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Journal of Manufacturing Systems 52 (2019) 198–204

Contents lists available at ScienceDirect

Journal of Manufacturing Systems

journal homepage: www.elsevier.com/locate/jmansys

# Service manufacturing: Basic concepts and technologies

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ARTICLE INFO

*Keywords:*
Smart manufacturing
Intelligent manufacturing
Digital manufacturing
Service systems
Engineering design
Modeling
Service manufacturing

ABSTRACT

Manufacturing is undergoing transformation driven the developments in process technology, information technology, and data science. The incoming changes are disruptive and will likely result in manufacturing solutions unimaginable in the recent past. A future manufacturing corporation will be highly digital, and it will function in new modes discussed in this paper. After decades of integration of engineering design and manufacturing, the design-for-dedicated manufacturing will gradually transform in the design-for-open manufacturing. In many instances, manufacturing processes will become manufacturing-as-service (service manufacturing) systems. An enterprise will be gradually dominated by formation of services in a cloud. The emerging service manufacturing will be open, shared, easy to configurable, efficient, and democratic. Designing a manufacturing system of the past will reduce to formulating and solving an enterprise configuration problem. The presence of services in the cloud will be facilitated by the autonomously generated models. A formal modeling approach to configuration of manufacturing enterprises is discussed. The computational complexity of the configuration problem calls for different modeling and solution approaches ranging from mathematical programming and data science to quantum computing.

## 1. Introduction

Manufacturing is undergoing transformation expressed in growing digital content and consequently a greater service orientation, resource sharing, openness, and democratization. The scope and the depth of this transformation has not been determined, and therefore understanding the potential implications of these developments is important.

The digital path has begun decades ago with the computer technology embedded in manufacturing equipment (e.g., numerically control machines, autonomous material handling), deployment of software technology (e.g., enterprise resource planning systems, customer relationship management systems), and introduction of digital models of components and products. Computerization of supply and distribution chains came along the digitization of the manufacturing floor. Digital representation of materials is the latest addition to the digitization of industry. In years to come, the digital content will be enhanced by the growing deployment of sensors (e.g., generating data reflecting equipment status) in manufacturing, digitization in the product development domain, and the existing services.

Manufacturing research has embraced a wide range of modeling approaches, methods, and theories. The quest for improvement of manufacturing performance has attracted diverse research communities from physics and chemistry to biology, management, and information technology. Besides the research in manufacturing processes, analytical, statistics, simulation, process (logistics and structure), and data-driven models, algorithms, and theories have been contributed by the engineering research and business community.

The progress in artificial intelligence has intensified interests in manufacturing architectures, standards, and models. Lia et al. [1] provided an overview of architectures, frameworks, and reference models surrounding smart manufacturing. Manufacturing process-specific frameworks have been discussed in numerous papers. An object-oriented model for additive manufacturing was presented in Bonnard et al. [2]. Cecil et al. [3] discussed a cyber-physical framework intended for micro-assembly. The latter two papers have focused on additive manufacturing and micro-assembly processes, respectively, as well as modeling data and information flow. Various forms of service approaches in manufacturing industry have been discussed in the literature. Vandermerwe and Rada [4] discussed the transformation (called servitization) from a product-based business model to a product-service business model. In their model, the service performed by a product rather than the product itself is sold. Gao et al. [5] and Wen and Zhou [6] provided insights into service-oriented manufacturing. Steen et al. [7] proposed a comprehensive approach for service modeling and model integration in manufacturing with emphasis on model execution, validation, support, integration, and ensuring consistency across the enterprise. Tao and Qi [8] offered a service-oriented approach to smart manufacturing. The integration of digital software tools with a service-

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https://doi.org/10.1016/j.jmsy.2019.07.002
Received 23 April 2019; Received in revised form 6 July 2019; Accepted 7 July 2019

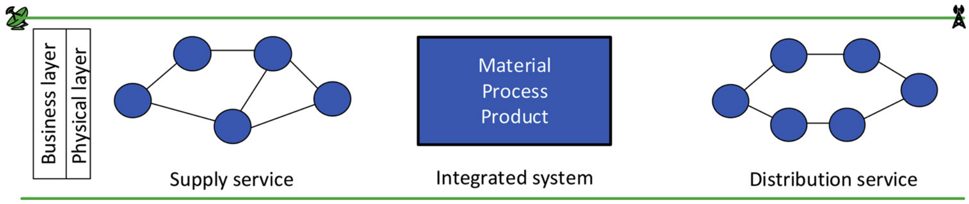


**Fig. 1.** Integrated manufacturing architecture.

oriented framework in support of design, configuration, analysis, validation, simulation, control and monitoring in a virtual environment was discussed in Leitão et al. [9]. The research results were implemented in an industrial environment. In a more theoretical setting, Gu et al. [10] researched expressive representations of data mappings between the input and output attributes of services.

