefed below.

Before production: Simulation can be used to model and validate factory layout design, customer demand, and market analysis. Simulation can also be used to evaluate new products and processes, perform sensitivity analyses, and validate products, processes, and system configurations. The results of the analyses help determine material, labor, equipment, tooling, material handling, maintenance requirements, inventory policy, throughput, and resource utilization. With these analyses, simulation helps develop and validate aggregate plans for long-term production.

During production: Simulation can be used to minimize production lead times, determine work flow, and evaluate and generate production plans and schedules (Boschert and Rosen 2016). Simulation also helps identify bottlenecks, plan for equipment breakdowns and repair, assess energy consumption and environmental impact, determine best ergonomic practices, and evaluate effects of inventory policy, location, size, deliveries, and inventory tracking. These help maximize the efficiency of production schedules on weekly or daily basis.

After production: Simulation, when integrated with supply chain models, can be used to analyze delivery requirements, minimize transport costs, and maximize customer satisfaction. For a new supply chain, simulation can help determine the location of distribution points, fleet capacity, and optimal inventory levels.

Simulation models within a digital surrogate do not have to be 3D models. However, Virtual Factory (VF) is often in the form of high-fidelity 3D simulation models (Jain et al. 2017). Tao and Zhang (2017) propose a four-level procedure to consider when modeling 3D simulation: (1) geometry, (2) physical, (3) behavior, and (4) rules. For example, to model a machining center based on the real machine's specification, first 3D geometries have to be built according to the shapes and dimensions of the machine. Second, physical properties such as functions, capacities, and cutting force need to be modeled. Third, the behavior models of the controller need to be integrated to respond to the Numerical Control (NC) commands. Finally, rules such as constraints, limitations, and domain knowledge need to be captured and modeled. The completed and validated machining center model is ready to be connected and synchronized with the real machine. NC program validation and collision detection can then be performed using the virtual machining center both online and offline (Shao et al. 2010).

2.2 Internet of Things and Digital Surrogates

IoT allows for large numbers of sensor-equipped devices that supply manufacturers with large amounts of real-time data, permitting higher levels of optimization (Wasserman 2017). All data from IoT are descriptive in nature, i.e., the data describe what happened and when it happened. Using data analytics and simulation, these data can be made predictive, i.e., indicating when something may happen. For example, if failures of a product or a system are predicted, the digital surrogates will inform the users to better schedule maintenance to avoid failures. Furthermore, the results of data analytics and simulation can prescriptively indicate how the systems will work and can detect design flaws early and minimize implementation cost (Brigham and Overton 2016; Shao et al. 2014). As a typical IoT application, predictive maintenance is case-based reasoning enabled by operational data. The digital surrogates handle this by incorporating product and production data, including maintenance history, from design to operation.

Many complex industrial processes are still equipped with Supervisory Control and Data Acquisition (SCADA) systems, which can also provide sensor data to the digital surrogates.

2.3 Machine Learning and AI Aspect of Digital Surrogates

Real-time production data are the basis for realizing digital surrogates. Through IoT, sensors, and AI, big data can be collected and generated. The manufacturing system components and processes often have multiple variables and multiple streams of data that require data analytics to provide insights. Machine learning algorithms can help discover patterns from the data. AI, represented by deep learning, specifically for image and video processing, and text and speech processing (with *convolutional neural network*s and recurrent neural networks respectively) can also be incorporated as input into models. For example, models with video input during manufacturing can be used to detect defective items (Vorhies 2018).

As a component of digital surrogates, data analytics techniques such as AI and machine learning can be used to dynamically analyze data and feed the results into simulations. The simulations can be updated as the states of the system change. This near-real-time update and continuous learning from multiple sources enable digital surrogates to represent the current status, condition, or position of the physical system.

Traditional data analytic models are typically retrospective. But recently, algorithms such as the Flojolet-Martin, Heavy Hitter, and Count-min sketch have been developed for making sense of constantly streaming data (Aggarwal 2007). This is the type of data expected from the operating physical system and the digital surrogates. The output of the streaming data algorithms will enable real-time predictive feedback.

