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From digital to universal manufacturing

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ABSTRACT
The transformation of the manufacturing industry over the last two decades has been largely inspired by data. Digitisation has made its mark in different areas of manufacturing, from digital materials and processes to data science in decision-making. The digital manufacturing is evolving towards universal manufacturing that is highlighted in this paper. Different manufacturing initiatives are benchmarked and their relationship to universal manufacturing is demonstrated. The representation of enterprises in the universal manufacturing cloud is discussed. Product- and process-based specifications of digital enterprises are defined. Using these specifications, the enterprise configuration algorithm proposed in the paper is applied for the selection of component models. Two different representations, a node–node and an input–output matrix, of the digital component models are considered. The extended topological sorting algorithm is applied to construct an integrated digital model.

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Digital manufacturing; universal manufacturing; Industry 4.0; manufacturing cloud; design structure matrix; smart manufacturing

1. Introduction

The development of industry has been rather steady over the recent decades. The course taken and disruptions that have occurred along the way were relatively minor and were managed to accomplish the best outcome. The recent pandemic has made the manufacturing industry aware that it is not immune to human and nature caused disasters, as well as other potential disruptions that could be attributed to technology, sustainability, or sources that are not known at this time (see Figure 1).

The COVID-19 pandemic has occurred amidst an ongoing industrial transformation involving data. Applications with historical data available or generated from designed experiments have benefited from data science. It is known that the manufacturing industry is not amenable to running experiments which has implications on data collection. It would be highly unlikely for any company to open a factory floor to conduct experiments producing data. Rather the opposite applies, where the goal is to manufacture a product meeting all specifications in the first run in a data poor scenario. There is no doubt that the manufacturing environment is becoming more uncertain and managing the decision space of progress is challenging. The digitisation path the industry has subscribed to might serve it well in a long run. In addition to the data acquisition from manufacturing hardware, the industry is encouraged to experiment in the digital space. The predictive component of data science will enrich the manufacturing decision space. The digitisation of the industry will naturally call for enlargement of the decision space beyond a single enterprise. The latter is addressed by the concept of universal manufacturing proposed in Kusiak (2021).

2. The path to universal manufacturing

The relationship between products and manufacturing has evolved over years. In the early years, a manufacturing facility (system) would be dedicated to one product, thus forming one-to-one relationship illustrated in Figure 2(a). In time, the relationship between products and manufacturing has become many-to-one as shown in Figure 2(b), where a manufacturing system (centralised or more frequently distributed) accommodates many different products or variants of a product. In universal manufacturing, this relationship becomes many-to-many as illustrated with the bipartite graph in Figure 2(c) (Kusiak 2021). In practice, this graph is not likely to be fully connected due to the constraints imposed by products and manufacturing. However, from the efficiency perspective, it is desirable that the product–manufacturing graph is densely connected. The manufacturing facilities in the many-to-many relationship are likely to be highly distributed.

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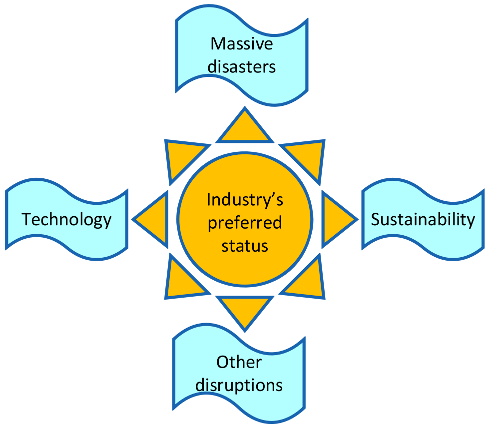

Figure 1. Manufacturing industry and potential disruptions.

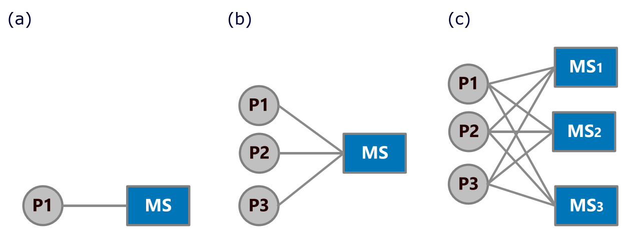

Figure 2. Evolution of the product–manufacturing relationship.

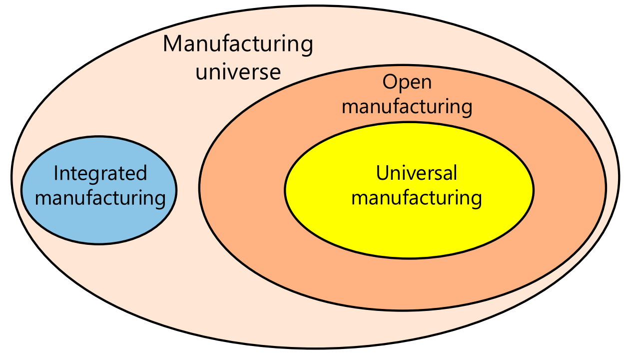

Figure 3. Emerging manufacturing concepts.

Table 1. Attributes of manufacturing.

	Manufacturing			
Attribute	Digital	Smart	Open	Universal
Flexible				o
Agile				o
Reconfigurable		o	o	o
Resource sharing		o	o	o
Data driven	o	o	o	o
Model-based	o	o	o	o
AI-based		o	o	o
Cloud-based			o	o
Service-based			o	o
Globally optimised				o

2.1. Universal manufacturing

The scope of implementation of the many-to-many configuration between products and manufacturing systems depends on the degree of openness of the manufacturing space. An open manufacturing system (Kusiak 2020b) is one that is prepared to engage in the production of products designed and owned by other corporations, in an extreme case by competitors. Though open manufacturing implies that the company owing the product maintains some degree of production control, the rules of business engagement are rather loose and not well formalised. Universal manufacturing proposed in Kusiak (2021) involves much higher degree of standardisation and formal representation of enterprises as well as production control, including quality.