Selection of service models in a manufacturing cloud was simulated by Zhou et al. [11]. Zhang et al. [12] offered a service encapsulation and virtualization model at the manufacturing machine tool level. A notion of sustainability was incorporated into the product-service model by Yang and Evans [13].

Ontology is key to modeling manufacturing systems. The two papers, Zaletelj et al. [14] and Mas et al. [15], presented examples of a general and an assembly specific manufacturing ontology, respectively. Wu et al. [16] introduced ontology of robots embedded in a manufacturing system. An object-oriented modeling and re-engineering of production flow in microelectronics was discussed in Carchiolo et al. [17]. Curry and Feldman [18] have assembled analytical approaches for modeling and analysis of manufacturing systems. Stochastic modeling and risk assessment approaches to manufacturing and service (continuous, pointwise, and flexible) enterprises are covered in the book by Matsui [19].

The manufacturing enterprises, small and large, will naturally seek representation in the global cloud, which over time, will need to be managed and likely regulated. A broad-based access to the cloud will promote democratization of manufacturing.

The enterprises of tomorrow will face two important phenomena: (1) shortened product lifecycles, and (2) variable demand for products over a short-time horizon. One can observe that while the product and market horizons are becoming shorter, the manufacturing equipment use-life remains relatively stable. As manufacturing equipment becomes more intelligent, its cost increases. The increasing manufacturing functionality is also noted, e.g., equipment with the integrated material removal and additive manufacturing capability is available on the market. The latter trends make the machine utilization rate a priority. A scenario where the demand for a product may increase *n*-fold in months' time is likely. Meeting such market conditions with a traditional model of internal expansion of production capacity would not be possible. However, a rapid expansion of production capacity based on the concept of shared manufacturing resources is feasible. In fact, the developments in digital manufacturing facilitate a path to shared manufacturing. The logistics layer of manufacturing and service enterprises needs to have some structure. At present, this structure is provided, e.g., by software solutions such as enterprise resource planning systems, manufacturing execution systems, and service management systems. The future manufacturing and service industry will be more dynamic (e.g., customized products, reconfigurable manufacturing systems, shared manufacturing resources) that will change the nature of the underlying physical and logistics processes. These changes will be reflected in the data and information to be used to build new models, repair the existing ones, or evolve the existing models into new ones. Such models may range from graphs (e.g., representing assembly sequences) and multicriteria transportation models to capacity balancing and prediction models of remanufactured assemblies. The digital enterprises are becoming increasingly polarized (integrated vs open manufacturing) with weakening integration between design and manufacturing (reversing the trend of the last few decades), increasing separation of services (acceleration of the trend), and manufacturing becoming a service (called here service manufacturing). A future manufacturing enterprise might be a collection of X-as-a-service entities rather than a single business entity. We are likely to witness design-as-as-service, manufacturing-as-as-service, maintenance-as-as-service, logistics-as-a-service, distribution-as-as-service, cloud-as-as-service business entities.

## 2. Integrated vs open manufacturing architecture

The developments in digital manufacturing as well as market dynamics will impact the manufacturing landscape. Two basic architectures of manufacturing systems are emerging, integrated and open (decoupled) [20,21]. The integrated architecture is amenable to disruptive products and technologies, e.g., simultaneous invention of a new material, manufacturing process, and a product (Fig. 1).

The novelty and intellectual property protection of these developments are natural barriers to opening of the manufacturing envelope. The traditional capacity expansion or replication of the newly created manufacturing facility over multiple sites will likely prevail in the integrated manufacturing architecture. Such an enterprise is not likely to promote its manufacturing services in the manufacturing cloud as its primary focus is to compete on products. However, an integrated enterprise could make its services, e.g., supply or distribution, available in the cloud.