2.4 Digital Thread and Digital Surrogates

Digital thread provides the ability of accessing, integrating, analyzing, and transforming data from disparate systems into actionable information. It helps deliver the right information at the right time to the right place. Through the digital thread, design engineers can work with manufacturing engineers to create models for production process instructions. Digital thread enables the use of cloud services, facilitates systematic shop floor control, and helps deliver real-time data for simulation.

The digital surrogate and digital thread concepts help manufacturers understand their operations by reflecting the exact operating conditions like performance and failure modes, but their applications and functionalities are different from one another (Joshi 2017). Digital thread is essential for the realization of digital surrogates by providing all the required product and production information and enabling various capabilities in the digital surrogates.

3 CHALLENGES AND IDENTIFIED NEEDS OF CREATING DIGITAL SURROGATES

In digital surrogates, simulation models need to be integrated with other systems such as data analytics and optimization. Multiple simulation models using different modeling methods and tools may need to be developed and integrated. However, most simulation tools have a low level of interoperability with other manufacturing applications. Riddick et al. (2011) noted that even when outward interfaces are provided, they are normally undocumented or proprietary. This interoperability problem persists today. Additional efforts are, therefore, needed to facilitate the integration of data, simulations, and virtual factory models. The workshop on "Research Challenges in M&S for Engineered Complex Systems" identified four key research areas to enable M&S to remain an effective method (Workshop 2016):

- Conceptual modeling: Advances in conceptual modeling are essential to enable correct, efficient, and effective translation of the conceptual model into a corresponding executable simulation model.
- Computational: M&S does not yet fully exploit the potential and opportunities offered by technologies such as mobile and ubiquitous computing, big data, IoT, cloud computing, and supercomputer architectures. More research is needed.
- Uncertainty quantification: During M&S development, there are uncertainties inherent in the data used to create the model and the behaviors and processes defined within the models. Understanding and managing these uncertainties are critical. New standards, guidelines, and approaches are required to guide users to incorporate and manage uncertainty correctly throughout the model lifecycle.
- Reuse of models: Developing and integrating model components and simulations of subsystems can be time consuming and expensive and also introduce more uncertainties. Advances are needed to enable better reuse of models and ensure efficient, reliable, and credible simulation integration.

Even when using commercial-off-the-shelf (COTS) simulation software, it is time-consuming to develop and verify complex models. Efficient methods for generating simulation models are needed. Appropriate levels of detail and fidelity for simulations need to be determined before the modeling. Focusing mainly on modeling and simulation, below we list some general challenges and requirements for implementing digital surrogates (Mourtzis et al. 2014; Tobe 2016):

- Lack of open architectures that allow for integrating simulations with different levels of fidelity.
- Lack of intelligent modeling tools for autonomous and self-adapting systems.
- Lack of modeling tools for lifecycle simulation.
- Lack of simulation applications that run in mobile devices.
- Lack of secure, reliable, and affordable cloud-based COTS simulation solutions.
- Lack of robust engineering change management processes to ensure that digital surrogates accurately maintain the physical configurations.
- Lack of model Verification and Validation (V&V) guidelines for users to maintain the validity of the model through its lifecycle.
- More-powerful CPUs for high performance simulations of complex manufacturing systems or processes.
- More-affordable real-time factory controlling and monitoring tools. The technologies related to virtual factory are still in their infancy.
- SMEs need to initiate the process towards digitization and convert design and manufacturing information to digital models.

All data within the CPS environment including historical data, data collected through IoT, and data generated from data analytics need a holistic approach to be stored, managed, and analyzed. The challenges regarding data include (Wasserman 2018):

- Data ownership: defining who owns the IoT data.
- Data governance: setting up a system of trust for sharing the IoT data.
- Data interoperability: ensuring data compatibility for easy exchange.
- Data management: manipulating data using existing tools and procedures.
- Data security: ensuring data are kept secure, secret, and accurate.

4 RELATED STANDARDIZATION EFFORTS

There is a wide range of formats used for collecting and sharing big data streams in the real world. Standards are needed to improve the interoperability of data exchange among different applications within the digital surrogates. In this section, relevant standards for different domains such as product design, production engineering, manufacturing operations from various functional categories including simulation, integration, data collection, data analytics; verification, validation, and uncertainty quantification (VVUQ); and digital surrogates are identified and organized according to the ISA 95 levels (ISA 2014). Please note that this list is not exhaustive. Some standards may belong to multiple levels to support different levels of resolution for modeling and analysis within the digital surrogates.

