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Universal manufacturing: enablers, properties, and models

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ABSTRACT
Globalisation of the manufacturing and service industry has increased complexity of the flow of materials and goods, magnified dependency on the underlying network, and made the industry more vulnerable to the changing market conditions. As manufacturing and service industry undergo transformation, an opportunity to rethink the design of future enterprises has emerged. Six enablers of miniversal manufacturing are discussed: digitisation, open manufacturing, service orientation, shared manufacturing, sustainability, and resilience. These enablers will form properties of universal manufacturing, with adaptability and affinity that are emerging. A universal manufacturing enterprise will be formed based on the distributed manufacturing facilities. The emerging standards for interoperability of systems needed for universal enterprises are discussed. The data and modelling standards will enable the synthesis of digital models into universal enterprises. Though there is no global standard for the representation of digital manufacturing models in a cloud, the existing process modelling methodologies and languages may offer the solutions needed. The evolution of production systems is illustrated with three snapshots, dedicated manufacturing, distributed manufacturing, and universal manufacturing. The modelling approach followed in this paper is bottom-up rather than top-down followed in the literature on modern manufacturing.

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Digital manufacturing; smart manufacturing; open manufacturing; manufacturing-as-a-service; resilient manufacturing; pandemics

1. Introduction

The industry is continuously evolving with spikes around significant developments in technology. For example, the automation technology of the 1980th has led to flexible manufacturing (e.g. ElMaraghy 2005) and the developments in artificial intelligence of this century contributed to progress in digital manufacturing (e.g. Jones et al. 2020). Manufacturing has evolved from being centralised and dedicated to a single product to globally distributed and serving many products (Kusiak 2020b). This evolution has been enabled by developments in:

(a) manufacturing process technology (e.g. increased functionality of traditional machine tools, emergence of additive manufacturing and hybrid machine tools),
(b) computing, sensing, and software technology (e.g. machine–machine communication), and
(c) design methods (e.g. design of products with consideration of manufacturing constraints, multi-criteria design of manufacturing systems).

The recent decades and years have contributed six new enablers (see Figure 1):

(d) digital manufacturing (growing use of data across process and system domains)
(e) open manufacturing (increasing presence in the cloud)
(f) manufacturing-as-a-service (to meet variable demand at a competitive cost)
(g) shared manufacturing (to increase access and utilisation of manufacturing equipment)
(h) sustainable manufacturing (driven by environmental concerns and dwindling supplies of raw materials), and
(i) resilient manufacturing (improved response to disruptions, in particular, the Covid-19 pandemic).

The first three enablers, (a)–(c), have reshaped the manufacturing landscape, and the more recent six enablers, (a)–(f), will lead to a more fundamental manufacturing transformation, which is captured in this research as *universal manufacturing* (see Figure 1).

These six enablers are supported by different concepts and developments, all embedded in initiatives such as smart manufacturing or Industry 4.0, invoke two important properties of universal manufacturing, adaptivity and affinity, discussed later in this paper. Note that these

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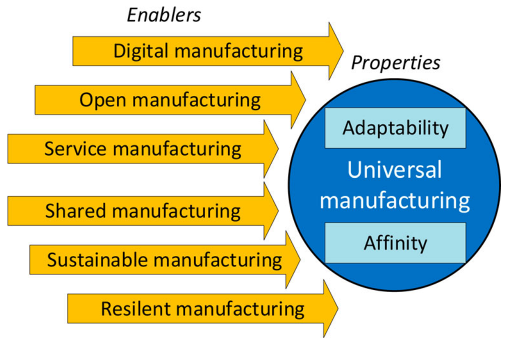

Figure 1. Key enablers and properties of universal manufacturing.

two system-level properties follow a different path than the characteristics such as autonomy or self-awareness attributed to smart manufacturing systems.

Universal manufacturing is emerging at different levels, manufacturing equipment and technology, operations, and software. Additive manufacturing is an example of a universal manufacturing process. A single process produces many components and even products. A hybrid additive-subtractive tool expands even further the range of items produced. The unified modelling language (uml.org) and cloud manufacturing platforms are also supportive of universal manufacturing. The universal manufacturing model will mature in time. Of the two extrema defined in (Kusiak 2018, 2020a), i.e. integrated and open manufacturing, universal manufacturing will dominate the latter. It will take a form of virtually organised factories delivering physical products. There is no doubt that the universal manufacturing journey might be long, and it may not embrace all forms of manufacturing; however, an early recognition of a universal manufacturing model could accelerate the progress. The path leading towards universal manufacturing is discussed in the next section.

2. Evolution leading to universal manufacturing

From its beginnings, manufacturing was closely related to a product. For example, an automotive assembly line was designed to produce a specific car model. Figure 2(a) illustrates such a dedicated manufacturing facility. The relationship between the product and the manufacturing system was one-to-one as illustrated with the graph in Figure 2(b).

The dedicated manufacturing model has evolved in distributed manufacturing shown in Figure 3(a). The distributed model has emerged largely due to the growing complexity of products and the market pressure to reduce manufacturing costs. The latter was largely accomplished by improving manufacturing efficiency and relocation of manufacturing to markets with low labour costs. A distributed manufacturing facility usually accommodates many different products and their models, e.g. three different products are manufactured in the example illustrated in Figure 3(a). The graph in Figure 3(b) shows the many-to-one relationship between products and the corresponding manufacturing system.

The idea of universal manufacturing proposed in this paper is illustrated in Figure 4(a). It follows the many-to-many model shown in Figure 4(b). Each product could be manufactured at more than one distributed manufacturing facility.

It is likely that the universal manufacturing model will naturally emerge in time due to the enablers shown in Figure 1. Rather than waiting for the evolutionary realisation of a fully developed universal manufacturing model, its implementation could be accelerated, and its benefits realised much earlier.

2.1. Definitions

Definition 2.1: *A universal manufacturing model, $\mathscr{U}$*, is a collection of digital models, D_i, $i \in |\mathscr{U}|$ residing in the cloud demonstrating adaptability and affinity properties, where $|\mathscr{U}|$ is the cardinality of $\mathscr{U}$. Universal manufacturing takes open manufacturing to a higher degree of standardisation and formal representation across the entire enterprise. The term universal emphasises agility that is large in scope rather than generalisability of the enterprises formed. The developments in universal manufacturing and artificial intelligence inspired initiatives, e.g. smart manufacturing, are quite independent.

Definition 2.2: An *enterprise model, $\mathscr{E}$*, is an optimised subset of the universal manufacturing model formed to meet the specific production needs. The optimisation criteria and constraints of the enterprise formation model will be enterprise specific and may become the strongest differentiators of enterprise business strategies.

Definition 2.3: A *smart manufacturing* model, $\mathscr{S}$, is an instance of the enterprise model, $\mathscr{E}$.

The enablers of universal manufacturing listed in Figure 1 are discussed next.