Figure 3 illustrates the relationship between universal, open, and integrated manufacturing in the manufacturing universe. The integrated and open manufacturing are defined in Kusiak (2017, 2020a).

The integrated manufacturing is one of the two extrema involving a high degree of novelty (e.g. a new material, product, and a process), and does not conform the open manufacturing requirements. Open manufacturing is the opposite extreme of integrated manufacturing with universal manufacturing being a subset of it. It is likely that in future years open and universal manufacturing will expand.

Four types of manufacturing, digital, smart, open, and universal are characterised based on the list of attributes provided in Table 1.

The entries in Table 1 mark the key attributes that apply to the corresponding manufacturing type. For example, digital manufacturing is primarily driven by data, however, some digital manufacturing initiatives may also address other attributes, e.g. the cloud. Table 1 demonstrates that universal manufacturing embodies the largest number of attributes.

The manufacturing attributes listed in Table 1 are briefly defined in Table 2 and supported by a reference.

3. Digital models of manufacturing systems

The literature on system modelling, including manufacturing, is extensive. Some of the papers published over the last decade are reviewed. The general principles of modelling products and processes were introduced in Cameron and Gani (2011). The book by Long (2014) offered numerous insights into process modelling. The author considered the business process model and notation (BPMN, bpmn.org) methodology as the most useful for process modelling. In the review paper, Aldin and de Cesare (2011) focused on the reusability of business process models. Eshuis and Van Gorp (2016) offered a data-centric approach to process modelling, leading

Table 2. Definitions of manufacturing attributes.

Manufacturing attribute	Definition	References
Flexible	Adapt to changes in the type and quantity of the product being manufactured	Wei, Song, and Wang (2017)
Agile	Quick response to changes in customer needs and markets under quality and cost considerations	Iacocca Institute (1991)
Reconfigurable	Interchangeable manufacturing resources, e.g. machines and material handling units	Kusiak and Lee (1995)
Resource sharing	Manufacturing resources, e.g. machine tools, software, used by more than one enterprise	Rožman, Diaci, and Corn (2021)
Data driven	Data usually collected by sensors is made available for development of different applications	Kuo and Kusiak (2019)
AI-based	Use of smart devices, e.g. robots and machine learning algorithms	Cheng et al. (1998)
Model-based	Use of data for the development of models and digital replicas for control and decision-making	Liu et al. (2021)
Cloud-based	Models of different nature posted in the universal manufacturing cloud	Wei, Zhou, and Liang (2020)
Service-based	Systems, e.g. manufacturing, in the form of x-as-a-service	Kusiak (2019)
Globally optimised	Large-scale optimisation in different criteria across different systems	Morariu et al. (2020), Valckenaers (2020)

to the generation of a complete model. Details of the approach, including the Guard-Stage-Milestone schema, were outlined in the paper. A graph-based approach for the development of reference models from the domain-specific models was presented in Rehse, Fettke, and Loos (2017). The approach proposed in the paper was tested in different cases studies. The latest developments in process modelling were compiled in the book by Nurcan et al. (2020), containing papers presented at two conferences, the 21st International Conference on Business Process Modeling, Development and Support and the 25th International Conference on Exploring Modeling Methods for Systems Analysis and Development. Erasmus et al. (2020) attempted to close the gap between modelling logistics and manufacturing processes by defining reusable process models, called fragments. They applied the fragments to model different manufacturing processes. The fragments and the processes were represented with business process model and notation (BPMN). Stacey, Eckert, and Hillerbrand (2020) argued that a design process model could be governed by rules. The following 12 conceptualisations of design process models were outlined in the paper: frames, pathways, positions, proclamations, projections, predictions, propositions, prophecies, requests, demands, proposals, and promises.

The basic tenant of universal manufacturing is to have manufacturing enterprises formally represented in the cloud. While details of such representation await research, the examples presented in Figure 4 illustrate the challenges that could be faced by representation of manufacturing systems. The example in Figure 4(a) illustrates the least detailed model of a manufacturing system that includes machine tool numbers, potentially machine types, and additional information. The model in Figure 4(b) is enriched with a machine layout. The process model in Figure 4(c) does not follow a formal notation, while the model in Figure 4(d) conforms the BPMN methodology. In addition to serial and parallel tasks it includes a logic gate (i.e. $x =$ exclusive OR) and two loops L1 and L2. Note that the BPMN methodology was approved as the ISO (International Organization for Standardization) standard, ISO/IEC 19510, in 2013.

Using a standard modelling approach offers several advantages such as ease of communication among different models, simplified model retrieval, and enabling development, deployment, and sharing model analysis tools. The existing process modelling methodologies and tools have additional features of interest to the manufacturing cloud such as hierarchical representation of processes, simple notation, and ease of annotation.

Searching digital models can be accomplished from a product or a manufacturing perspective. The former may largely apply to new products, while the latter could be driven by the need to rapidly expand production capacity. The implementation of the manufacturing perspective involves matching of different models which appears to be less complex than the product to manufacturing translation.

In this paper, hierarchical and distributed metrics are advocated in search of digital process models that apply to the product and manufacturing perspectives.

Any process modelling methodology can be hierarchical, and so are the products and processes. A typical product includes assemblies that may break down into subassemblies, and those in turn into components that may include features. Though most process modelling methodologies are intended for processes, they can be also used to represent products. In the product representation, tasks of process models are replaced with functions. A manufacturing facility includes processes performing operations (tasks) resulting in components and products. Examples of operations (tasks) in manufacturing include milling, 3D printing, assembly, inspection, and material handling.