Open manufacturing would involve decoupling of the design, logistic, and service layers from the physical assets (see Fig. 2).

Many enterprises will likely adopt the concept of open manufacturing in various forms, e.g., product design decoupled from manufacturing, logistics and service decoupled from the manufacturing assets. Services such as supply, distribution, and maintenance could be the first to detach from the manufacturing enterprises. An open manufacturing enterprise is a collection of physical assets and services configured for the purpose of producing products. In many instances, the physical manufacturing assets will naturally follow the service model. As a result of these developments, the competitiveness will gradually shift from the focus on the internally developed technology to acquiring the knowledge and ability to configure, reconfigure, and optimally operate the distributed services and their assets. The open manufacturing architecture will expand over time; however, integrated manufacturing will be key to the industrial advancement driven by the developments in materials, products, and processes. Many enterprises will be hybrids of integrated and open architectures.

The open manufacturing enterprise will be amenable to the X-as-a-service mode, where X is, e.g., manufacturing, supply, and distribution. It will support resource sharing and networking. There is little doubt that many of the manufacturing and support functions as well as the entities operating in the cloud will adopt the service architecture model, making a future enterprise a collection of dynamically assembled services.

The service orientation of manufacturing has its roots in the industry experience with the third-party service and subcontract models. For example, the rapid manufacturing (a predecessor of additive manufacturing) service model was established decades ago because of the high cost of technology, low equipment utilization, learning curve, and uncertainly about utility of the technology.

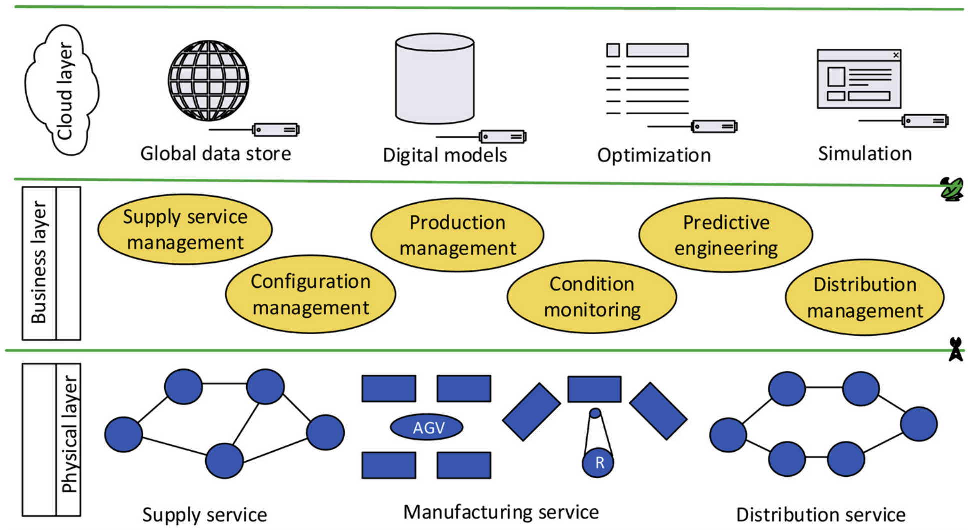


**Fig. 2.** Open manufacturing architecture.

## 3. Decoupled design and manufacturing

Over the past decades, the industry has been perfecting the design-for-manufacturing approach (see Fig. 3). The goal was to design products and components so that they could be manufactured according to their specifications without design changes.

The design-for-manufacturing (here dedicated manufacturing) principles have become widely practiced in industry. Tools have been developed in support of design-for-X beyond discrete manufacturing and assembly processes. Many future products are likely to be designed for manufacturing processes not known at the design phase, i.e., open manufacturing (see Fig. 4). Such design practice will be driven by:

(i) Growing market dynamics that may not tolerate the usual development time needed to build or expand the existing manufacturing facility;
(ii) Separability of the physical and cloud assets of manufacturing; and supported by
(iii) Experience with the design-for-manufacturing practice and tools; and
(iv) The concept of shared manufacturing resources.

Some designs will be created in the design-as-a-service enterprises. Design for a manufacturing-as-a-service in an instance of the design-for-open manufacturing. At least three existing industrial practices: (i) contract manufacturing (e.g., Foxconn manufacturing Apple products), (ii) subcontracting; (iii) outsourcing services offer the evidence that industry has been moving towards the manufacturing configuration model hypothesized in this paper.

