The Digital Twin in the Manufacturing Ecosystem of the Future

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ABSTRACT

A greenfield approach to manufacturing provides an avenue for realizing a vision for the manufacturing ecosystem of the future. It is proposed that manufacturing will evolve to a more amorphous and ever-changed ecosystem integrated horizontally and vertically. Rigid structures will be abandoned in favor of a flexible services-based model where a bidding process with objective and penalty functions is used to quantitatively evaluate services for interchangeability and ecosystem reconfigurability. The digital twin (DT) will play key roles in service emulation, pre-validation and prediction, and service and ecosystem maintenance. Technology challenges to realizing this vision include developing methods for ecosystem auto reconfiguration, and capabilities for DT to provide prediction quality and sensitivity information, and be self-creating, validating and maintaining. Implementation / infrastructure challenges include overcoming data quality issues, auto-incorporation of subject matter expertise, addressing data partitioning and intellectual property security, and addressing roles and responsibilities in complex operational, legal and safety environments.

KEYWORDS

Smart Manufacturing, Digital Twin, Production as a Service

1 Introduction

Manufacturing systems continue to evolve, adopting tenets of smart manufacturing (SM) / Industry 4.0 including digital twin (DT) to improve throughput and quality while reducing cost [1]. However, the evolution is hindered to a large extent by existing infrastructure, which serves as a resistance to change as well as a mechanism to direct the SM evolution in directions that may not be optimal. These infrastructure barriers include installed physical components such as aging equipment, programmable logic controllers (PLCs) and software system, but also include less tangible elements such as standards, definitions, education, social influences and business practices. As an example, the ISA-95 standard has helped facilitate development and interoperability in modern manufacturing automation by defining automation levels; however, artificial partitioning created unnatural barriers between levels, and ISA definitions have resulted in limiting the scope of manufacturing system discussion (e.g., to the "four walls") [2].

Outlining an ideal SM vision for the manufacturing ecosystem of the future requires implementing a process that is not encumbered by the installed base and the resistance to change; a greenfield vision process meets these requirements. The goal of this paper is to outline aspects of an ideal SM greenfield vision, focusing on the role of DT. Specifically, components of a vision of the future SM ecosystem will be outlined. The DT SM tenet will then be described in more detail including thoughts on how it will be realized and maintained, the role it will play in the manufacturing ecosystem, and key challenges that must be overcome to fully realize the vision.

2 Background: Digital Twin

"A digital twin refers to a digital replica of physical assets, processes and systems that can be used for various purposes" [6]. Generally speaking, DT combines modeling (e.g., simulation or emulation) technology with other analytics to deliver capabilities that allow us to better understand aspects of our current manufacturing operations (e.g., diagnostics) or to determine aspects of our manufacturing environment in the future (e.g., predictive maintenance). In today's "smart" factory, DT can play a role at all ISA-95 levels, or even provide capabilities across multiple levels [7]. There is a significant literature base devoted to the various DT types such as augmented/virtual reality, predictive maintenance, and model-based process control. Other researchers have focused on the organization and collaboration of DTs across the ISA-95 space, while industry efforts have focused on defining the SM and DT visions and roadmaps [8]. A consistent theme in these visions is SM movement from a purely reactive to a more predictive mode of factory operations, with DTs tasked to combine models and predictive analytics to predict future behavior.

3 Future Manufacturing Ecosystem: A Vision

In this paper, it is proposed that manufacturing will evolve to a more amorphous and ever-changed ecosystem integrated horizontally (from raw material through consumer environment) and vertically (from sensor through enterprise). The rigid structure associated with the ISA-95 levels will be abandoned gradually in favor of a more service-based model. A service in this vision is simply a specified capability; the capability could be anything that contributes in some way to the manufacturing ecosystem. Thus the

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service could include a component of physical production, analysis, control, optimization or reconfiguration for some portion of the ecosystem. A service offering is communicated as a quantified promise of a capability that could include production, analysis, optimization, or cost reduction, as well as any cost that could include cost of the service, risks, or confidence levels. Since everything is quantified there is no ambiguity or subjectivity in choosing an optimal service. Manufacturing service providers bid on providing capabilities (not necessarily aligned with an ISA-95 level) to achieve or better achieve the production financial goal. As shown in Figure 1, these services in-turn may be comprised of lower level (e.g., micro) services that utilize the same bidding process in the higher-level service providers financial system. The services will generally not be provided in-house, but by 3rd party service providers, and could be provided to multiple production companies that could be competitors. The services will extend beyond the "four walls"; e.g., they could include a predictor of future product demand or an advertising service that optimizes ad targeting based on the product quality distribution. Note that the bidding service is irrespective of the ecosystem service organization approach (e.g., fully-distributed vs. centralized). For example, any conflicting goals that might arise in a highly decentralized ecosystem could be identified and resolved before bidding or mitigated after bidding by a mitigation service.