Level 4 (The enterprise level):

- The Open Applications Group Integration Specification (OAGIS) standard defines business messages for application-to-application for business level integration (OAGi 2018).
- The High-Level Architecture (HLA) is an interoperability standard for distributed simulation systems across the supply chain. Using HLA, simulations can interact (i.e., for both data communication and time synchronization) with other simulations or manufacturing applications regardless of the computing platforms. The interaction between simulations is managed by a run-time infrastructure (RTI). HLA is the standard technical architecture for all US Department of Defense (DoD) simulations (Fujimoto 2015).
- ISO/AWI 23247, Digital Twin manufacturing framework, is intended to provide guidelines, methods, and approaches for the development and implementation of digital twins. This is a newly ISO-approved work item.

Level 3 (The manufacturing operations management (MOM) level):

- The Core Manufacturing Simulation Data (CMSD) standard was developed for exchanging data among simulation and other manufacturing applications at the National Institutes of Standards and Technology (NIST) (SISO 2012). CMSD can represent manufacturing production operations including stochastic characteristics of production processes using probability distributions, which is needed for simulation modeling. It can also be used for applications at level 2.
- IEC 62264 describes the MOM domain and its activities, and the interface content and associated transactions within Level 3 and between Level 3 and Level 4. This description enables integration between the manufacturing operations and control domain and the enterprise domain. Its goals are to increase uniformity and consistency of interface terminology and facilitate the implementations of these interfaces (IEC 2013; Trappey et al. 2016).
- ISO 15531 standard (MANDATE) addresses information exchanges between software applications according to five identified activities, i.e., planning, scheduling, simulation, control, and execution (ISO 2012; Cutting-Decelle et al. 2007).
- ISO 10303 is a standard for the computer-interpretable representation and exchange of product manufacturing information. It is also known as STEP (Standard for the Exchange of Product model data) (ISO 2014).
- QIF (Quality Information Framework) supports digital thread concepts in engineering applications ranging from product design through manufacturing to quality inspection. Based on the XML standard, it contains a library of XML schema ensuring both data integrity and data interoperability in Model Based Enterprise implementation. It also supports IoT (QIF 2015).
- PMML (Predictive Model Markup Language) is the de facto standard to represent predictive and descriptive models, and pre- and post-processed data (PMML 2018). PMML allows for interchanging data-analytics models among different tools and environments, mostly by avoiding proprietary issues and incompatibilities. The XML-based PMML allows for representing many data-mining models including neural networks and decision trees.
- PFA (Portable Format for Analytics), is a JSON-based specification for statistical models; while PMML's focus is on statistical models in the abstract, PFA's focus is on the scoring procedure itself. PMML can express only a fixed set of pre-defined model types whereas PFA represents models and analytic procedures more generally by providing generic programming constructs (PFA 2018).

Level 2 (The SCADA level):

- The OPC Unified Architecture (OPC UA) is a platform-independent standard through which various systems and devices can communicate by sending messages between clients and servers over various networks. OPC-UA enables syntactic interoperability between clients and servers (OPC UA 2017).
- IEC 62714 series is used for engineering data exchange in the industrial automation systems engineering domain. Automation Markup Language (AML), an XML schema-based data format, is used in the standard. It integrates engineering tools in different disciplines, e.g., mechanical plant engineering, process engineering, process control engineering, PLC programming, etc. (IEC 2014).
- ISO 15746 facilitates the integration and interoperability of software tools for Advanced Process Control and Optimization (APC-O). The modules at level 2 provide production information to the Manufacturing Execution System (MES) at level 3, and in return accept and execute the corresponding operational commands from the MES (ISO 2015; ISO 2017b).