In an enterprise of the future, some of these services can be owned and operated by the enterprise itself, others may constitute independent business entities and be spatially distributed across the globe (see Fig. 5).

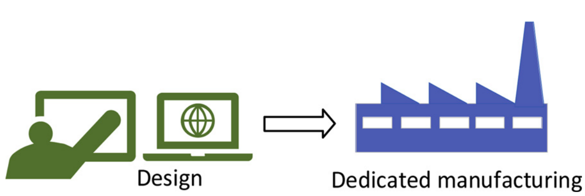


**Fig. 3.** Design for dedicated manufacturing.

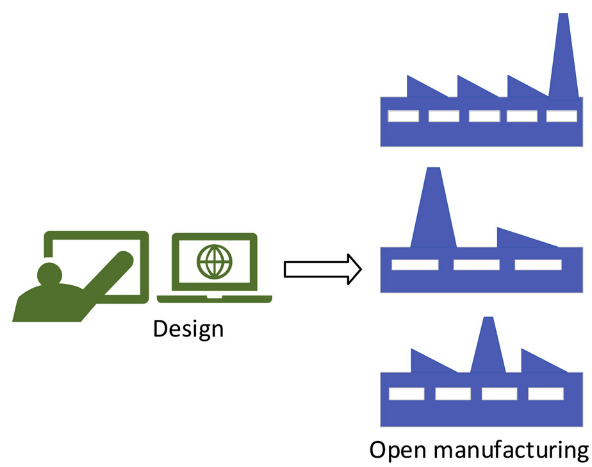


**Fig. 4.** Design for open manufacturing.

## 4. Manufacturing configuration modeling and management

Today's enterprises are evolving at a rather slow rate, usually by procurement of new assets or by merge and acquisition. Once acquired, the physical and logistics assets of manufacturing are utilized to the degree possible. Based on the future capacity outlook (related to the utilization rate of assets) an expansion or a sell-off of assets could be triggered. An open manufacturing enterprise will configure and reconfigure itself as needed. Attributes such capability, capacity, quality, and resiliency expressed in multiple parameters [22] will be key in determining its configuration. The emerging problem of configuration of enterprises will trigger developments of different modeling methodologies. Mathematical programming is one of the approaches for modeling the enterprise configuration problem. One could also envision configuring a manufacturing enterprise as a synthesis problem to be solved with genetic programming. Basic research is needed to model and solve the enterprise configuration challenge. In the first phase of this new challenge, a widely accepted ontology, standardization, and representation need to be developed.

To provide insights into the enterprise configuration problem, an illustrative example is presented.