3. Enablers of universal manufacturing

The enablers discussed here differ in the level of development and implementation across the industry. For the enablers that have been researched and the development has taken place, the progress is highlighted with a brief overview of the key research papers. The issues facing

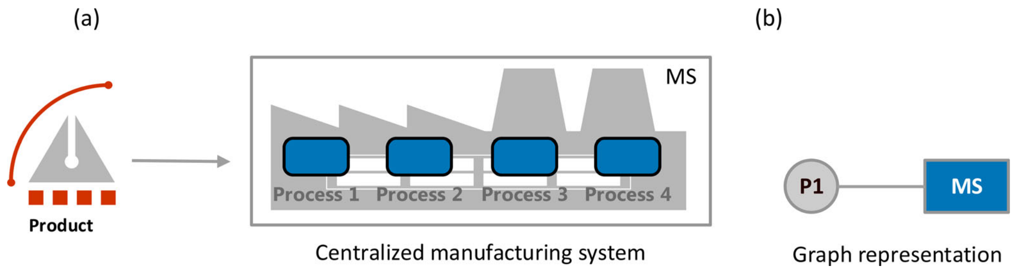

Figure 2. Dedicated manufacturing.

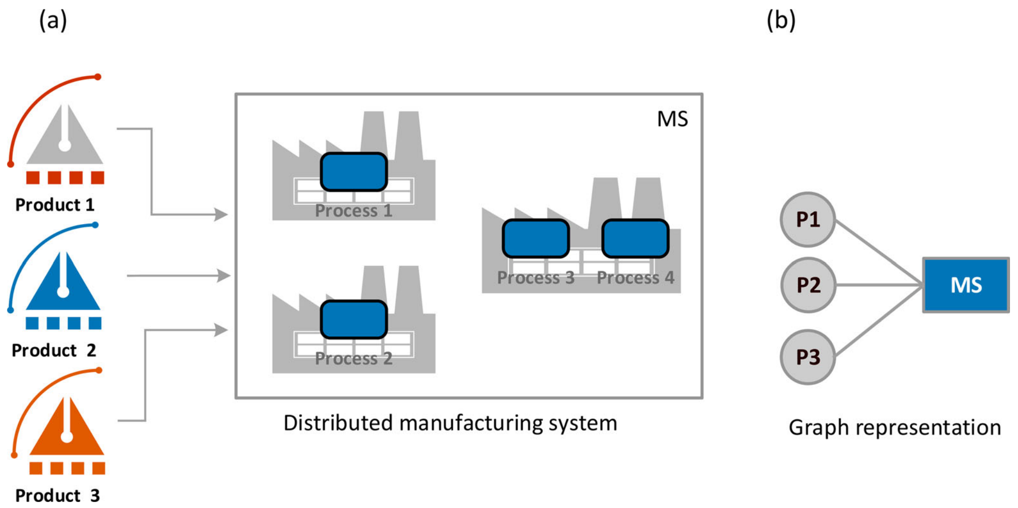

Figure 3. Distributed manufacturing.

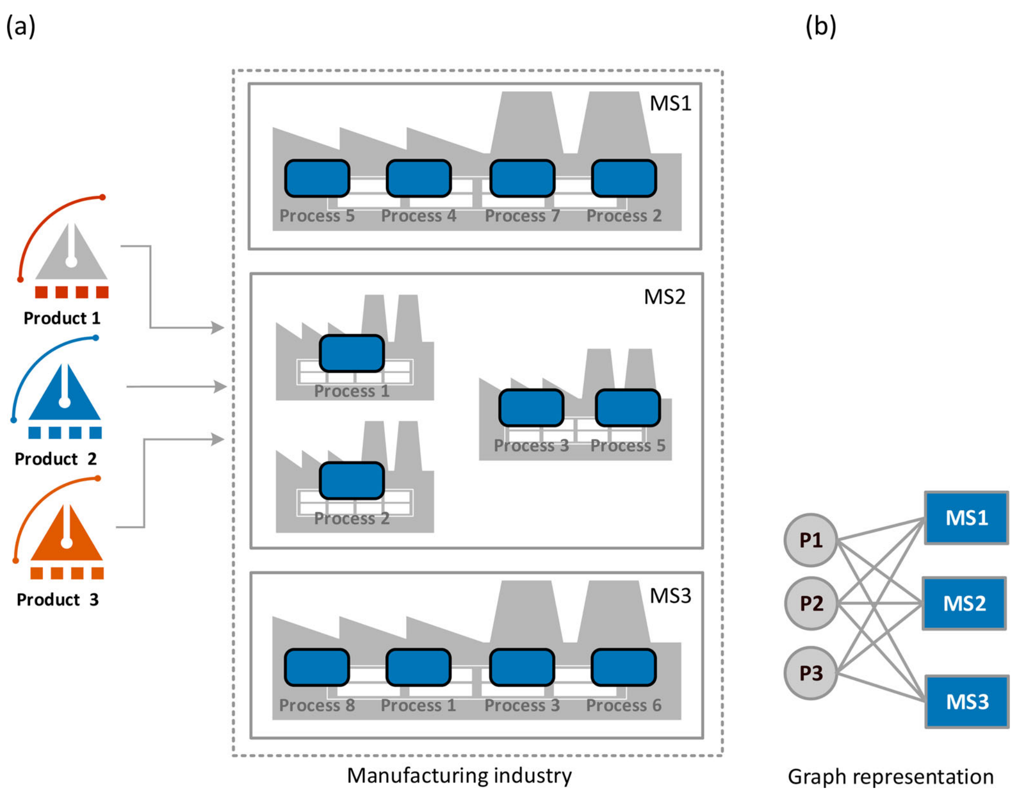

Figure 4. Universal manufacturing.

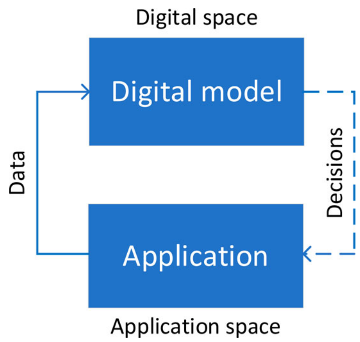

Figure 5. The concept of a digital twin.

enablers that have not received sufficient research attention will be discussed.

3.1. Digitisation in manufacturing

Digital manufacturing stems from growing computing applications versed in data. The most notable concept in digital manufacturing is that of a digital twin. Here, digital twin (see Figure 5) is defined as a model built based on data derived from phenomena versed in science (e.g. physics, biology), a process, a system, or an object (e.g. physical, information based).

