METHOD ARTICLE

Digital twin-driven complexity management in intelligent manufacturing [version 1; peer review: awaiting peer review]

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Abstract

Complexity management is one of the most crucial and challenging issues in manufacturing. As an emerging technology, digital twin provides an innovative approach to manage complexity in a more autonomous, analytical and comprehensive manner. This paper proposes an innovative framework of digital twin-driven complexity management in intelligent manufacturing. The framework will cover three sources of manufacturing complexity, including product design, production lines and supply chains. Digital twin provides three services to manage complexity: (1) real-time monitors and data collections; (2) identifications, diagnoses and predictions of manufacturing complexity; (3) fortification of human-machine interaction. A case study of airplane manufacturing is presented to illustrate the proposed framework.

Keywords

Cyber-physical system, Digital twin, Complexity Management, Intelligent Manufacturing, Engineering Design

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Introduction

The importance of complexity management in manufacturing can never be overstated. Complexity management significantly influences decision-making, lead time, reliability, flexibility and cost of manufacturing processes. Such influences appear to be more severe for large-scale manufacturing projects (airplanes, shield tunneling machines, precision machine tools, etc.) due to their interdisciplinarity, multisystem and multitasking. Conventionally, complexity management in manufacturing merely contains the trade-off among changeability, operational flexibility and responsiveness. Nowadays, as researchers tend to place more emphasis on lifecycle management, the coverage of complexity management is being broadened by additional issues. Manufacturing complexity has two typical definitions: In the physical domain, manufacturing complexity is defined as information required to describe the system. In the functional domain, manufacturing complexity is defined as uncertainties in achieving functional requirements. Complexity management is widely considered as one of the most challenging engineering objectives as it remains ambiguous and couples with abundant engineering factors.

Several factors push the rapid growth of manufacturing complexity. One such factor can be more features (functions, systems, concepts) in products. To achieve these additional features, the number of parts contained in products keeps climbing, which introduces more dimensional constraints, interferences and difficulties in connectivity. Besides, product features appear in a multi-discipline manner. For example, as a typical home appliance, a modern washing machine often contains a centrifuge (mechanical product), control panels (electronic product) and a dedicated application program (software product). Market competition is another important factor that promotes manufacturing complexity. In many industries, companies ought to keep compressing lead time, reducing costs, and improving usage rates of machines to gain advantages in competition. To achieve these goals, engineers keep optimizing operation processes and structures of manufacturing systems. Manufacturing complexity thus grows during this process. Moreover, manufacturing complexity is also promoted by global production (or distributed manufacturing). Globally distributed supply chains introduce information inconsistencies (miscommunication among suppliers, producers and consumers), environmental uncertainties and onerous logistics. Consequently, engineers are facing more and more challenges in complexity management in manufacturing.

Intelligent manufacturing is coevolving with complexity management. Compared to the conventional mode, intelligent manufacturing tends to be more digital, active, autonomous, adaptable and efficient. Following this trend, intelligent manufacturing will transform complexity management in three aspects: (1) Complexity management will be more data-contextualized to improve the reliabilities of decision-making. (2) Complexity management will be more autonomous. Many human interventions can be replaced by artificial intelligence (AI) and automatic machines. (3) Complexity management will investigate product lifecycles to consider their impacts on design, usage, maintenance and disposal. Meanwhile, complexity management guides the realization of intelligent manufacturing. Intelligent manufacturing is an intricate framework that consists of copious systems (e.g., automated systems, ergonomic systems, data-processing systems) and units (e.g., assembly machines, conveyance machines, inspection machines). Besides, intelligent manufacturing deals with fluctuating working environments. In this condition, complexity management becomes crucial to coordination, reliabilities and adaptability in intelligent manufacturing.

As an emerging technology, the digital twin (DT) plays a vital role in intelligent manufacturing. In the beginning, DT was proposed by Grieves in terms of lifecycle management. Later, Glaessgen and Stargel redefined DT as an integrated multiscale, multiphysics, probabilistic simulation to mirror the lifecycle of its physical twin. In this phase, DT was formulated as a three-dimensional model including the physical product, its virtual twin and their data exchanges. In recent years, the method of DT has been being enriched with more technologies, applications and concepts. Tao’s research team expanded DT into a five-dimensional model, including physical entity (PE), virtual entity (VE), twin data (TD), services (SV) and connections. Compared to conventional interactions between physical and virtual spaces, DT has three unique features: (1) DT achieves the synchronization between PE and VE. (2) DT dramatically raises the volume of data via its real-time and comprehensive data collections. (3) DT builds high-fidelity virtual models to reflect details in the physical world. To date, DT is used chiefly for the maintenance and operation of large-scale products such as airplanes and wind turbines. For example, Tugel et al. firstly proposed to implement DTs to predict the airplane structural life. General Electric applied DTs to its wind farms. There have been limited investigations on applications of DT on manufacturing design.