Level 1 (The device level):

- MTConnect is a manufacturing interoperability standard that provides a semantic vocabulary for equipment to generate structured contextualized data with no proprietary format. MTConnect data sources include production equipment, sensor packages, and other factory floor devices. Applications using MTConnect data provide better interoperability, more efficient operations, improved production optimization, and increased productivity (MTConnect, 2018).
- ISO/IEC 20922 is a client server publish/subscribe messaging transport protocol. It is lightweight, open, simple, and designed to be easy to implement. These characteristics make it ideal for use in constrained environments such as communication in Machine-to-Machine (M2M) and IoT contexts, where a small code footprint is required and network bandwidth is at a premium (ISO/IEC 2016b). It is also known as MQ Telemetry Transport (MQTT).
- ISO/IEC 30128 describes the generic sensor network application's operational requirements, the sensor network capabilities, and mandatory and optional interfaces between the application layers of service providers and sensor network gateways (ISO/IEC 2014).
- ISO 13374 series provide the basic requirements for open software specifications that allow for condition monitoring and diagnostics of machines for data processing, communication, and presentation, independent of platform and hardware (ISO 2017a).

The following standards can be applied at any of the ISA 95 levels:

- ISO/IEC 17826:2012 specifies the interface to access cloud storage and to manage the data stored (ISO/IEC 2016a).
- The American Society of Mechanical Engineers (ASME) V&V standards committee is to create best practices, general guidance, and a common language for verification, validation, and uncertainty quantification for Computational modeling and Simulation in advanced manufacturing (ASME 2018). The guidelines for incorporating VVUQ for data-driven models and throughout model lifecycle are especially applicable to digital surrogate creation.

Major vendors also provide packages such as Dassault Systèmes' 3DEXPERIENCE Platform, PTC Creo CAD program, and Siemens PLM Software's Simcenter to support industry-standard 3D exchange file formats such as STEP, STL (STereoLithography), IGES (Initial Graphics Exchange Specification), OBJ (.OBJ), and JT (Jupiter Tesselation). These tools may be useful for digital surrogate development.

The applications of these standards and tools for digital surrogate implementations depend on the specific problem domain. For example, the combination of CMSD, MTconnect, and PMML may be enough for a machine shop digital surrogate implementation.

5 AN ILLUSTRATIVE EXAMPLE

We demonstrate the role of M&S in a digital surrogate with a case of production planning, scheduling, and control, the most popular application area for discrete-event simulation in a manufacturing system (Negahban and Smith 2014). Production planning, scheduling, and control functions require real-time data from different functions of the production system including shop floor machine status, work in progress, customer orders, and procurement. Production-planning activities are generally carried out at three levels:

1. At the aggregate level, simulations are used for generating and evaluating a proposed production plan. Simulation helps investigate the feasibility and stability of an original plan and test how sensitive it would be to changes in the operating environment.
2. At the operational level, simulations help ensure a feasible schedule, based on the production plan, by investigating its flexibility should unforeseen events occur.
3. At the dispatching and control level, simulation is used to determine if the plan and schedule can be executed using currently available resources.

The aggregate planning simulation needs real-time data such as material stock, work-in-progress inventory, human workload, equipment capacity, product life-cycle data, process documents, and forecast demand data. If the original plan is not valid, it will be revised until the simulation shows that the level of output can be executed for a given planning period. The plan can then be passed on to the operational planning level.

At the operational planning level, simulation requires more detailed information such as status of individual machines and other assets to develop a schedule to execute the plan. Each physical asset in the production system (such as machines and material handling equipment) has a corresponding virtual component in the digital surrogate. Simulation models of machines within the digital surrogate, for example, provide prediction of equipment failure and assessment of human resource availability and performance. These data are incorporated into a revised operation plan that results in a more accurately assessed production level plan. Tao and Zhang (2017) have proposed the concept of fusing physical system and simulation system data as production plans are formulated and generated. The digital surrogate in this context resolves conflicts in the plan before actual production by providing the necessary feedbacks to enable modification.

The verified operational plan is executed at the shop floor level with the allocation of individual resources to production tasks. If the real-time states of resources change, changes to the operational plan can be evaluated through simulation modeling. The sequence of production tasks from the simulation is used to start the production process and is synchronized with the predefined order.

The simulation needs to interact with data analytics to make sense of the large number of variables and parameters to achieve optimal performance. Considering the large volume and variety of collected data, performing data analytics reveals parameters that are associated with a given type of system output. Data analytics can determine data associations and dependencies, and relate inputs and outputs from simulation models. Data analytics can generate variables and parameters related to the required performance so that modelers can use these variables and parameters as inputs to the simulation models.