Advances in manufacturing methods in support of digital manufacturing were presented in Lin, Kollipara, and Zheng (2019). Lu, Liu, et al. (2020) and Lu, Xu, et al. (2020) offered three scenarios for automation in manufacturing, digital thread, self-organising manufacturing networks, and cloud-based manufacturing equipment as a service. The role of standards in smart manufacturing was emphasised. Jones et al. (2020) surveyed the digital twin papers published in the last decade. The terminology and definitions used in various papers were reviewed. Research gaps and areas for future research were identified. Yi et al. (2020) presented a three-layer digital twin reference model for a smart assembly process. The virtual space layer involving assembly process planning, simulation, predication, and control management was discussed in detail. The proposed approach was demonstrated with an industrial case study of satellite assembly. Tong et al. (2020) introduced a digital twin of an intelligent machine tool intended for data analysis and optimisation of machine tool dynamics and contour error estimation and compensation. The approach advocated in the paper involving multi-sensor fusion of the MTConnect (MTConnect.org) collected data was illustrated with digital machine twins. A modelling approach for the development of multi-scale and multi-dimensional digital twins of machining processes was proposed in Liu et al. (2020). Details of a geometry model, a behaviour model, and a process model were presented. The biomimicry principle advocated in the paper was illustrated with monitoring and control of the machining process of an air rudder. Verboven et al. (2020) formulated requirements for digital twins of agri-food processes, such as reduced product variability, improved quality and shelf life, reduced losses and use of resources, lower costs, optimal production planning, improved logistics, energy savings, and increased transparency. The role of physics-based, data-driven, and hybrid models in a twin was discussed. A digital twin of the cyber-physical production system was proposed in Ding et al. (2020). Details of the configuration and operations mechanisms as well as real-time data-driven operations management were provided.

3.2. Open manufacturing

Manufacturing is evolving in two divergent directions, integrated and open (Kusiak 2018, 2020a). The integrated manufacturing model is driven by the novelty of materials, processes, and products, while the open manufacturing model emerges from largely globally distributed production facilities. The fact that production takes place at different locations has made companies less protective about their processes and physical assets. In fact, the manufacturing equipment is designed and produced by companies operating globally. Other factors impacting manufacturing openness include digitisation, expanding service orientation, and growing presence in the cloud which is discussed next.

3.2.1. Cloud manufacturing

Cloud manufacturing has been researched for at least a decade. In the earlier review paper, Wu et al. (2013) reported the latest developments in cloud manufacturing. Example industrial implementations were presented. Henzel and Hertzwurm (2018) summarised developments in cloud manufacturing an identified six research gaps. Liu, Wang, and Wang (2018) and Liu, Xu, et al. (2018) reviewed 112 papers on cloud manufacturing published after 2015. The articles were grouped into different topical categories. Research issues and suggestions for future research were provided. The literature of service composition and optimal selection was surveyed in Bouzary and Chen (2018). Suggestions for future research were offered. The literature on cloud manufacturing included in the Springer digital library was organised in 12 cluster by Ellwein, Neff, and Verl (2019). Several statistics based on regional and topics were published. Ghomi, Rahmani, and Qader (2019) reviewed and categorised the past developments in cloud manufacturing in five groups: architectures, resources, services, resource allocation, and service matching.

A summary of research challenges was provided. The review of 92 research papers on cloud manufacturing published between 2009 and 2019 was published by Bello et al. (2021). Key technologies of cloud manufacturing and barriers to their adoption in the construction industry were highlighted. A smart manufacturing platform, Advanced Manufacturing Cloud of Things (AMCoT), utilising the Internet of Things, cloud computing, big data analytics, cyber-physical systems, and prediction technologies was discussed in Lin et al. (2017). The platform was designed and implemented based on a methodology developed by the authors. Pedone and Mezgár (2018) introduced cloud-based manufacturing and presented two standardisation frameworks, the Industrial Internet Reference Architecture (IIRA) and the Reference Architectural Model Industrie (RAMI 4.0). The relationship of the two architectures to the service-oriented architecture, Open Connectivity Unified Architecture (OCUA), was discussed. An approach for the decomposition of business processes in cloud manufacturing was presented in Zhang et al. (2020). A three-phase customisation of manufacturing business processes was discussed. Mourad et al. (2020) analysed the financial feasibility of a changeover from traditional cloud manufacturing to interoperable cloud manufacturing. The literature on the interoperability as an enabler for cloud manufacturing was provided. Suggestions for further research were outlined. Cloud manufacturing brings interoperability to the forefront of developments. The most influential papers in this domain are highlighted next.

3.2.2. Enterprise interoperability

The literature reviewed in this section illustrates the developments in enterprise interoperability. Ducq, Chen, and Vallespir (2004) addressed requirements for a unified enterprise modelling language. A methodology for the collection of requirements and attributes for their assessment was described. Doumeingts et al. (2000) discussed the evolution of software in production management. The use of GRAI methodology in the implementation of enterprise software was emphasised. The issues related to interoperability in an enterprise were addressed with system modelling and architecting approaches in Zacharewicz et al. (2020). A model-driven system engineering architecture versed in GRAI was introduced. Application of the model-driven interoperability system engineering framework in cyber-physical systems was suggested. Varnadat (2010) presented technical, semantic, and organisational aspects of enterprise interoperability and networking and addressed open research issues in the context of the European Interoperability Framework. The need to consider trust, confidentiality, legal aspects, and cybersecurity was emphasised. A Domain-Specific Language (DSL) supporting engineering interoperability was discussed in Weichhart, Guédria, and Naudet (2016). The authors extended the ontology of enterprise interoperability based on the theory of complex adaptive systems. Panetto et al. (2016) summarised research challenges in interoperability of enterprise systems in context-aware systems, semantic interoperability, assessment of interoperability, cyber-physical systems, and cloud-based systems. The use of modelling methodologies in support of organisational interoperability of enterprises was addressed in Blanc-Serrier, Ducq, and Vallespir (2018). The level of interoperability was assessed based on the developed graph model. Jardim-Goncalves, Grilo, and Popplewell (2016) reviewed strategies for interoperability of global manufacturing and grouped them into four categories: sensing manufacturing enterprise, semantics and knowledge management, service orientation, and business aspects. A two-phase approach for semantic interoperability of enterprises involved in a collaborative product development was presented in Khalfallah et al. (2016). The OWL (web ontology language) was selected to ensure syntactic interoperability. Semantic interoperability was addressed with a reference ontology. A cloud-based platform was established to support the collaborating enterprises.

Various aspects of open manufacturing have been discussed in the literature for over two decades. Winkler, Stellmach, and Byvoet (2010) linked innovation with open manufacturing in the form of networked microplants in the garment industry. An open control architecture for automated 'plug & produce' manufacturing systems was proposed in Garetti et al. (2013). Runge et al. (2016) discussed the open manufacturing information system framework in the context of digital assurance of product quality at low cost. Cloud manufacturing supports distributed resources and therefore is embraced by open manufacturing. Open manufacturing in the presence of resiliency considerations was explored in Kusiak (2020b).

3.3. Manufacturing-as-a-service

The notion of manufacturing-as-a-service has been emerging for years and it usually addressed some aspects of manufacturing. A novel concept of manufacturing-as-a-service (MaaS) was proposed in Kusiak (2019, 2020c). A model for the configuration of an enterprise from the services needed to handle the intended volume and quality of products was presented. As suggested in Kusiak (2020c), the MaaS concept is a natural extension of shared manufacturing. Manufacturing processes of the MaaS systems represented in a cloud will make the building blocks of an enterprise. The transition to MaaS can be facilitated by the design-for-open manufacturing. Gao et al. (2011) discussed the integration of services and products into a product-service system (PSS). Companies offering manufacturing services could form a service-based manufacturing network. A production-as-a-service (PaaS) framework connecting consumers or product developers with manufacturers facing underutilised resources was offered in Balta et al. (2018). PaaS was envisioned as a cloud-based service-oriented architecture handling various service requests. A small-scale implementation of the proposed framework was tested on new designs.