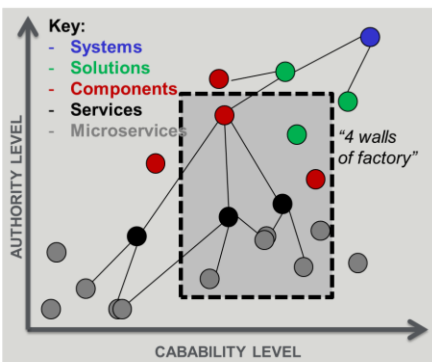

Figure 1: Future Manufacturing Ecosystem Services-based Operational Model (circles are instances of a service)

In executing the bidding process, the potential service consumer identifies and maintains both an *objective/cost function* and a *penalty function*. The objective/cost function quantifies and prioritizes desired benefits such as throughput and quality, and costs such as materials, safety, and delay in delivering the service, from the perspective of the service consumer (e.g., one consumer may emphasize quality while another emphasizes low cost and safety). The penalty function identifies costs to the service provider that would be incurred if promises made toward the objective/function are not kept.

There are three common bidding scenario types, which are illustrated in Figure 2; the scenario invoked depends on the objectives of the (potential) service user and provider:

- Optimization service interchangeability bidding scenario: In this scenario the bidding process would emanate from a parent service looking for a capability that is defined and quantified with an objective/cost function and a penalty function. For example, a product distribution service might be searching for the "best" lower-level delivery service. Bidding services would promise to deliver capabilities with respect to the objective/cost function as well as pay penalties per the penalty function. The result of the bidding / rebidding process is an interchange of services for continuous optimization. In most ecosystems this scenario type is the most common.
- Innovation service interoperability bidding scenario: In this scenario the bidding process would emanate from a service that may or may not (yet) be in the ecosystem. It recognizes that it could provide a new capability within the existing ecosystem structure. For example, a quality binning service might be able to combine customer quality requirement data with production quality data and deliver an optimized product re-distribution plan. As with all bidding processes, objective/cost and penalty functions must be used in the communication for service evaluation by the consuming parent service. The result of the bidding is potentially providing a new capability that interoperates with the existing ecosystem to improve objectives.
- Reconfiguration bidding scenario: In this scenario the bidding process could emanate from a service that is requesting a reconfiguration of the ecosystem (rather than simple replacement of a service or addition of a capability within the existing ecosystem) in order to deliver a capability. As an example, a service might offer a new production approach that changes from supply-based to demand-based requiring changes to production as well as up and downstream supply chain service. The bidding process here would be much more complex as it is requiring reevaluation of the ecosystem structure, with the objective/cost and penalty functions being difficult to conceive and pre-evaluate.

Supporting a highly flexible and dynamic service environment requires that the manufacturing ecosystem be highly flexible and adaptable so as to quickly accommodate new and improved services and service configurations for improved profit. It also requires that (along with the aforementioned objective/cost and penalty functions) each service be delivered with a clear indication of the capability it provides as well as the authority level it requires within the ecosystem (decision making, data access, etc.) to deliver the promised capability. Note that, depending on ecosystem restrictions, the authority level that is willing to be granted to a service might be part of the bidding negotiation.