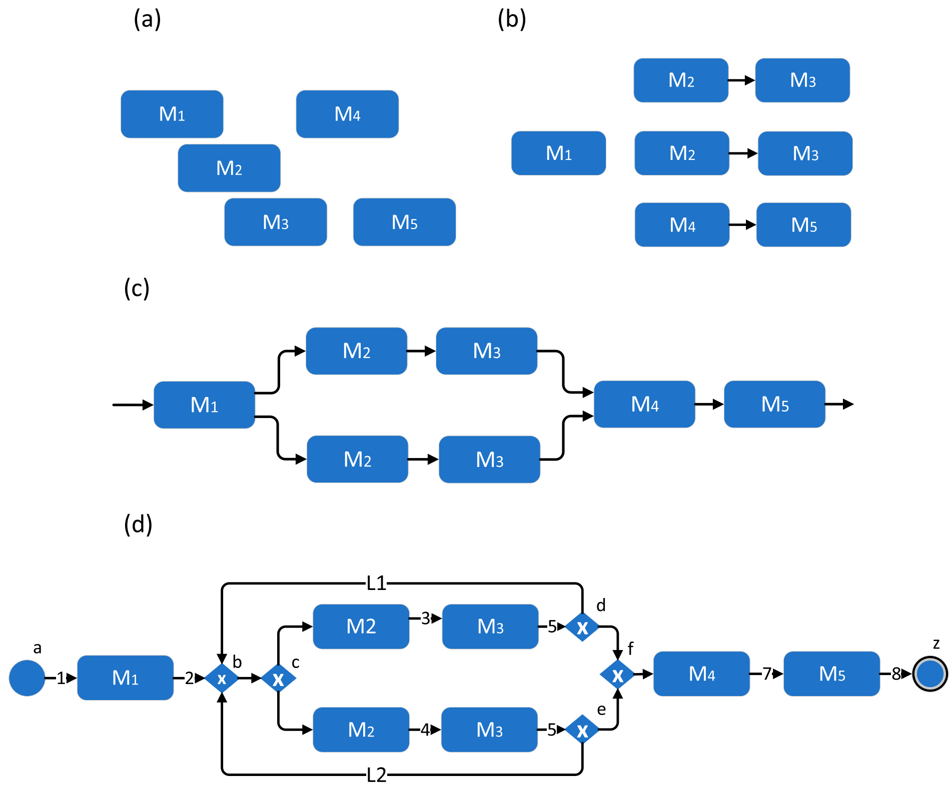

Figure 4. Different degree of detail representations of manufacturing systems.

The example presented next illustrates the basic concepts discussed in this paper.

3.1. Illustrating example

Consider a simple product, the squeezable bottle produced out of polyethylene by Grainger (grainger.com), shown in Figure 5. This product includes three different components: a bottle, a cap, and a tube.

The bottle in Figure 5 is manufactured in the system represented in Figure 6 using the BPMN methodology. The model in Figure 6 involves three injection moulding processes (tube, cap, and bottle) and the assembly process.

Manufacturing systems such as the one presented in Figure 6 are designed to meet certain production capacities. Any increase in production demand is handled by capacity expansion. The capacity expansion model is well suited for growing the system over a long-term horizon. Procurement of new equipment, installation, and workforce expansion and training take time. The capacity expansion mode is not suited to handle rapid spikes in the demand. The spikes in the demand that are frequent, short lasting, and involve process capabilities that are not currently available require a different approach. Assume that the production capacity for the bottle in Figure 5 has increased by 300%. This additional

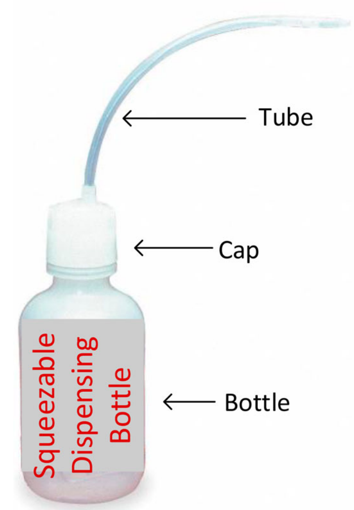

Figure 5. A bottle consisting of three parts (grainger.com).

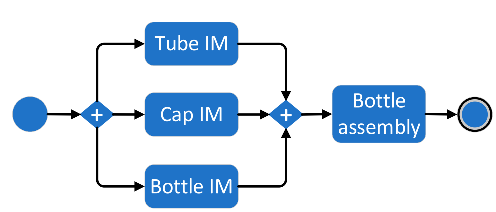

Figure 6. Digital process model of manufacturing the bottle from Figure 5.

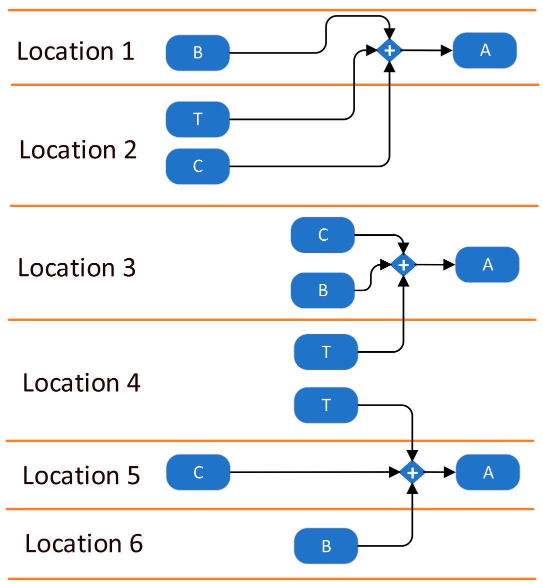

Figure 7. The digital model identified in the cloud.

capacity could be easily identified in the universal manufacturing environment by assembling the model in Figure 7, where B = Bottle IM, C = Cap IM, T = Tube IM, and A = Assembly. This model involves processes distributed over six different locations, locations 1–6.

Universal manufacturing enables efficient search and synthesis of manufacturing capabilities cross its network.

To implement the concept of universal manufacturing the following is needed:

(a) A widely accepted standard modelling methodology
(b) Manufacturing cloud solutions and the presence of enterprises in the cloud
(c) Enterprise specifications.