Cloud manufacturing-as-a-service (CMaaS) platforms promise instant access to a large capacity of manufacturing nodes. However, many of the CMaaS platforms are centralised with data flowing through an intermediary agent connecting clients with service providers. Hasan and Starly (2020) developed a middleware software architecture to connect customers with manufacturing service providers. A solution was proposed to enhance communication and collaboration across decentralised CMaaS platforms.

3.4. Shared manufacturing

The concept of shared manufacturing has its roots in shared economy. It has been pursued in the manufacturing context for about a decade. Kondoh, Komoto, and Salmi (2012) discussed resource sharing among multiple production systems driven by the reduction in the investment cost. A transferability benefit index was defined to identify the most promising resources to be shared. Sharing manufacturing resources to meet growing production demand was discussed in Becker and Stern (2016). The basic concepts and developments of shared manufacturing in China were characterised by He, Zhang, and Gu (2019). Comparative analysis between traditional and shared manufacturing was made. The logistics and organisational needs to implement shared manufacturing were discussed. Some of the benefits of shared manufacturing were supported by simulation experiments. Three types of service systems in the context of shared manufacturing, PSS, configuration-service system, and resource-service system, were considered in Yu, Xu, et al. (2020). A shared manufacturing framework was proposed and illustrated with a prototype system and a case study. In the companion paper, Yu, Jiang, et al. (2020) proposed a blockchain-based framework in support of shared manufacturing. Li, Wu, et al. (2018) and Li, Zhou, et al. (2018) presented a multi-agent system for scheduling of shared and distributed manufacturing resources.

3.5. Sustainable manufacturing

The developments in sustainable manufacturing are largely inspired by environmental concerns, diminishing supply of traditional materials, and the societal pressure to preserve the environment. The central issues of sustainable manufacturing have been addressed in the bibliometric literature survey by Bhatt, Ghuman, and Dhir (2020). The main result of the analysis was a call for the integration of various sustainability principles, including circular economy, life cycle engineering, and corporate sustainability assessment. Sustainability in the context of intelligent manufacturing was presented in He and Bai (2020). Applications of the concept of a digital twin and future developments in intelligent manufacturing were discussed. The central topic in sustainable manufacturing is circular economy. Examples of issues and strategies in circular economy are discussed next.

The quest for sustainability implies a shift from linear economy (produce, consume and dispose) and to a circular (closed-loop) approach that involved inverse logistics. Suzanne, Absi, and Borodin (2020) reviewed the literature on: (i) disassembly for recycling, (ii) product to raw material recycling, and (iii) by-products and co-production. Morseletto (2020) discussed an expanded set of targets (10R), i.e. recover, recycle, repurpose, remanufacture, refurbish, repair, reuse, reduce, rethink, and refuse, paving the way to circular economy. Reike, Vermeulen, and Witjes (2018) argued that a high level of circularity has been accomplished in energy recovery and recycling that fall into the category of long loop options. Coughlan, Fitzpatrick, and McMahon (2018) discussed repurposing (i.e. finding a new use of a product that can no longer function in its original form) of end-of-life notebook computers as thin client computers. Based on their methodology, 9% of the notebook computers were repurposed as thin client computers. Veleva and Bodkin (2018) discussed opportunities in the end-of-life management of laboratory equipment in the biotechnology industry. A framework involving product reuse and remanufacturing for sustainable end-of-life management of equipment with a short lifespan was proposed. Strategies in support of zero-waste manufacturing such as reduction of the paper products, packaging containers, and identification of other recyclable products were discussed in Eike et al. (2020). The methodology of waste reduction was versed in the DMAIC (define, measure, analyse, improve, and control) process. Sustainable business models and contributions of collaboratively developed product-service systems to sustainability were presented in Sousa-Zomer and Cauchick-Miguel (2019).

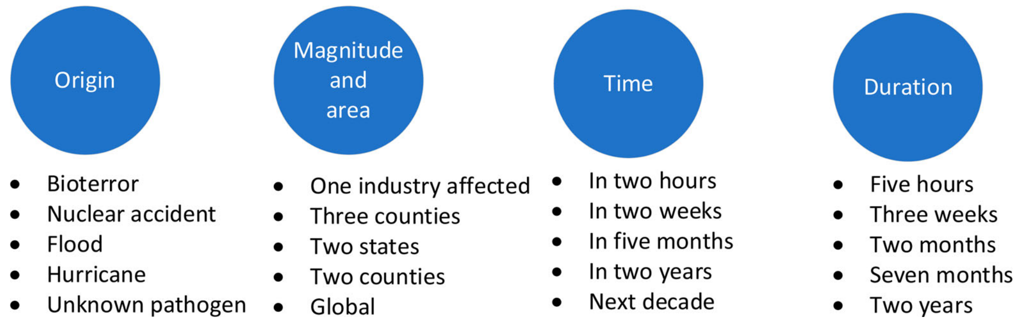

Figure 6. Characterization of adversities facing industry and their characteristics.

3.6. Resilient manufacturing

The industry has largely assumed that the impact of any disruption such as an earthquake or a hurricane could be managed to make the impact tolerable. As the disruptions increased in frequency and scale, a common industrial response was to increase the robustness of supply chains. The environmental science community has been signalling growing changes in the environment for decades. However, the response to this call has been slow and limited. For example, the energy industry has responded with expanding renewable energy portfolios and manufacturing industry has engaged in sustainability initiatives. The recent decades have witnessed a growing number of extreme events. Such extreme events can be observed in nature (e.g. earthquakes), human activities (green gasses), and industry (integrated vs open systems (Kusiak 2020a)). An ideal solution would be to eliminate the source of each extreme event, however, the years of struggle to reduce harmful emissions and the spread of Covid-19 have demonstrated that such as a solution is not feasible in the timeframe needed. As the extreme phenomena are not likely to disappear, but rather new ones may emerge in growing numbers and intensity. Since we do not have control over adverse events, preparing for them would serve well the industry. The science offers some solutions to problems with uncontrollable variables. The control problem in wind turbines could serve as an example. Most control systems have been developed for applications where the input signal can be controlled, from a car with its speed regulated by the fuel rate to an air conditioner adjusting the flow of cool air bringing the room temperature to the level set by a user. In fact, this classical control problem analogy fits the status of control in manufacturing and service industry. The industry has operated under the assumption that the input is largely known with small deviations permissible. The control problem in wind industry represents an extreme scenario where the input (wind speed and conditions) is highly variable and unknown. A wind turbine controller needs to anticipate the wind speed (anticipatory control, Kusiak, Song, and Zheng 2009) to provide good quality control of the generated power. The wind power control problem makes a good analogy of the worldwide problem of dealing with adversities involving uncontrollable variables such as the spread of pandemics or massive hurricane-caused electricity, communication, and transportation disruptions. Following the wind turbine anticipatory control scenario, the best strategy to handle unanticipated disruptions in the industry is to be prepared for it. The latter can be accomplished by design, here a resilience by design approach is recomended. For the best result, anticipating the future system state is needed. The wind energy control problem and manufacturing control follow different dynamics and timescale and therefore the solutions will differ. The best strategy that the industry may follow is that of design for disruptions of different origins, magnitude, and duration (see Figure 6).