Figure 2 illustrates the interactions among models and standards used for production planning and control of a machine shop. Our previous work developed a framework of a virtual factory for multi-level production planning (Kibira and Shao 2016; Kibira et al. 2016). Data, such as processing times, machine status, and energy use, are collected from the shop floor and input to data analytics. Data analytics generates relevant variables and parameters suitable for simulation modeling. Optimization systems, tightly integrated with simulation, exchange information through CMSD to derive optimal production plans that are generated by the simulation. The final output to the physical machine shop is the optimal plan and the control parameters.

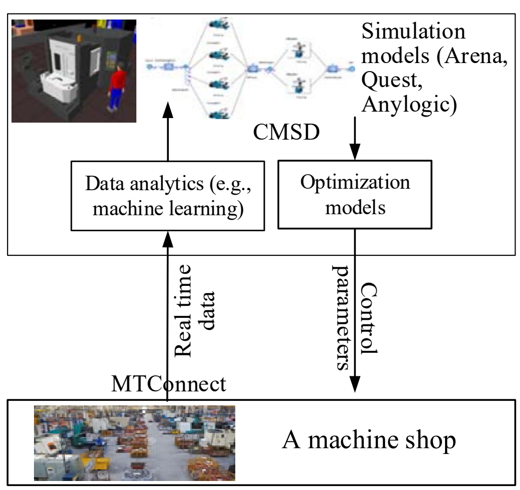

Figure 2: Simulation role in a digital surrogate for production control in a machine shop.

6 DISCUSSION, CONCLUSION AND FUTURE WORK

In this paper, we define "digital surrogate" as an alternative to "digital twin" and discuss the digital surrogate concept, relevant technologies, standards, and challenges. Combined research efforts from industry, government, and academia are needed to overcome the challenges and expedite the realization and the adoption of digital surrogates. The relevant technologies include M&S, virtual factory, optimization, and data analytics including AI, and machining learning. Applicable standards include common agreement on data collection, data analytics, knowledge representation, information modeling, model exchange, communication, interoperability, and other digital-twin-related standards. Research results that industry needs include modeling methodologies and frameworks that provide a systematic view for model creation; integration; VVUQ; reusable model component library that enables more efficient model building; standard development for specific digital surrogate needs; as well as implementation guidelines for digital surrogates in specific manufacturing domains.

We will collaborate with industry to identify case studies, develop digital surrogate prototypes for demonstration, and participate in relevant standard development, testing, and validation.

DISCLAIMER

No approval or endorsement of any commercial product by 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.

REFERENCES

AIChE (American Institute of Chemical Engineers). 2012. Smart Manufacturing: The Next Revolution. *Skype for Business Industry News*. http://www.lyncmigration.com/news/2012/10/22/6667845.htm#, accessed March 10th, 2018.

Aggarwal, C. C. 2007. *Data Streams: Models and Algorithms*. Boston/Dordrecht/London: Kluwer Academic Publishers.

ASME. 2018. ASME V&V 50 Verification and Validation of Computational Modeling for Advanced Manufacturing. https://cstools.asme.org/csconnect/CommitteePages.cfm?Committee=101978604, accessed February 8th, 2018.

Bolton, D. 2016. What Are Digital Twins and Why Will They Be Integral to The Internet Of Things? https://www.applause.com/blog/digital-twins-iot-faq/, accessed February 8th, 2018.

Boschert S. and R. Rosen. 2016. "Digital Twin – The Simulation Aspect". In *Mechatronic Futures*, edited by P. Hehenberger and D. Bradley. Cham: Springer.

Brigham, J. C. and J. Overton. 2016. The Digital Twin. https://blogs.dxc.technology/2016/09/08/the-digital-twin/, accessed March 15th, 2018.

Cutting-Decelle, A. F., R. I .M. Young, J. J. Michel, R. Grangel, J. Le Cardinal, and J. P. Bourey. 2007. "ISO 15531 MANDATE: A Product-Process-Resource Based Approach for Managing Modularity in Production Management." *Concurrent Engineering: Research and Applications* 15: 217–235.

Fujimoto, R. 2015. The High Level Architecture: Introduction. http://www.acm-sigsim-mskr.org/Courseware/Fujimoto/Slides/FujimotoSlides-20-HighLevelArchitectureIntro.pdf, accessed March 15th, 2018.