Of the three items above, the enterprise specifications are emphasised in this paper. The BPMN methodology is used to represent models. Future research and applications will determine the most viable and acceptable methodology. The development of cloud solutions will meet the demand of enterprises ready to be represented in the cloud.

4. Enterprise specifications

It is assumed that enterprise specifications are captured by the standard interface envisioned in Figure 8.

The specifications for a manufacturing system addressed to the universal manufacturing cloud may originate from a product (see Figure 9(a)) or a process (see Figure 9(b)) perspective. The former primarily applies to new product designs where the dedicated manufacturing systems might be not available. The tree in Figure 9(a) shows the requirements of Product 1 (P1) for the three manufacturing systems MS_1, MS_2, and MS_3 of Figure 8.

Product P1 in Figure 9(a) contains three assemblies, A1, A2, and A3 that are built from six different components, C1–C6. These components are manufactured in three manufacturing systems, MS_1, MS_2, and MS_3.

The process-based specifications apply to scenarios where the existing production facilities are well established and a rapid demand for large manufacturing capacity emerges. The tree in Figure 9(b) provides requirements for the three manufacturing systems, MS_1, MS_2, and MS_3 of Figure 8. All machines shown in Figure 8 are also included in the tree of Figure 9(b). The manufacturing specifications may call for different services, e.g. Service 1–3, in Figure 9(b). Service 2

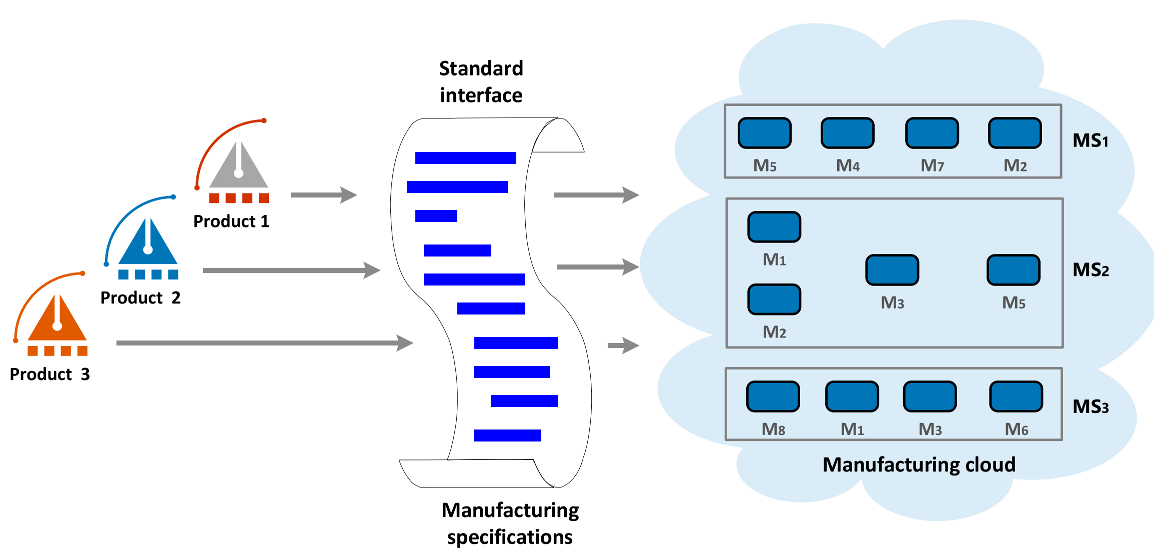

Figure 8. Standard interface of universal manufacturing.

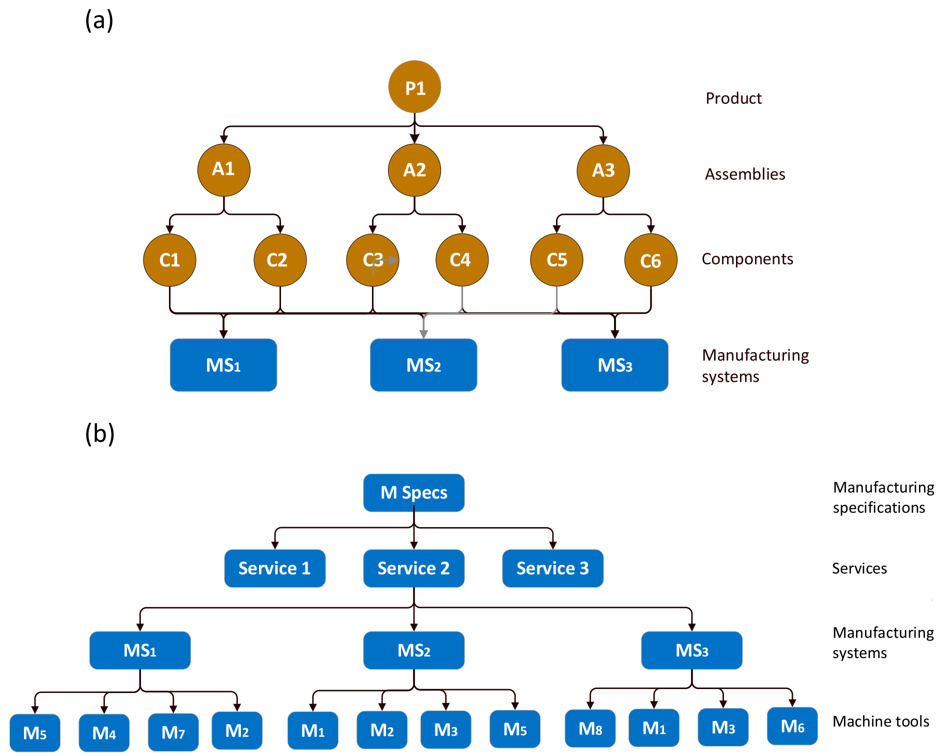

Figure 9. Manufacturing specifications: (a) product-based and (b) process-based.

specifies requirements for manufacturing capability and capacity, MS_1–MS_3, which are realised by machine tools M_1–M_8.