This paper is written to envision the DT-driven complexity management in intelligent manufacturing. For the rest of this paper, Section 2 will review conventional complexity management and intelligent manufacturing to indicate the importance of digital twins. Section 3 will envision an innovative framework of DT-driven complexity management. This framework will cover three important sources of manufacturing complexity, including product design, production lines and supply chains. Section 4 will illustrate the proposed framework with a case study of airplane manufacturing. Section 5 will conclude and discuss future work. Nomenclatures used in the paper are shown in Table 1.

Importance of digital twin: a simple review from complexity management to intelligent manufacturing

Manufacturing complexity and growing challenges

Complexity exists in every single corner of manufacturing. In 2012, EIMaraghy et al. summarized sources of manufacturing complexity and classified them into three categories, including: (1) design and product development complexity (number of parts, manufacturability, size, etc.); (2) manufacturing systems...
complexity (changeability, flexibility, and operations of production line); (3) business and market complexity (supply chain, global competition, and market turbulence)\(^3\). In this paper, discussions about manufacturing complexity will concentrate on those from product design, production lines, and supply chains.

As introduced, there are two typical definitions of complexity: In the physical domain, manufacturing complexity is defined as information required to describe the states of a system\(^1\). In the functional domain, manufacturing complexity is defined as uncertainties in achieving functions\(^4\). Based on states and periods, manufacturing complexity in both definitions can be further classified. Manufacturing complexity that remains constant is classified as static complexity in the physical domain. Manufacturing complexity that fluctuates over time is classified as dynamic complexity in the functional domain. Manufacturing complexity generated by product design (‘Product design’) in this paper represents the design for product fabrication rather than functional or conceptual design) is mainly caused by varieties in physical features of product design (size, surface, materials, etc.). Distinct products will naturally comprise various physical features, even for products of the same family. Fabrication strategies (selections of tools, machines and molds) must be customized to suit different physical features and thus introduce manufacturing complexity\(^19\). Meanwhile, product design also determines segmentations of parts to affect manufacturing complexity. Similar to varieties in physical features, fabrication processes must be customized for different segmentation. Besides, segmentation design determines subsequent assembly strategies, bringing manufacturing complexity\(^19,20\).

Three factors affect manufacturing complexity generated by production lines, including product varieties, operation deviations and quality inspections. Product varieties call for a mixed-model production line to handle different fabrication requirements. As trade-offs, a mixed-model production line causes extra uncertainties and lower productivities. In terms of operation deviations, tolerances inevitably exist through operations. Manufacturing complexity is hence generated by differences between design expectations and fabrication outcomes\(^5\). In terms of quality inspections, inspections are conducted at an early stage of the product lifecycle. However, during usage, information contents of products fluctuate as cyclic loads accumulate\(^19\). Besides, working environments in practice are often more intricate than inspection conditions. Consequently, differences in working environments introduce uncertainties to quality inspections.

\(M\) represents the number of resources, \(N_i\) represents the number of possible states at resource \(j\). \(P_{ij}\) represents the probability of resource \(j\) being in state \(i\). In Formula (2), in addition to Formula (1), \(P\) represents the probability that the system is under control, \(P^b\) represents queues with length longer than 1, \(P^q\) represents queues with a length between 0 and 1, \(P^s\) represents the non-programmable states\(^\text{s}\). In the functional domain, Suh\(^18\) proposed to measure by effective information content:

\[
I = \log_2 \left( \frac{R_s}{R_c} \right)
\]

(3)

As shown in Figure 1, the system range is defined by the performances and capabilities of design concepts proposed to achieve corresponding functional requirements. Design range is determined by design expectations of functional requirements and design tolerances. \(R\) represents the range defined by system probability density, which is equal to 1. \(R_s\) represents the common range between system range and design range. The information content \(I\) is the logarithm of the ratio between \(R_s\) and \(R\) with a base of 2.

As aforementioned, manufacturing complexity has three important sources: product design, production lines and supply chains.
Fluctuating market demands and uncertainties of supply chain units (factories, warehouses, logistics stations, etc.) introduce manufacturing complexity in supply chains. Affected by abundant factors, market demands are continuously changing. Hence, supply chain managers must keep adjusting procurements, inventories and supplies to match dynamic market demands. In other words, supply chain managers must introduce changeability to handle fluctuating markets. Besides, market patterns are often unpredictable and thus bring uncertainties to supply chain planning. Such changeability and uncertainties form into manufacturing complexity caused by fluctuating market demands. Meanwhile, uncertainties exist through each unit in supply chains. Internally, each unit can encounter unexpected problems such as safety hazards, machine breakdowns and power failures. Externally, local situations like environmental disasters, shortages of infrastructures, and strikes can interrupt supply chains’ working. Such uncertainties also generate manufacturing complexity in supply chains.