3.6.1. The industrial resilience problem

The industrial resilience problem could be formulated as follows: Given the origin-magnitude-duration space of all plausible adversities, the industry should be prepared to fence-off any possible combination of adversities occurring at any time.

3.6.2. Solving the industrial resilience problem

The industrial resience problem is complex, and a formal, e.g. mathematical programming or data-driven model is not likely to emerge soon. Even if serious formal modelling efforts were undertaken, getting the necessary data would be difficult. Given the urgency of the task and limited timeframe, any approach that would improve handling of the adversities faced by the industry is welcome. The fleury of reactive responses (largely by applying management principles) aimed at mitigating the impact of adverse events experienced during the Covid-19 pandemic is certainly not acceptable as the decision-making space is limited due to the previously made design decisions. The industry would have been served best if any

Table 1. Main challenges and opportunities of manufacturing enablers.

Manufacturing enabler	Main challenge	Main opportunity
Digitization	Generating data needed	Delivery of value from data
Openness	Adoption of widely agreed modelling methodology and standards	Presence in the cyber space and connectivity
Service orientation	Conversion to the system-as-a-service mode of operations	Generate benefits of the system-as-a-service concept
Shared resources	Identification of available resources	Better resource utilization
Sustainability	Resolution of legislative and business issues	Address environmental concerns
Resiliency	Development of comprehensive resilience models	Increase ability to withstand disruptions

system affected by adversities had been designed to fence-off these adversities.

The industry design for resilience space is complex largely due to the unknown origin, magnitude, time, and time of adversities (see Figure 6). The main challenges and opportunities of manufacturing enablers are provided in Table 1.

The two properties of universal manufacturing, adaptability and affinity, highlighted in Figure 1 are discussed in the next section.

4. Adaptability in universal manufacturing

The definition of adaptability used in this paper includes those of flexible, reconfigurable, and agile manufacturing. The term flexible has been widely used since 1980th to describe the routing flexibility on the shop floor of a factory. Flexible manufacturing systems handle different parts, in different quantities, and allow different process routings. The increased flexibility is usually realised by automatic tool changers of machine tools, automated guided vehicle systems, and robots. Sethi and Sethi (1990) surveyed the literature on flexibility in manufacturing. Different types of manufacturing flexibility were defined including their purpose and measurements. Future research directions were outlined. A more recent systematic review of the literature on manufacturing flexibility was conducted by Pérez-Pérez et al. (2018). The breadth of research issues and future research opportunities were identified.

Agile manufacturing implies flexibility at an enterprise level, and it is realised by creating processes, tools, and training to address changing customer needs. DeVor, Graves, and Mills (1997) defined agile manufacturing as the ability of a producer of goods and services to thrive in the face of continuous change. The paper offered as a summary of agile manufacturing research. Dubey and Gunasekaran (2015) defined manufacturing agility as an operational strategy to deal with uncertainties resulting from the worldwide economic recession, shortening of product life cycle, supplier constraints, and obsolete technologies.

A reconfigurable manufacturing system is designed for rapid change of its structure and hardware and software components in response to the market changes or intrinsic system changes. The term reconfigurability in manufacturing was likely coined by Kusiak and Lee (1995). Its wide use in the literature was contributed by the research centre established at the University of Michigan. The definition and review of enablers, drivers, and techniques applicable to reconfigurable manufacturing systems were provided in Mehrabi, Ulsoy, and Koren (2000). Singh et al. (2017) reviewed the literature on reconfigurable manufacturing systems and identified research areas awaiting future research. Bartolini et al. (2018) published another literature survey on reconfigurable manufacturing that highlighted application areas, methodologies, and tools. Emerging trends and research areas ranging from conceptual models to empirical applications were discussed. The relationship of reconfigurable manufacturing to Industry 4.0 was highlighted. Reconfigurable process planning combined with the crowdsourcing contracting strategy was presented in Ma, Gang, and Jiao (2020). The relationship between flexible and reconfigurable manufacturing was discussed in ElMaraghy (2005). While manufacturing flexibility is built-into the system with the intent to handle anticipated shop-floor variations, reconfigurability offers customised flexibility on demand in a short time period.

5. Affinity in universal manufacturing

The manufacturing equipment used by different companies is usually produced by a limited number of original equipment manufacturers (OEMs). A superset of manufacturing equipment across many companies would serve as a basis of universal manufacturing factories. A virtual factory would manufacture the products using the equipment produced by OEMs. Such a factory would exploit affinity among products, resources, processes, and services. A virtual factory would naturally offer more alternatives for product delivery, some of which could be more advantageous than the corresponding traditional company. The benefits derived from the virtual factory would be largely production related such as higher capacity utilisation, lower transportation costs, large production volumes, would offer benefits such as sustainability, resilience, and product personalisation.

The concept of a virtual factory has been practiced to some degree in industry, e.g. in the form of mergers and acquisitions, resulting in corporations offering benefits similar to those of a virtual factory. The idea of similarity of products, resources, processes, and services can be considered as analogous to group technology introduced by Mitrofanov (1959). The foundation of group technology was to group components of similar geometry into part families. The geometric similarity of parts implied process similarity which has led to forming manufacturing cells. Each manufacturing cell could be considered as a generalised machine tool able to accommodate one or more part families. The group technology concept has increased manufacturing efficiency and it is used to date in various forms across manufacturing and service industry, including healthcare. Different techniques, methodologies, and models have been applied to form machine cells and part families. Classification and coding systems were widely adopted in the industry. Each part was assigned a code describing its geometry and process characteristics. The coding process was usually manual; however, attempts to automate it have been made.

The group technology codes have been largely abandoned, however, the core idea of being able to identify similar components, assembles, products, resources, processes, and services has merits in manufacturing.

The industry and the public have engaged in an intense search for facilities to manufacture components and products needed during the recent pandemic, e.g. facilities able to produce ventilators. It is difficult to imagine that email searches aimed at identifying suitable manufacturing facilities would yield optimal solutions. The outcome could be even more damaging if more severe disruptions occurred.

Knowing the basic information about components, assembles, products, resources, processes, and services would allow to assess capability and capacity to produce Covid-19 items such as personal protective equipment. Alternative manufacturing facilities would be identified in case of any large-scale nature or human caused disaster.

Today we have data and information technology solutions that were not available when the group technology concept was proposed and practiced. The focus needs to shift from physical parts and machines to information and data. Likely any component designed in the recent years has a digital footprint. The same applies to manufacturing resources, from a cutting tool to a 3D printer. Data around products, resources, systems, and services are plentiful.

The key is to identify the right data and information and then package them into a code. Different modalities of the proposed manufacturing affinity concept (versed in classification and coding) could be considered. For example, (i) it could be applied to products and manufacturing facilities that are critical, (ii) the codes could be computed in advance for products or facilities, (iii) the codes could be computed whenever a need for emergency capacity and capability arises; (iv) the codes could be used to manage capacity and capability of the manufacturing-as-a-service systems.