Enterprise specifications serve as a basis for configuring an enterprise. A methodology for forming enterprises is discussed in the next section.

5. Enterprise configuration

The data surrounding concepts illustrated in Figures 8 and 9 are captured in two matrices discussed next (see matrix (1) and (2)). The data in matrix (1) show the relationship between machines (M_k) and manufacturing systems (MS_l) making the space of universal manufacturing. Such a matrix could be extracted from the digital models present in the universal manufacturing cloud.

		MS1	MS2	MS3	MS4	MS5	MS6	MS7	MS8	MS9	MS10	MS11	MS12
	M1		x	x			x			x			x
	M2	x	x	x	x				x			x	
	M3		x			x		x			x		
	M4	x					x						
[m_{kl}] =	M5	x	x			x					x	x	
	M6			x				x		x			x
	M7	x				x							x
	M8			x			x				x		x
	M9				x			x	x	x		x	
	M10						x		x		x		x

(1)

With the growing number of enterprises in the universal manufacturing space, matrix (1) will expand in size and content. Other than the machine tools, all manufacturing resources, including tools, fixtures, material handling, and software solutions, are of interest.

Matrix (2) contains similarity data between the machines M_1–M_{10} listed matrix (1). As machines originate in different manufacturing systems that may belong to different corporations, it is not likely that a consistent labelling of them can be accomplished, especially ahead of analysis. Even two identical machine tools could carry different labels. Any two identical machines have the similarity value equal to 1 in matrix (2), e.g. Machine 4 (row M_4) and Machine 3 (column M_3) are identical as opposed to Machine 5 (row M_5) and Machine 4 (column M_4) with the similarity value of 0.4 which is low.

		M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
	M1	o									
	M2		o								
	M3			o							
	M4	0.6		1	o						
[s_{ij}] =	M5		0.6		0.4	o					
	M6	0.7		1			o				
	M7	1			0.7			o			
	M8					1			o		
	M9		0.5					0.6		o	
	M10			0.6			0.5		0.8		o

(2)

The similarity metric can be applied to resources other than machines, e.g. fixtures and software. In addition, different attributes could be considered in the definition of the similarity metric, e.g. capability, functionality, and precision.

Once implemented in the universal manufacturing cloud, the machine tool-manufacturing system incidence matrix and the machine tool-machine tool similarity matrix will be large due to a number of companies and resources involved. An efficient, simple, intuitive, and visualisation-friendly algorithm for configuring enterprises is needed. The enterprise synthesis algorithm presented next meets this challenge.

5.1. The enterprise configuration algorithm

Step 1: Incorporate the manufacturing specifications of the original system as vector $MS_l = [M_1, \ldots, M_l, \ldots, M_m]$ of machines in the machine tool-manufacturing system incidence matrix. Select a threshold value $\tau \in [0.6, 1]$ of the machine tool-machine tool similarity used in Step 3.

Step 2: Incorporate machines $[M_1, \ldots, M_k, \ldots, M_m]$ into the machine tool-machine tool similarity matrix and compute the missing similarity values.

Step 3: Identify all machines M_i, M_j of the machine tool-machine tool similarity matrix with the similarity value $s_{ij} \geq \tau$ and merge M_j with machine M_i.

Step 4: For every pair of machines identified in Step 3, merge row M_j with row M_i in the machine tool-manufacturing system incidence matrix. The resultant matrix is the reduced the machine tool-manufacturing system incidence matrix.

Step 5: Draw a horizontal line through the rows corresponding to the machine in $[M_1, \ldots, M_l, \ldots, M_m]$.

Step 6: Draw a vertical line through the single crossed entries of every MS_k of the reduced the machine tool-manufacturing system incidence matrix that includes as many machines in $[M_1, \ldots, M_k, \ldots, M_m]$ as needed.

Step 7: Form a universal enterprise from the systems (columns) containing double crossed elements. If an enterprise is formed, go to Step 8, otherwise go to Step 1.

Step 8: Stop.

The enterprise configuration algorithm is illustrated with the data in matrix (1) and (2). It is assumed that (i) each machine in either of the two figures has capacity 1 and (ii) manufacturing system MS_2 (column 2 in (1)) has been selected for expansion; and (iii) manufacturing systems to accommodate a 200% increase in capacity over the existing facility are sought.

Step 1: The manufacturing system MS_2 (column MS_2 in (1)) is the system selected for expansion. The threshold value $\tau = 1$ is selected.

Step 2: Since machines M_1, M_2, M_3, and M_5 already exist in the similarity matrix $[s_{ij}]$, there is no need to compute new similarity values.

Step 3: The machines included in following four pairs are identical ($s_{ij} = 1$), (M_1, M_7), (M_3, M_4), (M_3, M_6), (M_5, M_8).

Step 4: The rows of the machine tool-manufacturing system incidence matrix, $[m_{kl}]$, are merged. Based on the data in similarity matrix (2), matrix (1) is reduced by merging rows corresponding to the identical machines. For example, the similarity index $s_{4,3}$ between machines M_4 (row M_4 in (1)) and machine M_3 (column M_4 in (1)) is 1 and therefore all entries of row M_4 of matrix (1) are moved to row M_3, thus leading to the matrix (3). Note that row M_4 has been removed.

	MS_1	MS_2	MS_3	MS_4	MS_5	MS_6	MS_7	MS_8	MS_9	MS_{10}	MS_{11}	MS_{12}
M_1		x	x			x			x			x
M_2	x	x	x	x				x			x	
M_3	x	x			x	x	x			x		
M_5	x	x			x					x	x	
M_6			x				x		x			x
M_7	x				x							x
M_8			x			x				x		x
M_9				x			x	x	x		x	
M_{10}						x		x		x		x

(3)

Due to the similarity $s_{6,3} = 1$ between machines M_6 (row M_6 in (1)) and machine M_3 (column M_3 in (1)), all entries of row M_6 in matrix (3) are moved to row M_3, thus leading to matrix (4).