### 4.1. Illustrative example

Consider the enterprise specifications expressed in two attributes,

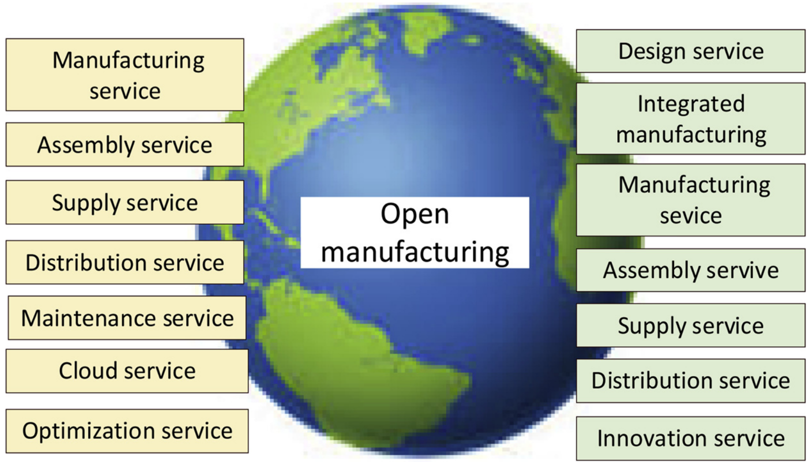


**Fig. 5.** Distributed services in open manufacturing.

**Table 1**
Service capability matrix.

| Service capability | C1 | C2 | C3 | C4 | C5 | C6 | C7 | Required capability |
|---|---|---|---|---|---|---|---|---|
| S1 | 0.55 | | | 0.98 | 0.49 | | 0.74 | 0.95 |
| S2 | | | | 0.95 | | | 0.77 | 0.95 |
| S3 | | | 0.79 | 1.00 | | | 0.66 | 0.97 |
| M1 | 1.00 | | | | 0.95 | 0.97 | | 0.95 |
| M2 | | | 0.88 | | | 0.96 | | 0.95 |
| M3 | | 0.96 | | | | | 0.99 | 0.95 |
| M4 | | 0.98 | | | 0.85 | | | 0.90 |
| D1 | | | 0.86 | 1.00 | | | | 0.96 |
| D2 | | 0.98 | | | | | 0.99 | 0.96 |
| Cost | 70 | 50 | 90 | 100 | 120 | 50 | 150 | |

**Table 2**
Service capacity matrix.

| Service capacity | C1 | C2 | C3 | C4 | C5 | C6 | C7 | Required capacity |
|---|---|---|---|---|---|---|---|---|
| S1 | 0.70 | | | 0.60 | 0.90 | | 0.35 | 1.50 |
| S2 | | | | 1.00 | | | 0.80 | 1.00 |
| S3 | | | 0.79 | 1.00 | | | 0.55 | 0.80 |
| M1 | 0.33 | | | | 0.60 | 0.60 | | 1.00 |
| M2 | | | 0.88 | | | 1.00 | | 1.00 |
| M3 | | 1.00 | | | | | 0.10 | 1.00 |
| M4 | | 0.70 | | | 0.40 | | | 1.00 |
| D1 | | | 0.86 | 1.00 | | | | 0.80 |
| D2 | | 0.98 | | | | | 0.99 | 0.80 |
| Cost | 70 | 50 | 90 | 100 | 75 | 50 | 150 | |

service capability in Table 1 and service capacity in Table 2. Service capability is loosely defined as the ability of a system (e.g., manufacturing, supply chain) to meet all specifications. Service capacity is defined in a similar way. The matrices illustrate two of many specification types that need to be considered in configuring an enterprise.The service capability matrix (Table 1) involves specifications for supply services S1, S2, and S3; manufacturing services M1, M2, M3, and M4; and distribution services D1, D2. The columns C1 - C7 of the matrix Table 1 indicate the capability offered by the services selected from the cloud. The last column of the matrix lists the required capability. Some services may be specialized and narrow in scope while other services may be bundled.

Each service bundle (column) in Table 1 offers the capability of its services and the corresponding cost.

Analogous to the capability matrix in Table 1, the service capacity matrix is presented in Table 2.

Each service bundle (column) in Table 2 provides the capacity of each service offered and the total cost.

The open manufacturing configuration problem is to select an optimal set (e.g., minimum cost) of the service bundles meeting the open enterprise specifications, e.g., required capability, capacity, resiliency. The multiple matrices, different measurement units of the data illustrated in the body of each matrix, as well as the algorithms needed to derive data (e.g., resiliency) make the configuration problem complex. Sources of some of the data would need to be identified, with some values to be computed while other values might be predicted.

A feasible cost solution to the service capability model (i.e., meeting the required capability) is shown in Table 3. It involves three service bundles C2, C4, and C6 at the total capability cost $50 + 100 + 50 = 200$. This solution ensures that each of the nine required service capabilities (the last column of the matrix in Table 3) is met.

A feasible solution to the bi-criterion model (i.e., meeting the required capability and capacity requirements) is shown in Table 4 (using the matrix of Table 3). It involves four service bundles C2, C4, C5, and C6 at the total capacity cost of $50 + 100 + 75 + 50 = 275$. This solution ensures that each required service capability and capacity (the last column of the matrix in Tables 1 and 2) is met.

The analysis illustrated with the matrices in Tables 1–4, would need to be performed on multiple levels (e.g., business, machine tool, fixture) and different granularity (e.g., process, material) of information. A basic mathematical programming model of enterprise configuration is presented next.