Based on the product code, alternative manufacturing systems (factories) would be identified. Of many alternative manufacturing systems, an optimal configuration would be selected. Figure 7 illustrates a primary manufacturing facility (PMF) and a secondary manufacturing facility (SMF) selected based on 12 processes (represented by 12 process-as-a-service models) belonging to three different manufacturing systems, MS1 – MS3. The extent to which the alternatives could be considered would be managed, e.g. for the essential products.

The primary facility includes three processes (Process 1, 2, 3) of manufacturing system MS1, while the secondary facility includes four processes (Process 6, 7, 11, 12) belonging to two different manufacturing systems (MS2, MS3). The two factories, PMF and SMF, mimic numerous factories that would be formed for products of any complexity. Other services, including supply and distribution chains, would be included in the optimisation process. The affinity property is a key challenge of universal manufacturing involving three basic issues: (i) unified representation of processes and products; (ii) system connectivity and interoperability; and (iii) similarity of digital models.

5.1. Unified representation of processes and products

Visibility of manufacturing systems is key to universal manufacturing. One way to make manufacturing systems visible in the cloud is by building digital models. Such models would generally be not granular enough to meet the definition of a digital twin, and therefore here they are referred to as digital models. Due to the diversity and complexity of manufacturing systems, digital models may take different forms. To date, dozens of system modelling languages and methodologies have been developed. The papers on process modelling published over the last decade were reviewed in Dani, Dal Sasso Freitas, and Thom (2019). The BPMN (Business Process Model and Notation, bpmn.org) methodology was most frequently used across all papers reviewed. The reasons behind its popularity could be that BPMN is an ISO standard and it is supported by many software tools.

The BPMN methodology is used in this paper to construct example digital models. Using any existing model-based system modelling methodology is an asset. Any

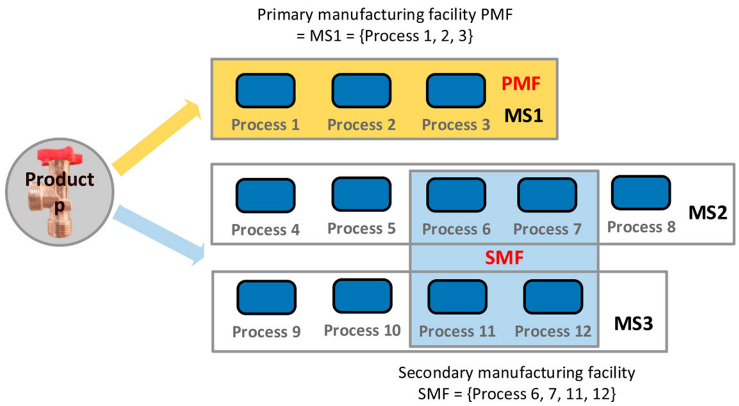

Figure 7. The primary PMF and secondary manufacturing facility SMF for manufacturing product P.

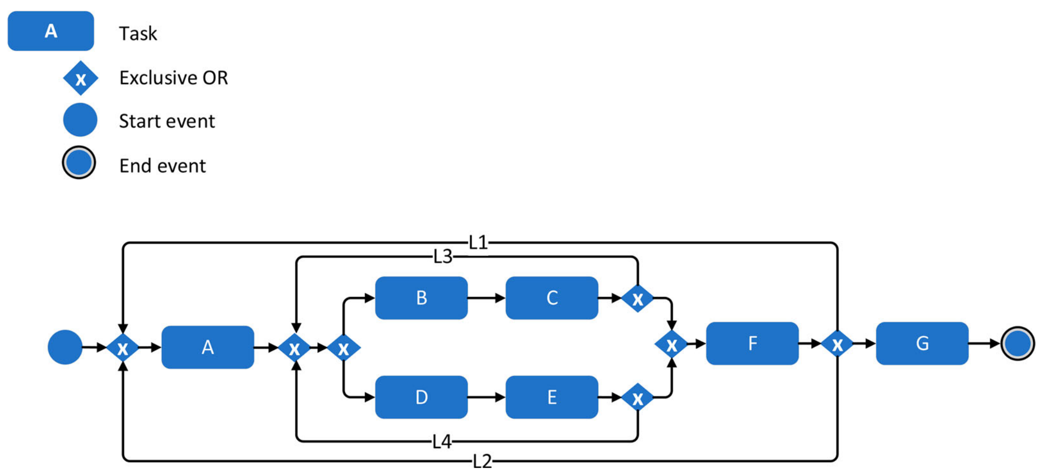

Figure 8. Digital model of a manufacturing process.

process model can by represented by a graph that allows for the deployment of formal modelling and analysis algorithms.

Consider the digital model of a manufacturing system presented in Figure 8. The model includes seven tasks, A, . . . , G, and it follows the BPMN (bpmn.org) notation where:

Since models of products and manufacturing systems are related, a tree representation of digital models is unifying the two. The model in Figure 8 is transformed in a tree shown in Figure 9. In addition to the notation of Figure 8, the following two symbols are used in the tree model:

An example representation of a product, P, containing five components, C1, . . . , C5, is shown in Figure 10. Besides the Exclusive OR, the following logic AND symbol is used:

Note that two logical symbols, & (AND) and X (exclusive OR) are used in the product model in Figure 10. To distinguish between the process and product graphs, squares denote tasks in the model of Figure 9, and circles represent components in the model in Figure 10. Process modelling methodologies usually use the two operators (& and X) as well as an OR operator. The two models in Figures 9 and 10 offer representational uniformity. The process model in Figure 9 employs 'Sequence' and 'Loop' operators that could be also used to model complex products.

5.1.1. Benefits of unified product and process representation

To fully implement the concept of universal manufacturing, detailed process or product information is needed, which is not the case in industrial practice. Using the unified tee representations of products and manufacturing systems would allow for decision-making based on partial product and process information. Models and algorithms could be developed to search for manufacturing capabilities with the scattered information available. It is expected that once universal manufacturing gains more maturity, the information content would grow in time.