	MS_1	MS_2	MS_3	MS_4	MS_5	MS_6	MS_7	MS_8	MS_9	MS_{10}	MS_{11}	MS_{12}
M_1		x	x			x			x			x
M_2	x	x	x	x				x			x	
M_3	x	x	x		x	x	x		x	x		x
M_5	x	x			x					x	x	
M_7	x				x							x
M_8			x			x				x		x
M_9				x			x	x	x		x	
M_{10}						x		x		x		x

(4)

Finally, row M_7 is merged with row M_1 and row M_8 is merged with M_5 resulting in the reduced matrix (5).

	MS_1	MS_2	MS_3	MS_4	MS_5	MS_6	MS_7	MS_8	MS_9	MS_{10}	MS_{11}	MS_{12}
M_1	x	x	x		x	x			x			x
M_2	x	x	x	x				x			x	
M_3	x	x	x		x	x	x		x	x		x
M_5	x	x	x		x	x				x	x	x
M_9				x			x	x	x		x	
M_{10}						x		x		x		x

(5)

Step 5: Four horizontal lines are drawn as shown in matrix in (6).

	MS_1	MS_2	MS_3	MS_4	MS_5	MS_6	MS_7	MS_8	MS_9	MS_{10}	MS_{11}	MS_{12}
M_1	x	x	x		x	x			x			x
M_2	x	x	x	x				x			x	
M_3	x	x	x		x	x	x		x	x		x
M_5	x	x	x		x	x				x	x	x
M_9				x			x	x	x		x	
M_{10}						x		x		x		x

(6)

Step 6: Three vertical lines are drawn in matrix (7). Thus, manufacturing systems MS_1 and MS_3 are selected as both include all machines included in MS_2.

	MS_1	MS_2	MS_3	MS_4	MS_5	MS_6	MS_7	MS_8	MS_9	MS_{10}	MS_{11}	MS_{12}
M_1	x	x	x		x	x			x			x
M_2	x	x	x	x				x			x	
M_3	x	x	x		x	x	x		x	x		x
M_5	x	x	x		x	x				x	x	x
M_9				x			x	x	x		x	
M_{10}						x		x		x		x

(7)

Step 7: The enterprise formed by the enterprise configuration algorithm includes systems MS_1, MS_2, and MS_3.

Step 8: The algorithm terminates.

The proposed enterprise configuration algorithm offers one of many approaches to construct manufacturing systems in the universal manufacturing cloud. As more details of digital models will emerge, the scale and complexity of the configuration problem will increase with new variables and constraints to be considered (Kusiak 2019). For example, algorithms utilising partial updates to the machine tool-manufacturing system incidence matrix and the machine tool-machine tool similarity matrix may be designed. Data science and evolutionary system ideas could expend the modelling horizon.

6. The necessary conditions for universal manufacturing

The transition to universal manufacturing requires that certain conditions are met. The core list of the necessary conditions is listed next.

Condition 1. Critical mass of industries supporting the concept of universal manufacturing is needed.

Justification: Universal manufacturing involves a paradigm shift in the way businesses have operated in the past.

Condition 2. Standard process modelling methodologies and languages

Justification: Though many process modelling methodologies exist, it is important that the industry agrees on the core process modelling methodologies and languages to be used in support of universal manufacturing. For example, the BPMN methodology is an ISO standard (ISO/IEC 19510; see ISO 2013) and therefore it remains a candidate methodology.

Condition 3. Metrics and algorithms for similarity of process models.

Conditions 1 and 2 above belong to the implementation category and therefore they are not discussed in this paper. Condition 3 is elaborated on in the subsequent sections as it is fundamental to universal manufacturing.

Table 3. Similarity metrics for models of different degree of completeness.

Model completeness	Model example	Metric type	Reference
Unconnected tasks	Figure 4(a)	Vector	Carbó–Dorca (2021)
Partially connected tasks	Figure 4(b)	Vector or network	Rodriguez et al. (2015)
Streamlined process models	Figure 4(c)	Network or graph	Sabarish, Karthi, and Gireeshkumar (2020)
Process models with loops	Figure 4(d)	Process model	Dijkman et al. (2011)

A brief discussion of the similarity metrics is presented next.

As illustrated in Figure 4, digital models could be incomplete, yet they might be posted in the universal manufacturing cloud. To compute similarity of such models, different types of similarity metrics are used. The types of metrics and sample references applicable to the various models are provided in Table 3.

One of the most known vector similarity metrics, the Minkowski metric, was discussed in the context of theoretical considerations of high-dimensional spaces in Carbó–Dorca (2021). Rodriguez et al. (2015) introduced a similarity metric for networks of patents. Edge and vertex-based metrics for similarity of graph-based models representing moving objects were discussed by Sabarish, Karthi, and Gireeshkumar (2020). Dijkman et al. (2011) offered three metrics of process similarity. The labels and attributes of a process model were considered is the first similarity metric. The labels and the process model topology were incorporated in the second metric. The third metric considered labels and causal relations of the process model.

Retrieving digital models stored in the cloud is key to universal manufacturing. In this section, the research published in similarity of process models and related constructs such as networks and graphs is presented.

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. Digital twin which is widely discussed in the literature is an instance of digital model.

7. Synthesis of digital models

The universal manufacturing cloud will be populated with many digital models that would need to be synthesised to meet specifications of the enterprise being formed. Model synthesis is related to the concept of the design structure matrix. An extensive background and

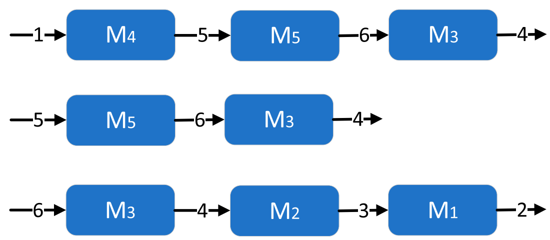

Figure 10. Three component digital models.

applications of the design structure matrix are discussed in the review paper by Browning (2016). Algorithms are needed to facilitate synthesis of such models. The model synthesis is illustrated with the extended topological sorting algorithm, based on the matrix implementation of this algorithm presented in Kusiak (1999). Here, two different matrices representing graphs corresponding to the digital models are considered, a node–node matrix and an input–output matrix. Both matrices will include integer rather than the binary entries in the incidence matrices usually considered in the literature.