Grieves, M. 2014. "Digital Twin: Manufacturing Excellence through Virtual Replication". White Paper, http://innovate.fit.edu/plm/documents/doc_mgr/912/1411.0_Digital_Twin_White_Paper_Dr_Grieves.pdf, accessed March 15th, 2018.

Grieves, M. and J. Vickers. 2016. "Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems (Excerpt)". Florida Institute of Technology/NASA.

Hedberg Jr, D. T., J. Lubell, L. Fischer, L. Maggiano, and A. B. Feeney. 2016. Testing the Digital Thread in Support of Model-based Manufacturing and Inspection. *Journal of Computing and Information Science in Engineering* 16(2), doi:10.1115/1.4032697.

IEC. 2013. IEC 62264-1: *Enterprise-control System Integration – Part 1: Models and Terminology*.

IEC. 2014. IEC 62714: *Engineering Data Exchange Format for Use in Industrial Automation Systems Engineering – Automation Markup Language*.

ISA, 2014, ISA-95: *Enterprise-System Integration*.

ISO. 2012. ISO-15531-1: *Manufacturing Management Data Exchange (MANDATE) Standard*.

ISO. 2014. ISO 10303: *Industrial Automation Systems and Integration – Product Data Representation and Exchange*.

ISO. 2015. ISO 15746-1: *Automation Systems and Integration – Integration of Advanced Process Control and Optimization Capabilities for Manufacturing Systems – Part 1: Framework and Functional Model*.

ISO. 2017a. ISO 13374: *Condition Monitoring and Diagnostics of Machines – Data Processing, Communication and Presentation*.

ISO. 2017b. ISO 15746-2: *Automation Systems and Integration – Integration of Advanced Process Control and Optimization Capabilities for Manufacturing Systems – Part 2: Activity Models and Information Exchange*.

ISO/IEC. 2014. ISO/IEC 30128: *Information technology – Sensor Networks – Generic Sensor Network Application Interface*.

ISO/IEC. 2016a. ISO/IEC 17826: *Information Technology – Cloud Data Management Interface (CDMI)*.

ISO/IEC. 2016b. ISO/IEC 20922:2016. *Information Technology – Message Queuing Telemetry Transport (MQTT) v3.1.1*.

Jain, S., G. Shao, and S. J. Shin. 2017. “Manufacturing Data Analytics Using a Virtual Factory Representation”. *International Journal of Production Economics*. 55(18):5450-5464.

Joshi, N. 2017. “Digital Twin and Digital Thread” https://www.allerin.com/blog/digital-twin-and-digital-thread, accessed March 15th, 2018.

Kibira, D. and G. Shao. 2016. “Virtual Factory for Supporting Production Planning and Control”. In *Proceedings of the IFIP Advances in Information Communication Technology*, *APMS 2016*, September 3rd-7th, Iguassu, Brazil, 291–298.

Kibira, D., G. Shao, and B. Johansson. 2016. “Framework for Standardization of Simulation Integrated Production Planning”. In *Proceedings of the 2016 Winter Simulation Conference*, edited by T. M. K. Roeder et al., 2970–2981. Piscataway, New Jersey: IEEE.

Manenti, P. 2015. Becoming a Smarter Manufacturer: How the Internet of Things Will Change the World. SCM World, http://www.scmworld.com/wp-content/uploads/2016/11/Becoming-a-Smarter-Manufacturer.pdf, accessed March 15th, 2018.

Maurer, T. 2017. What is a Digital Twin? https://community.plm.automation.siemens.com/t5/Digital-Twin-Knowledge-Base/What-is-a-digital-twin/ta-p/432960, accessed March 15th, 2018.

Mourtzis, D., M., Doukas, and D. Bernidaki. 2014. “Simulation in Manufacturing: Review and Challenges”. In *Proceedings of the CIRP Sponsored DET 2014 Conference*. Procedia CIRP 25 (2014) 213-229.

MTConnect. 2018. *A free, open standard for the factory*.

Negahban, A. and J. S. Smith. 2014. “Simulation for Manufacturing System Design and Operation: Literature Review and Analysis”. *Journal of Manufacturing Systems* 22: 241–261.

OAGi. 2018. *Open Application Group’s Integration Specification*.

OPC UA. 2017. *OPC-UA Services Specification*.