The unified representation of components and products deserves a separate consideration, and it is not a subject of this research. There are existing developments in this space, especially in the electrical and software

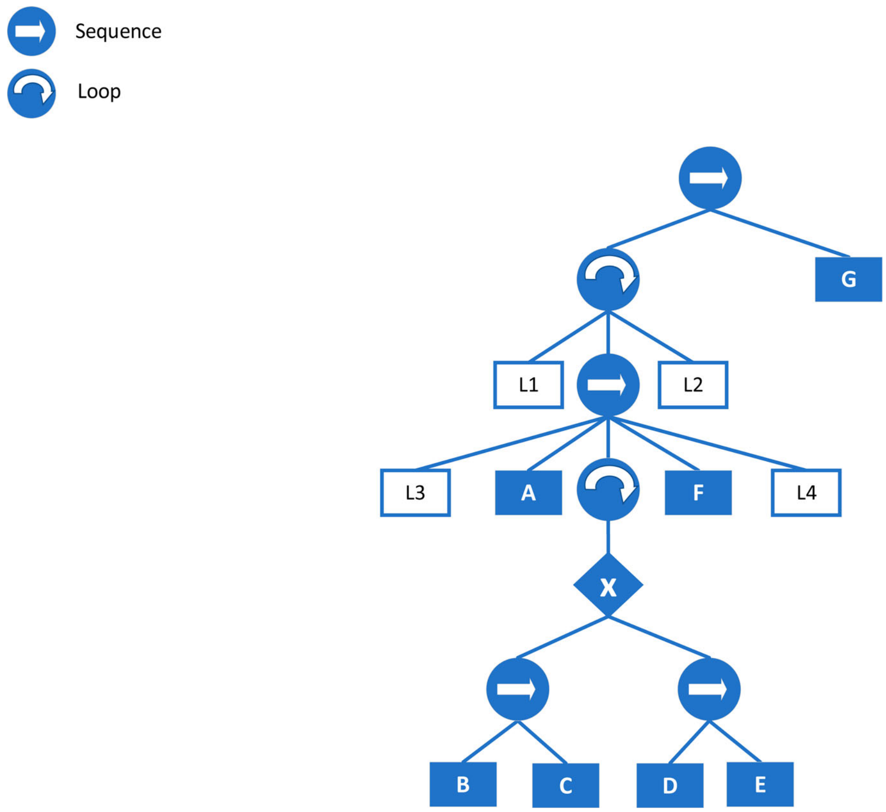

Figure 9. Tree representation of the digital model in Figure 8.

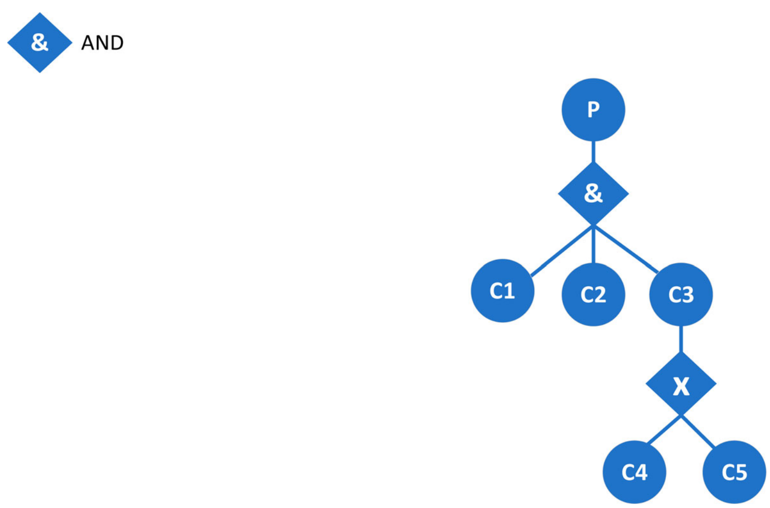

Figure 10. Tree representation of product P with five components, C1, . . . , C5.

engineering. A viable methodology in the mechanical engineering domain could be rooted in group technology with a manufacturing process derived from geometry of components. The fact that the geometry is usually available in a digital form simplifies the problem.

The concept of universal manufacturing has merits irrespectively of the developments in unified modelling of components and products. One of the promising enablers of modelling and enhancing system connectivity and interoperability is the MTConnect standard and software discussed in the next section.

5.2. System connectivity and interoperability

Connectivity and interoperability of manufacturing models and data sharing are key to the success of universal manufacturing. Standards are needed to facilitate systems interoperability. A candidate standard for data collection of manufacturing-as-a-service and other services is MTConnect. MTConnect (ANSI/MTC1.4-2018) is an open and free of charge standard supporting interoperability between devices, sensors, and software applications by publishing data over a network. By establishing an open and extensible communication, MTConnect facilitates the exchange of data between the workpiece, sensors (including personnel data), and shop-floor equipment and tools (low level in the manufacturing hierarchy) and the high-level design and process planning applications. It is expected that over time third-party solution providers will develop software and hardware products based on the MTConnect standard for seamless interoperability across the entire enterprise and beyond.

The MTConnect standard offers domain-specific vocabulary and data models. The MTConnect data allow the solution providers and integrators to focus on the development of applications rather than data translation. The initially defined terms in MTConnect are specific to discrete manufacturing and have application-specific semantic meaning. The vocabulary has been established and is supported by industrial stakeholders.

MTConnect has been applied and is used by more than 50,000 devices in over 50 countries. The most frequent applications of MTConnect include factory floor monitoring, overall equipment effectiveness calculation, predictive analytics or maintenance, integration of manufacturing equipment, and production planning integration.

Some of the manufacturing equipment and devices, software, and systems available on the market support the MTConnect standard. An MTConnect implementation requires an adapter (translating the native device data into MTConnect) for each device and one or more software agents (performing data aggregation, formatting, and temporary storage). Adapters are supplied by device manufacturers, control manufacturers, or third parties. They are usually proprietary, offered for a fee software. Some adapters run on their own hardware, such as an industrial PC, managed switch, or a gateway device. The current and archival versions of MTConnect available at no cost to the public at www.mtconnect.org/documents. The open-source developer tools can be downloaded from www.github.com/mtconnect.

5.2.1. Related standards

The major manufacturing initiatives, including Industrie 4.0, Made in China 2025, and Make in India/Digital India, point to standards as enablers of technology. The key reference architectures, the Reference Architecture Model for Industrie 4.0 (RAMI) and the IIRA specify functional areas addressing the collaboration and coordination across industries.

In many cases, standards organisations are working on the integration of the existing standards. MTConnect is compatible with the ISA-95/B2MML guidelines for device integration with higher level enterprise planning and management systems. The MTConnect companion specifications include MTConnect-OPC UA, MTConnect-B2MML, and the Universal Machine Tool Interface.

The MTConnect standard was deployed to a Sherline 3-axis milling machine (Liu, Wang, and Wang 2018; Liu, Xu, et al. 2018). Data from sensors including RFID (radio frequency identification) tags, accelerometer, dynamometer, and rotational speed were collected and used to develop applications such as machine tool structure representation, machine status monitoring, data visualisation and analysis, and historical data archiving. Implementation of additional solutions such as data visualisation, production control, and cloud-based decision-making systems as well as the deployment of wearable devices and smart phones was considered. The interoperability between the OPC UA and MTConnect standards was demonstrated in the follow-up paper by Liu et al. (2019). An interface was developed to transform the MTConnect model and data to the OPC UA applications. Rodriguez et al. (2019) applied MTConnect to connect an Arduino additive manufacturing machine to the TCP/IP network. Two different configurations were considered: (i) the MTConnect adapter was separated from the machine; (ii) the MTConnect adapter was embedded in the machine controller.

5.3. Similarity of digital models

Universal manufacturing is in its infancy and the modelling paradigm awaits research. It is anticipated that process models will gain prominence. Retrieving digital models stored in the cloud is key to universal manufacturing. In this section, the research published in the similarity of process models and related constructs such as networks and graphs is outlined.