7.1. The node–node digital model representation

The node–node incidence matrix is illustrated with three models shown in Figure 10. The nodes in the model of Figure 10 represent machine tools, M_1–M_5. The arrows in Figure 10 represent interactions between the machine tools (modes) and they are labelled 1, . . . , 6. The term ‘interaction’ may have different meanings ranging from a process precedence to the physical layout.

Since the models in Figure 10 include five nodes (machine tools), a 5 × 5 interaction matrix in (8) represent these models. In this representation, the interactions 1, . . . , 6 are not considered.

$$[a_{ij}] = \text{Input (to)} \quad \begin{array}{c|ccccc} & \multicolumn{5}{c}{\text{Output (of)}} \\ & M_1 & M_2 & M_3 & M_4 & M_5 \\ \hline M_1 & & 1 & & & \\ M_2 & & & 1 & & \\ M_3 & & & & & 2 \\ M_4 & & & & & \\ M_5 & & & & 1 & \end{array} \tag{8}$$

Each entry $a_{i,j}$, $i = 1, \ldots, 5$; $j = 1, \ldots, 5$, of matrix (8) denotes the number of interactions between the corresponding machine tools (nodes) M_j and M_i. The entry value $a_{3,5} = 2$ indicates that there are two interactions between machine tools (nodes) 5 and 3. An entry value 1 indicates one interaction, while the empty entries point to zero interactions.

Organising the data in matrix (8) organises the models that it represents, and thus enables their synthesis. The implementation of the extended topological sorting algorithm presented next illustrates transformation of ‘as-is’ matrix into a lower-diagonal form that streamlines the component processes.

The following two definitions are introduced for use in the algorithm.

Node: Depending on the nature of the model it may denote a task, activity, machine tool, input, output, or an object.

Origin node: A node that does not have any inputs.

Destination node: A node that does not have any outputs.

The extended topological sorting algorithm searches for either the origin or the destination node. If the origin is identified it is placed at the beginning of the solution sequence, while the destination node is placed at the end of the solution sequence. This extension makes the algorithm more efficient, and it enhances its visibility.

The extended topological sorting algorithm

Step 1: Set iteration number $r = 1$. The solution set $S = \{\text{Empty}\}$.

Step 2: Draw a horizontal line through empty row k of incidence matrix $[a_{i,j}]$ or draw a vertical line through empty column l of incidence matrix $[a_{i,j}]$.

Step 3: Draw a vertical line through column k of the incidence matrix (same column number k as the row number in Step 2) of the incidence matrix or draw a horizontal line through column l (same row number l as the column number in Step 2).

Step 4: If horizontal line k drawn first, include label k corresponding the cross-out row k and column k of the matrix at the beginning of the solution set S. Delete row k and column k from the matrix. If horizontal line l is drawn first, include label l corresponding to the cross-out column l and row l of the matrix at the end of the solution set S. Delete column l and row l from the matrix.

Step 5: If each row and column of the incidence matrix has been labelled, stop; otherwise set $r = r + 1$ and go to Step 2.

The extended topological sorting algorithm is illustrated with the data in matrix (8) representing the three digital models of Figure 10.

Iteration $r = 1$. A horizontal line is drawn through the empty row M_4, and a vertical line is drawn through column M_4 as shown in (9). M_4 is the origin.

$$\begin{array}{c|ccccc} & M_1 & M_2 & M_3 & M_4 & M_5 \\ \hline M_1 & & 1 & & & \\ M_2 & & & 1 & & \\ M_3 & & & & & 2 \\ M_4 & & & & & \\ M_5 & & & & 1 & \end{array} \tag{9}$$

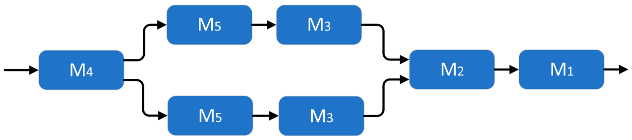

Figure 11. The integrated digital model.

The solution set is updated, $S = \{M_4\}$. Row M_4 and column M_4 are crossed out in matrix (9).

Iteration $r = 2$. A vertical line is drawn through the empty column M_1, and a horizontal line is drawn through row M_1 of the reduced matrix (9) resulting in matrix (10). M_1 is the destination.

	M_1	M_2	M_3	M_5
M_1		1		
M_2			1	
M_3				2
M_5				

(10)

The solution set is updated, $S = \{M_4, M_1\}$. The column M_1 and row M_1 are crossed out in matrix (10).

Iteration $r = 3$ leads to matrix (11) with the solution set $S = M_4, M_5, M_1$.

	M_2	M_3	M_5
M_2		1	
M_3			2
M_5			

(11)

Iteration $r = 4$ results in matrix (12) with the solution set $S = M_4, M_5, M_3, M_1$.

	M_2	M_3
M_2		1
M_3		

(12)

The final iteration produces the solution set $S = \{M_4, M_5, M_3, M_2, M_1\}$ is illustrated in matrix (13) with the '$*$' entries placed on the diagonal to enhance visibility of the lower triangular matrix.

	M_4	M_5	M_3	M_2	M_1
M_4	*				
M_5	1	*			
M_3		2	*		
M_2			1	*	
M_1				1	*

(13)

The only difference between the original matrix (8) and the solution matrix (13) is in the sequence of rows and columns.