Utilizing this capability and authority level information, the manufacturing ecosystem develops and maintains an operation model, as shown in Figure 1, that links these capabilities to optimize profit objectives. Note that this operation model spans the entire ecosystem, including production, design, marketing, product maintenance and upgrade, human resources, supplier base and customer base (marketing, advertising, etc.). In order to deliver a competitive solution, the ecosystem must be continually maintained, and be easily adaptable, i.e., able to accept and take advantage of bids from services that do not fit the current configuration (e.g., innovation and reconfiguration scenarios as

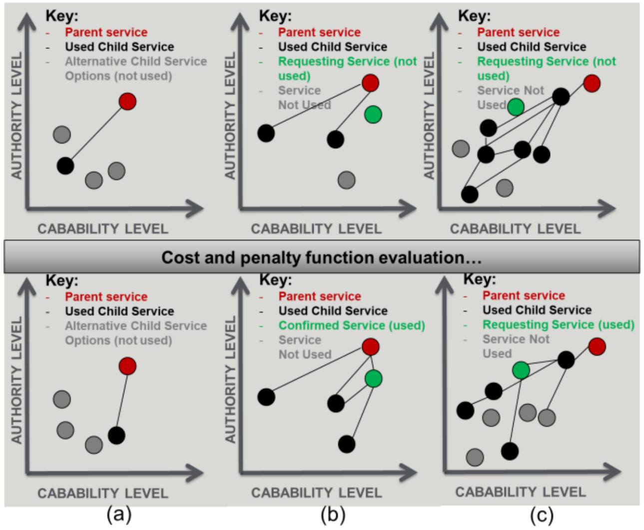

Figure 2: Future Manufacturing Ecosystem Bidding Scenarios; (a) interchange, (b) innovation interoperation, and (c) reconfiguration

noted above), determine cost of change, net benefit, requirements for reconfiguration, etc.).

In the envisioned environment, profit and competitiveness will be defined less by product innovation and cutting costs arising from the human element, and more on (1) developing services that have the ability to get more benefit out of data, and (2) infrastructures that can better (more completely and more quickly) incorporate and maintain these services in the ecosystem. In addressing aspects of these needs, other industries will flourish, and new industries will emerge to provide capabilities such as data commissioning and management, prediction verification, and reconfiguration simulation and verification. DT technology will play a key role in providing many of these capabilities; however, challenges must be overcome. The role of DT and key challenges are discussed in sections 4 and 5 respectively.

4 Digital Twin Technology in the Manufacturing Ecosystem of the Future

DT technology will play a key role in the manufacturing ecosystem of the future. Specifically, DT will combine modelling and prediction technology to predict behavior of various aspects of the manufacturing ecosystem. This will become increasingly important as manufacturing continues to evolve to a more predictive mode of operation, but also as the environment becomes more dynamic, and requires more flexibility and adaptability. Thus, in addition to the task of predicting aspects of the manufacturing environment, DT will be used to emulate, predict and pre-validate new services and new service configurations in the ecosystem as part of the aforementioned bidding process, with the goal being unambiguous pre-evaluation of service capabilities, seamless auto service interchangeability, and auto-reconfigurability of the ecosystem operational model.

This expanded role of DTs places four important requirements on DTs that are not usually associated with current DT technology. The first requirement is that DTs will have to be delivered as part of a service so that the impact of the service can be pre-determined as part of the pre-evaluation and validation in the ecosystem. This requirement also places requirements on minimum DT capabilities and quality (see below). The second requirement is that DTs will need to provide prediction quality and sensitivity analysis associated with their predictions. Determining the impact of a service in a complex ecosystem requires a complete understanding of the service behavior including the boundaries of performance and the susceptibility of performance to variations in the performance of other services. For example, a high-performance service that is highly susceptible to variation in other services might be abandoned in favor of a lower performing service that leads to lower variability of key performance indicators. The third requirement is that the DT must convey a concise understanding of its emulation and prediction capabilities in terms of accuracy, horizon for prediction, etc., as these capabilities are used to pre-evaluate and pre-validate the service capability in the ecosystem. The forth requirement for future DTs is that they will have to be self-creating, self-validating and self-maintaining. For the bidding system to be effective, any promised capabilities of both the services and DTs must be trusted. This requires that any capability for human bias be eliminated. While mechanisms such as standards compliance and 3rd party verification would help, ultimately mechanisms that fully automate the DT development and maintenance process would be needed in highly complex ecosystems and would represent a competitive advantage in terms of accuracy and performance.