5.3.1. Process model similarity

Three metrics of process similarity were introduced in Dijkman et al. (2011). The first metric considered node similarity by comparing the labels and attributes throughout a process model. The second one assessed structural similarity by comparing the process model topology and the labels. The third metric assessed behavioural similarity by considering labels and causal relations captured by the process model. The accuracy of the metrics was evaluated in a computational study. Dijkman et al. (2013) summarised research is the similarity of process models. Directions for future research were outlined. Neumuth, Loebe, and Jannin (2012) introduced five metrics to determine similarity of surgical process models. The metrics assessed process compliance in terms of granularity, content, time, order, and frequency of surgical activities. Computational experience with 20 clinical data sets validated the metrics. Lupinetti et al. (2019) introduced four metrics to assess similarity between assemblies at local, partial, and global level. The proposed metrics were validated using a labelled dataset. A clustering approach for searching business process models was presented in Ordoñez et al. (2017). The similarity metric is based on fuzzy logic that considered structural and textual information of process models. The validity of the proposed model was confirmed in computational experiments. Gao and Zhang (2009) have addressed the issues arising in modelling process models using the same modelling language by human modellers. A concept of similarity propagation was introduced to map activities and data. The model similarity is measure with the Jaccard coefficient. Tan and Wang (2017) addressed the gap between the structural and behavioural similarity of process models. They introduced a process similarity metric versed in traces, i.e. the constrained longest common subsequences retaining the behavioural and structural properties of the original process model. An approach called, meta-model for process model registration (MFI-5), was introduced in Li, Wu, et al. (2018) and Li, Zhou, et al. (2018) to measure the similarity of process models. The approach involved the determination of features considered in similarity determination. The model similarity was computed using the Tanimoto coefficient-based algorithm. Similarity of process models representing processes at various degree granularity and using different vocabulary was considered in Baumann et al. (2014). The proposed metric considered task levels, data objects, and the task sequences. Suggestions for future research were provided. Yan, Dijkman, and Grefen (2012) proposed an algorithm for computing similarity of process models based on model fragments, called features. Results of computational experiments were reported. In addition to the algorithm, a software architecture and a prototype similarity search engine were discussed.

5.3.2. Network similarity

A dynamic time-series approach to measure the similarity between nodes of networks was presented in Yang, Huang, and Li (2019). The similarity index combined local and global properties of the network topology. Yu and Li (2020) proposed a connective Steiner k-eccentricity index to express network similarity. Comparative analysis has demonstrated the advantages of this index with other indices, including the graph energy and connective eccentricity index. Similarity of networks was applied to study the relationship between diseases by Le and Dang (2016). The authors have constructed such network from the phenotype ontology data base and integrated them with gene and protein networks. A similarity measure for the analysis of networks of patents was introduced in Rodriguez et al. (2015). The proposed measure has shown advantages when tested against the Jaccard similarity index.

5.3.3. Graph similarity

Zager and Verghese (2008) proposed a graph similarity measure based on the structural similarity of local neighbourhoods to determine similarity scores for the nodes of two different graphs. This measure was applied to the graph matching problem. The issues facing representation designs by graphs and their assessment were discussed in Strug (2013). Kernel functions were used to compute the similarity of designs. The proposed approach was approach was applied to evaluate layout designs. A graph similarity approach for the detection of bearing faults was proposed by Sun et al. (2020). Hamedani and Kim (2017) proposed a similarity measure for graphs, JacSim, that had overcome the shortcomings of the SimRank measure. The measure has been extended to weighted graphs. Contextual similarity between pairs of nodes was introduced in Dutta et al. (2018). Subsequently, graph matching was formulated as a node and edge selection problem. The Tanimoto index measuring the topological similarity of graphs was studied in Dehmer and Varmuza (2015). The properties of the index applied to chemical alkane trees were studied. Bopche and Mehtre (2017) proposed graph distance metrics based on the maximum common subgraph and graph edit distance (GED) for assessment of security risk of networks. Computational results for 11 different metrics tested on a set of three different network models were provided. Theoretical considerations of graph similarity measures based on three graph matrices, the adjacency matrix, the Laplacian matrix, and the Markov matrix were reported in Avrachenkov, Chebotarev, and Rubanov (2019). Additional graph similarity and distance metrics were analysed in Chartrand, Kubicki, and Schultz (1998). Sabarish, Karthi, and Kumar (2020) developed a graph-based model for trajectory graphs of moving objects such as vehicles, humans, animals, or phenomena. The similarity between the graphs was computed using the edge and vertex-based metrics. The problem of searching graphs with noisy and incomplete data was considered in Zheng et al. (2015). Computational experience has confirmed the performance advantage of the approach proposed in the paper over the existing graph similarity approaches. Kwon et al. (2006) proposed a similarity metric to address interoperability issue in semantic web ontologies represented with graphs. The metric was applied to compute similarity across multiple web ontologies. Digital models of universal manufacturing will take different forms, including process models enriched with additional information imposed by application-specific model requirements. The additional information could include resources such as machine tools, their process characteristics and time-based availability, control software, and edge solution. The widely discussed in the literature digital twin is an instance of digital model.

6. Conclusion

The proposed concept of universal manufacturing is intended for forming enterprises to meet production needs of any type and magnitude. To implement universal manufacturing digital models are needed. It is imperative that these models have become visible in a cloud. The latter would democratise manufacturing as small and large companies would be present in the universal manufacturing space, and thus have similar opportunities to compete. The universal manufacturing space would be large and allow optimisation in different criteria amidst constraints imposed by the market, environment, and natural or human-caused disasters. The solutions generated based on such model space would benefit all member companies of the universal manufacturing space as well as the society. The large scale of decision space and increased model visibility would allow the benefits to exceed those of traditional manufacturing.

Before the concept of universal manufacturing would be implemented, modelling is needed to assess and quantify its benefits. The results of such research would be used by industry to engage in the development of prototypes and before a full-scale deployment would take place. It is envisioned that universal manufacturing would be implemented gradually with large corporations taking a lead. Small manufacturing companies would be gradually integrated to meet the production needs. Six enablers of smart manufacturing including digital, open, service, shared, sustainable and resilient manufacturing were discussed. Each enabler was characterised, and its status was supported by the literature. These enablers would promote the evolution of properties of universal manufacturing such as adaptability and affinity that were discussed in the paper. Additional properties are likely to emerge in the course of future developments of universal manufacturing enablers.

Notes on contributor

Andrew Kusiak is a Professor in the Department of Industrial and Systems Engineering at The University of Iowa, Iowa City. He has served as chairman of two departments, Industrial Engineering (1988–1995) and Mechanical and Industrial Engineering (2010–2015). His current research interests include applications of computational intelligence and big data in manufacturing, automation, renewable energy, sustainability, and healthcare. He is the author or coauthor of numerous books and hundreds of technical papers published in journals sponsored by professional societies, such as the Association for the Advancement of Artificial Intelligence, American Society of Mechanical Engineers, Institute of Industrial and Systems Engineers, Institute of Electrical and Electronics Engineers, and other societies. He speaks frequently at international meetings, conducts professional seminars, and consults for industrial corporations. Dr Kusiak has served in elected professional society positions as well as editorial boards of over fifty journals, including editor positions of five different IEEE Transactions.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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