This solution in matrix (8) allows to synthesise the three models in Figure 10 in the integrated models shown in Figure 11.

The models contained in the universal manufacturing cloud may be of different degree of completeness. The labelled inputs and outputs 1, ..., 6 of the models in Figure 10 were not considered in the algorithm leading to the model in Figure 11. They are incorporated in the representation discussed in the next section.

7.2. The input–output digital model representation

The representation in matrix (14) lists interaction (inputs and outputs) rather than tasks considered in matrix (8). For example, the entry (6, 5) in matrix (6) indicates that the relationship between input 5 and output 6 of the models in Figure 10 has occurred twice.

	1	2	3	4	5	6
1						
2			1			
3				1		
4						3
5	1					
6					2	

(14)

The extended topological sorting algorithm is illustrated with the data in matrix (15).

Iteration $r = 1$. A horizontal line is drawn through the empty row 1, and a vertical line is drawn through column 1 of (15). Row (output) 1 is the origin.

	1	2	3	4	5	6
1						
2			1			
3				1		
4						3
5	1					
6					2	

(15)

The solution set is updated, $S = \{1\}$. The row 1 and column 1 are deleted from matrix (15).

Iteration $r = 2$. A vertical line is drawn through the empty column 2, and a horizontal line is drawn through row 2 of the reduced matrix (15) resulting in matrix (16). Node (input) 2 is the destination.

	2	3	4	5	6
2		1			
3			1		
4					3
5					
6				2	

(16)

The solution set is updated, $S = \{1, 2\}$. Column 2 and row 2 are deleted from matrix (16).

Iteration $r = 3$ leads to matrix (17) with the solution set $S = \{1, 5, 2\}$.

	3	4	5	6
3		1		
4				3
5				
6			2	

(17)

Iteration $r = 4$ leads to matrix (18) with the solution set $S = \{1, 5, 6, 2\}$.

	3	4	6
3		1	
4			3
6			

(18)

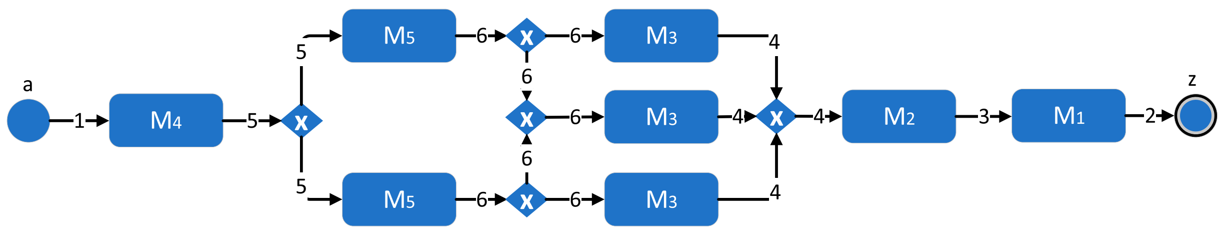

Figure 12. An integrated model.

Iteration $r = 5$ leads to matrix (19) and the final solution set $S = \{1, 5, 6, 4, 3, 2\}$.

	3	4
3		1
4		

(19)

The lower triangular matrix (20) derived from matrix (14) represents the final solution $S = \{1, 5, 6, 4, 3, 2\}$.

	1	5	6	4	3	2
1	*					
5	1	*				
6		2	*			
4			3	*		
3				1	*	
2					1	*

(20)

The solution in matrix (20) is synthesised in the digital model presented in Figure 12.

The integrated model in Figure 12 is one of many models representing the solution in matrix (20). It includes elements that were present in matrix (20). They include the process start node a and end the node z as well as the exclusive OR (x) logical connectors, all following the BPMN methodology. While the start and end nodes could be naturally incorporated in any model, the logical connectors require additional information that could be stored elsewhere. In the absence of such information, no connectors would be specified.

The models in Figures 11 and 12 differ in the topology as they were constructed using different data. Matrix (14) contains more information than matrix (7) and therefore the former has recognised the existence of three machine tools M_3 captured in the model in Figure 12.

7.3. How to handle cycles in digital models?

The extended topological sorting algorithm synthesises the component models that once integrated do not form cycles. The latter may occur in most applications for various reasons, e.g. the phenomenon represented by a digital model may contain it or they may result from errors. The triangularisation algorithm presented in Kusiak, Larson, and Wang (1994) can be applied to discover cycles in models using the matrix representation of this paper. Any cycle located calls for action. It is natural to expect that some cycles will form due to data errors. Identifying such errors is an added benefit of using algorithms for model synthesis.

8. Conclusion

The industry is evolving to best respond to potential interruptions, which in the recent decades have been relatively minor. This evolution is likely to take a new course due to the increasing pressure around resiliency and sustainability. The fact that industry has embraced digitisation makes it more amenable to absorbing changes as software offers an adaptation advantage over the manufacturing hardware. It is obvious that manufacturing delivers only when the hardware and software coexist. The concepts and solutions offered in this paper focused on using the data platform of manufacturing to make it more efficient and resilient in the face of disruptions that are known or could be unknown. Increased presence of manufacturing enterprises, from small to large, in a cloud was suggested. The universal manufacturing concept advocated in the paper requires greater formalisation and standardisation of digital models represented in the cloud. A framework for forming enterprises based on product and process specifications was offered. The proposed framework includes matrix representations designed to meet the cloud reality and algorithms illustrating its operations. The ideas presented in the paper may open door to further research endeavours aimed at increased resiliency of manufacturing enterprises and democratisation of manufacturing by broadening participation of small and previously unseen enterprises in the universal manufacturing cloud.

Notes on contributor

Dr Andrew Kusiak is a Professor at the Department of Industrial and Systems Engineering at The University of Iowa, Iowa City and Director of Intelligent Systems Laboratory. He has chaired two different departments, Industrial Engineering, and Mechanical and Industrial Engineering. His current research focuses on applications of computational intelligence in manufacturing,

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Disclosure statement

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

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