The following notation is used in the model:

$I$ = set of services

$J$ = set of service bundles (offers)

$K$ = set of enterprise attributes (e.g., capability, capacity, resiliency)

**Table 3**
Service capability solution.

| Service capability | C1 | **C2** | C3 | **C4** | C5 | **C6** | C7 | Required capability |
|---|---|---|---|---|---|---|---|---|
| S1 | 0.55 | | | **0.98** | 0.49 | | 0.74 | 0.95 |
| S2 | | | | **0.95** | | | 0.77 | 0.95 |
| S3 | | | 0.79 | **1.00** | | | 0.66 | 0.97 |
| M1 | 1.00 | | | | 0.95 | **0.97** | | 0.95 |
| M2 | | | 0.88 | | | **0.96** | | 0.95 |
| M3 | | 0.96 | | | | | 0.99 | 0.95 |
| M4 | | 0.98 | | | 0.85 | | | 0.90 |
| D1 | | | 0.86 | **1.00** | | | | 0.96 |
| D2 | | 0.98 | | | | | 0.99 | 0.96 |
| Cost | 70 | **50** | 90 | **100** | 120 | **50** | 150 | |

**Table 4**
Service capability and capacity solution.

| Service capacity | C1 | **C2** | C3 | **C4** | **C5** | **C6** | C7 | Required capacity |
|---|---|---|---|---|---|---|---|---|
| S1 | 0.70 | | | **0.60** | **0.90** | | 0.35 | 1.50 |
| S2 | | | | **1.00** | | | 0.80 | 1.00 |
| S3 | | | 0.79 | **1.00** | | | 0.55 | 0.80 |
| M1 | 0.33 | | | | **0.60** | **0.60** | | 1.00 |
| M2 | | | 0.88 | | | **1.00** | | 1.00 |
| M3 | | **1.00** | | | | | 0.10 | 1.00 |
| M4 | | **0.70** | | | **0.40** | | | 1.00 |
| D1 | | | 0.86 | **1.00** | | | | 0.80 |
| D2 | | **0.98** | | | | | 0.99 | 0.80 |
| Cost | 70 | **50** | 90 | **100** | **75** | **50** | 150 | |

$c^kj$ = cost of service bundle $j$ in attribute $k$
$a^kij$ = level of service $i$ of service bundle $j$ in attribute $k$
$R^ki$ = service level required from service $i$ in attribute $k$

$$x_j = \begin{cases} 1 & \text{if service bundlejis selected} \\ 0 & \text{otherwise} \end{cases}$$

$$\min \sum_{k \in K} \sum_{j \in J} c_j^k x_j \tag{1}$$

$$\sum_{k \in K} \sum_{j \in J} a_{ij}^k x_j \geq R_i^k \quad i \in I,\ k \in K \tag{2}$$

$$x_j = 0, 1 \quad j \in J \tag{3}$$

Objective function (1) minimizes the total cost of the services needed to configure the enterprise. Constraint (2) makes sure that all service requirements are met. Constraint (3) imposes integrality. Model (1)–(3) is formulated at a high level and it involves only two attributes (i.e., capability, capacity) and the basic constraints. High granularity models containing detailed parameters of the resources (e.g., manufacturing equipment, software), systems, and data are needed.

To make the enterprise configuration model more realistic, research on formal representation of services, e.g., manufacturing, distribution, is needed. For example, a manufacturing model is expected to integrate models of machine tools, robots, and control functions. To warrant industrial progress, such formal representations and models should be autonomously generated. The autonomous generation of process models is discussed next.

## 5. Autonomous generation of models

A process model (e.g., equipment fault diagnosis) is composed of activities that receive inputs and produce outputs.

Process model $M_c$ is the vector presented in (4).

$$M_c = [\mathrm{I, O, S, C, R, P}] \tag{4}$$

where:
I = set of independent variables (input)
O = set of dependent variables (output) S = set of status variables
C = controls
R = resources
P = set of performance metrics

Multiple process models $M_c$, c = 1, …, N (e.g., at different levels of granularity and scope) are assembled in process model $M = [M_1, \ldots, M_N]$.

Process models communicate information across multiple domains, and they serve different users, e.g., managers, process engineers, or maintenance personnel. The latter calls for different representations of process models, from a high-level overview to the detailed process or functional perspectives. A graphical process representation is usually received by users with different backgrounds and interests. The standard business process model and notation, BPMN (bpmn.org), is intended for graphical representation of models. The system modeling language, SysML (sysml.org), can be considered for execution of the process models. The BPMN and SysML are well suited to serve the industry in the development of cloud applications. The interest in generation of process models from data has intensified in the last decade [23]. Process mining aims at building process models using event data [24]. It involves process discovery, model enhancement, and conformance checking. The process discovery deals with the extraction of process models from event logs. Model enhancement aims at improvement of process models based on the event log information. The conformance test is designed to check whether the discovered process model meets the expected behavior. Some algorithms construct procedural models that are difficult to interpret, especially for unstructured applications. For complex and dynamic processes, declarative process models are used. They specify allowed behavior of the process with constraints, i.e., rules to be followed.