5 Discussion: Key Challenges to Realizing the Future Manufacturing Ecosystem

5.1 Technical Challenges

As noted in Section 4, the ecosystem service automated interchangeability and reconfigurability requires that the DT must provide prediction quality sensitivity analysis, be able to report its accuracy with respect to the service it is emulating, and be self-creating, self-validating and self-maintaining. Each of these requirements is a technology challenge. While some DT technologies today can convey a concept of an accuracy distribution for a prediction horizon [9], the general capability is not well-developed or consistent, especially with respect to matching the accuracy conveyance to objective/cost and penalty functions. Most DTs today are created off-line using processes that are largely manual requiring significant human interaction, and generally not consistent or standardized. Validation and maintenance of DTs is an even more ad hoc process.

Ecosystem auto-reconfiguration is another challenge. While research efforts exist for auto-reconfiguration in response to events such as anomalies, work in reconfiguration in response to changing services is just beginning with efforts focused on realizing the bidding process [10, 11].

5.2 Implementation / Infrastructure Challenges

Data quality has been and will continue to be a limiting factor in DT prediction systems, with the primary quality issue being insufficient (historical) length or breadth of data. This insufficiency is not a result of data storage limitations, but rather the dynamics and context richness of manufacturing environments, which oftentimes convolutes the data to the extent that quality prediction models cannot be realized. Prediction systems will continue to have issues with quality of prediction, and therefore must convey this quality information with any prediction.

The incorporation of subject-matter-expertise (SME) is currently a key component of many of today's DT systems as it reduces the impact of poor data quality (specifically in the form of insufficient data), by allowing us to make better sense out of the data we have, thereby improving the signal-to-noise ratio for the development and maintenance of DT systems. In many respects however, SME can just be thought of as the incorporation and interpretation of larger quantities of relevant data into the analysis. For example, an SME might use her knowledge of physics obtained from years of study and practice to partition data from a machine into four data sets associated with four different types of failures, even though there is not enough data to determine this partitioning (to a defined standard of quality) using data science. From this perspective, an argument can be made that the human will serve as a conduit for understanding which new information sources should be incorporated to provide improvements in DT capabilities, with the boundaries of the data science space constantly expanding through SME pioneering. Automated DT creation and maintenance then must require a mechanism for understanding when SME might be needed, and accommodating SME in an automated fashion, whether solicited or unsolicited. It also must be considered that the SME brings creativity to the solution space and it is not clear that creativity can be achieved solely through the application of math sciences. Thus, the SME will continue to provide benefit throughout the manufacturing ecosystem as long as (1) there are new information sources to incorporate and (2) creativity is considered to be a unique human contribution.

The new paradigm of manufacturing is characterized by increased complexity, analysis, integration, distribution, data sharing and collaboration. While this provides opportunities for improved productivity and quality and reduced cost, it also raises issues associated with security, safety and responsibility. The need for data sharing among unaffiliated parties leads to opportunities for data and IP "leaks" that could be intentional or unintentional. Data and IP security has quickly risen to the top as the primary impediment to the implementation of many SM tenets, and this problem will only be exasperated in the manufacturing ecosystem of the future. The highly heterogeneous and dynamic service environment leads to a much more complex safety environment from both a capabilities and responsibilities perspective. Finally, the resolution of responsibility in the case of unexpected issues also is much more complex, in much the same way as responsibility is determined in an autonomous vehicle accident. Addressing each of these issues will undoubtedly involve standards, software infrastructures, and potentially legal statutes. However, it is argued that there are also research opportunities, e.g., for application specific data transformation to convey information while protecting IP or delegating analysis to edge devices in services [8,9].

6 Looking ahead

New paradigms for manufacturing will be driven by competition and cost pressures, and accelerated by the tenets of smart manufacturing, the increasing benefits of rapid ramp-up, and the increasing pervasiveness of technologies that support interoperability and reconfigurability. A greenfield approach to determining a vision for the manufacturing ecosystem allows us to explore optimality without impediments of existing infrastructure, however existing infrastructure will likely significantly impact the evolutionary path to this vision. The flexible services-based model bidding process is the cornerstone of the vision and leverages many of the tenets of SM. The process enables optimization through service interchangeability and ecosystem reconfiguration, and relies heavily on the DT to define, validate and evaluate objective and penalty functions used to quantitatively and comparatively evaluate services for interchangeability and ecosystem reconfigurability. Challenges to the vision will include traditional research challenges such as determining and improving prediction quality, but also new challenges such as data partitioning and IP security; addressing these latter challenges represents a new and rapidly growing area for research.

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