Panetta, K. 2017. Top Trends in the Gartner Hype Cycle for Emerging Technologies. https://www.gartner.com/smarterwithgartner/top-trends-in-the-gartner-hype-cycle-for-emerging-technologies-2017/, accessed February 22nd, 2018.

PFA. 2018. *PFA: Portable Format for Analytics* (version 0.8).

PMML. 2018. *The Predictive Model Markup Language (PMML) 4.3*.

Riddick, F., D. Kibira, Y. T. Lee, and S. Balakirsky. 2011. "A Component-based Approach for Manufacturing Simulation". *SpringSim (EAIA)*, April 3rd-7th, Boston, MA, USA, 54–61.
QIF. 2015. *The Quality Information Framework Standard*.
Shao, G., D. Kibira, and K. Lyons. 2010. "A Virtual Machining Model for Sustainability Analysis" In *Proceedings of ASME 2010 International Design Engineering Technical Conference & Computers and Information in Engineering conference*. August 15th - 18th, Montreal, Canada, 875-883.
Shao, G., S. Jain, and S. Shin. 2014. "Data Analytics using Simulation for Smart Manufacturing". In *Proceedings of the 2014 Winter Simulation Conference*, edited by A. Tolk et al., 2192–2203. Piscataway, New Jersey: IEEE.
SISO. 2012. *Simulation Interoperability Standards Organization (SISO): Core Manufacturing Simulation Data (CMSD) Standard*.
Tao, F and M. Zhang. 2017. "Digital Twin Shop-Floor: A New Shop-Floor Paradigm Towards Smart Manufacturing". *IEEE Access*. *Special Section on Key Technologies for Smart Factory of Industry 4.0.* Volume 5:20418-20427.
Tobe, F. 2016. "Challenges for the Digital Twin Concept". *Design World Articles*, https://www.designworldonline.com/challenges-digital-twin-concept/, accessed March 15th, 2018.
Trappey, A. J. C., C. V. Trappey, U. H. Govindarajan, J. J. Sun, and A. C. Chuang. 2016. "A Review of Technology Standards and Patent Portfolios for Enabling Cyber-Physical Systems in Advanced Manufacturing". *IEEE Access, Special Section on Industry 4.0*. Volume 4: 7356–7382.
Vorhies, W. 2018. Digital Twins, Machine Learning & AI. https://www.datasciencecentral.com/profiles/blogs/digital-twins-machine-learning-ai, accessed March 22nd, 2018.
Wasserman, S. 2017. What is the Digital Twin and Why Should Simulation and IoT Experts Care? https://www.engineering.com/DesignSoftware/DesignSoftwareArticles/ArticleID/16070/What-is-the-Digital-Twin-and-Why-Should-Simulation-and-IoT-Experts-Care.aspx, accessed March 22nd, 2018.
Wasserman, S. 2018. SAE to Create Standards for IoT, Big Data and the Digital Twin in the Aerospace Industry. https://www.engineering.com/IOT/ArticleID/16278/SAE-to-Create-Standards-for-IoT-Big-Data-and-the-Digital-Twin-in-the-Aerospace-Industry.aspx, accessed March 22nd, 2018.
Workshop. 2016. *Research Challenges in Modeling & Simulation for Engineering Complex Systems*. Workshop report, the National Science Foundation, Arlington, Virginia. http://www.trainingsystems.org/publications/Research-Challenges-in-Modeling-and-Simulation-for-Engineering-Complex-Systems.pdf, accessed March 29th, 2018.

AUTHOR BIOGRAPHIES

GUODONG SHAO is a computer scientist in the Life Cycle Engineering Group in NIST's Systems Integration Division of the Engineering Laboratory. His current research topics include modeling, simulation, and analysis; data analytics; and optimization for Smart Manufacturing. He served as a *member* of the *WSC Board of Directors* and on the editorial board of the International Journal on Advances in Systems and Measurements. He holds a PhD in Information Technology from George Mason University. His email address is gshao@nist.gov.

DEOGRATIAS KIBIRA is Adjunct Professor in the Department of Civil Engineering at the University of the District of Columbia. His research background is in modeling and simulation applications of advanced manufacturing systems. His current research is in harnessing smart technologies for performance assurance of Smart Manufacturing Systems. He has a PhD in Manufacturing Engineering from the University of New South Wales. His e-mail address is deogratias.kibira@udc.edu.