Research on automated process discovery aiming at generation of process models from information sources such as customer relationships management systems has been reported in the literature [25]. Its roots go back to the sequence process mining [26,27]. Augusto et al. [28] provided a systematic review and assessment of automated process discovery methods in different quality metrics. Various approaches for mining unstructured [29] and structured [28,30] processes have been researched. Chapela-Campa et al. [31] and Han et al. [32] discussed extraction of frequently occurring patterns in processes, e.g., sequences, loops. Fabrizio et al. [33] proposed an elaborate approach for model mining involving the Apriori algorithm and a sequence of analysis algorithm. Analysis of factors impacting understandability of process models has been reported in Dikici et al. [34] based on review of 1000 published papers.

The existing automated process discovery methods have two weaknesses: (i) they produce large and spaghetti-like models; and (ii) the models have either poor fitness or they over-generalize [28]. Research is needed to overcome these deficiencies.

### 5.1. Evolutionary computation

Evolutionary computation is suited for learning models and model evolution. One of the leading algorithms is the genetic programming algorithm [35,36], originally developed to generate computer programs. Positive experiences with applications of genetic programming algorithms have been reported in the literature, e.g., evolution of graphs [37], generation of priority rules [49], synthesis of computer programs [38], and design of printed circuit boards in the presence of constraints [39].

### 5.2. Computing strategies

Digitization of manufacturing elevates the value of data. It is important to recognize the trends in data generation and data characteristics of the computing environment of an enterprise. One of the key computing functionalities differentiating smart manufacturing from the past is the predictive capability. The latter is driven by the need to develop models that are dynamic and optimizing enterprises over future horizons. Such time-based optimization involving predictive models, calls for massive computing power that could be delivered by quantum computing.

Deep learning and quantum computing dominate the research headlines. While deep learning applications are feasible to deploy, general-purpose quantum computers face research and technology challenges. The technology choice is complicated by the fact that deep learning and quantum computing are codependent, e.g., algorithms could be designed differently if they were to run on quantum rather than classical computers.

### 5.3. Quantum computing

Quantum computing is worthy consideration in the design of future strategies for modeling manufacturing systems. In a quantum computer, the classical two-circuit element (a bit) is replaced with a quantum bit (qubit) that has two states. Usually, the internal electron momentum (a spin) serves as a qubit. In contrast to the classical bit, a qubit can be in a continuum of possible states, e.g., two states with probability $p_1 = .61$ and $p_2 = .39$, respectively. The estimated number of logical qubits for a viable quantum computer is 1000–100,000. At this time (year 2019) quantum computers based on chips with 49 qubits (Intel) to 72 (Google) have been built. Quantum systems are efficient in producing patters similar to those of machine learning algorithms. Biamonte et al. [40] discussed quantum algorithms that could be used in machine learning applications. They pointed out the hardware and software challenges ahead of quantum learning. Havlicek et al. [41] demonstrated machine learning with prototype quantum hardware. In many machine learning applications, the number of variables may be relatively large to the number of their values (e.g., binary). The kernel theory of machine learning and quantum theory share commonality in processing data. Kernel-based machine learning algorithms [42], map low-dimensionality data spaces into high-dimensionality spaces, possibly infinitely large spaces. Havlicek et al. [41] and Schuld [43] have linked the large data spaces of quantum computers to kernel-based machine learning algorithms. Both research teams proposed two computing strategies: (1) use quantum computer hardware in support of conventional machine learning, e.g., quantum hardware computing high-dimensionality similarity metrics and passing the values to conventional machine-learning algorithms, (2) build quantum-learning computers. While many research groups are optimistic about progress in quantum computing and foresee significant expansion [44] some skeptical assessments have been published as well [45].

## 6. Expected benefits from service manufacturing

The greater service orientation of a manufacturing enterprise will be driven by business metrics such as profit. However, the distribution of the benefits may be affected. Two concepts, shared manufacturing and democratization of manufacturing, have been selected to illustrate the implication of service manufacturing.

### 6.1. Shared manufacturing service

Shared manufacturing stems from the concept of shared economy. Success of the resource sharing concept has been demonstrated by, e.g., the bicycle and vehicle sharing programs. Bicycles are used by different riders who do not own them. The vehicle sharing program has emerged from the need to reduce the traffic flow on streets and highways and it has taken different forms such as public transportation and dedicated highway lanes. One may presume that once autonomous vehicles will be fully developed, shared transportation will rise.

The digital presence of enterprises in the cloud will accelerate shared manufacturing. The cloud will offer an unprecedented display of manufacturing capabilities. This combined with open manufacturing will in turn promote sharing manufacturing resources. The latter will emerge as a natural outcome of manufacturing capacity and capability optimization. While a digital manufacturing model in the cloud could be formed in a short time, its implementation in the physical space is a major effort. It is complicated by the fact that neither of the two spaces (digital and physical) are static. Predictive engineering emerges as a natural coupling between the digital and physical space. Prediction models will allow designing physical configurations of manufacturing systems that will meet the resiliency requirements of the primary enterprise.

The concepts of networked and shared enterprises have been partially implemented in industry. For example, Boeing aircrafts are designed and manufactured in a globally distributed network; iPhones are designed in the US and manufactured at the facilities (not owned by Apple) in China along with other products produced at the same facility; some electric utilities are operated by competitors not owning them.

Open manufacturing will take decupling between the physical and logistic and service layers of enterprises to yet another level. Shared and distributed use of physical manufacturing assets will be a key driver in drawing manufacturing maps of the future. The concepts that have begun to work in electronic and software industry may not directly translate into other industries, e.g., electromechanical, machine, or construction equipment, and thus, a research opportunity emerges.

### 6.2. Democratization of manufacturing

The digitization of industry will facilitate designing new enterprises, including open original equipment manufacturers (OOEMs). Such an openness will promote democratization of manufacturing which to some degree is not new to the technology domain. It has been advocated that open manufacturing enhances innovation [46–48]. The developments in social networks (e.g., Facebook), web products (e.g., Wikipedia) are usually cited as the examples of innovation democratization. Industry has a long way to adopting and implementing the democratization concept. The connectivity and presence of small manufacturing companies in the cloud will level the field of competition. Small companies could gain the same level of visibility in the cyberspace as the large companies. This will offer an opportunity to forge new relationships rather than follow the traditional business paths. The reach of the cloud will determine the width and strength of the formed business interactions. The concept of democratization applies to the traditional service industry, e.g., financial institutions. The manufacturing and service businesses that have made progress towards virtualization of their operations are likely to be the first beneficiaries of the democratization climate.

## 7. Enterprise modeling alternative

Getting all data necessary to configure a service-based manufacturing enterprise is difficult and costly. Details on service systems available in the cloud could be missing, information needed is not likely to be uniformly presented, and the granularity of information might lack consistency. An alternative approach to the identification of candidate service systems is to analyze products. Products that are similar in some features are likely to be realized in similar service systems, e.g., manufacturing, supply chain. Information on products that are offered in various markets is more readily available at different sources, ranging from the websites of producers to product catalogs and product reviews. Analysis of the product information would identify candidate services for configuration of an enterprise. The proposed approach will simplify the configuration process by reducing the number of service systems that would need to be analyzed.

## 8. Conclusion

The concept of service manufacturing was proposed. Three main structural changes in industry were discussed: (i) design for open manufacturing as a successor of the design for dedicated manufacturing, (ii) separation of the physical manufacturing assets from the logistics layer, and (iii) transformation of manufacturing and business functions into specialized service systems. In the enterprise of the future, the engineering design and manufacturing domains will be separated rather than integrated. The physical manufacturing assets will become services loosely coupled with the business and logistics assets. The manufacturing logistics and allied areas (e.g., supply, distribution) are likely to become services present in a cloud. The service manufacturing enterprise will be open, shared, efficient, reconfigurable, and democratic. The traditional design of a manufacturing company will likely reduce to formulating and solving an enterprise configuration problem. The emerging approaches for autonomous generation of the models needed to configure a manufacturing enterprise were introduced. An integer programming model for configuration of a manufacturing company was discussed. Different modeling and solution approaches were introduced. The scale of the emerging manufacturing service enterprise problem warrants computing power offered by quantum computing.

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