As aforementioned, manufacturing complexity is rapidly growing nowadays. In this condition, conventional strategies of complexity management tend to be incompetent. Wiendahi and Scholtissek summarized three traditional strategies that enterprises implement to deal with manufacturing complexity, (as shown in Figure 2): (1) Decentralization of company functions. (2) Exploitation of creativity, experience and competence of employees. (3) Concentration on the core skills of the company. These strategies have evident drawbacks in modern manufacturing. Decentralization of company functions often sacrifices efficiency and management costs as it brings tremendous collaborative work and information inconsistency among departments. Besides, these strategies depend on managers’ and employees’ empirical thinking to manage complexity, often subjective and unreliable. Also, these strategies lack long-term plans to manage complexity through product lifecycles, which have become particularly important in modern manufacturing. Therefore, conventional complexity management is incompetent, and a new framework is in need.

Complexity management in the era of intelligent manufacturing and challenges

Intelligent manufacturing formulates the blueprint of future industries. Enabled by multiple emerging technologies such as cyber-physical spaces (CPS), internet of things (IoT), augmented reality (AR) and AI, intelligent manufacturing promotes an autonomous, digital and collaborative production system. Besides, in business terms, intelligent manufacturing will improve productivity and reduce risks to boost incremental revenue.
As aforementioned, there is coevolution between intelligent manufacturing and complexity management. However, such coevolution can be restricted by three challenges of intelligent manufacturing: insufficient quality of virtual models, gaps within virtual-physical communications, and limited data. Insufficient quality of virtual models reduces precisions of virtual simulations and thus hinders self-awareness, self-reasoning and self-direction of the manufacturing system. As for gaps within virtual-physical communications, in one aspect, virtual-physical communications are conventionally planned, supervised and operated by human efforts. Considering tremendous data related to intelligent manufacturing, such human efforts can be significantly onerous. In another aspect, virtual-physical communications are also discontinuous, which extends the lead-time of data exchanges. As for limited data, it represents both “limited amount” and “limited categories”. Both limitations hamper services related to data analysis such as identifications, diagnoses and predictions. Thus, overcoming these three challenges is the key to enhance complexity management in the era of intelligent manufacturing.

Meanwhile, intelligent manufacturing introduces extra manufacturing complexity. Intelligent manufacturing is a sophisticated system that requires tremendous components and systems to support data collections, data processing, function outputs and communications. Intelligent manufacturing will inevitably introduce abundant information contents, states, and resources in the word of complexity definitions. Besides, the working of these components brings extra coordination, interferences, couplings and rigidity to manufacturing systems. Thus, overall complexity will dramatically increase in the era of intelligent manufacturing.

Call for digital twin
As emerging information technology, DT can overcome the challenges of intelligent manufacturing and thus enhance complexity management. In this paper, DT will be based on Tao’s five-dimensional model, including PE, VE, TD, SV, and connections. PE represents physical products, their working environments and other items that interact with them. PE is the foundation of DT as it is the primary source of data collections and the terminal to interact with the physical world. VE represents the digital mirror of PE, including virtual models and simulations. Virtual models in VE are classified into geometrical models, physical models, behavior models and rule models. Interactions between PE and VE are bidirectional, data collections in PE guide the modeling of VE. In reverse, simulations and verifications in VE drive the work of PE. TD represents all data relevant to DT. While collecting data from the PE, VE, SVs and external resources, TD also serves as feedbacks to improve PE, VE and SS. TD Center is the hub to process and manage TD. SVs represent applications provided internally and externally. SVs are classified into functional services (FSV) and business services (BSV). The former is defined as essential applications that support the work of DT, and the latter is defined as output applications for users. Connections represent data transmissions within DT. Besides, connections also undertake data security.
Intelligent manufacturing is challenged by gaps within physical-virtual communications, while DT synchronizes the two spaces. DT aims to exchange data between physical and virtual spaces in real-time. Data collected from PE will be continuously forwarded to VE for updates, while new data generated by VE will guide the work of PE. Besides, those data will be dynamically extracted, cleansed, analyzed and packed by the TD Center. Its outcomes will drive the work of DT.

Intelligent manufacturing is challenged by the insufficient quality of virtual models, while DT aims to build a digital mirror to reflect the physical world completely. Enabled by sensing and modeling technologies (e.g., solid modeling, rule modeling, wireframe modeling), DT captures all elements to build a high-fidelity virtual mirror of the physical world. Supported by plentiful data collections, the similarity between virtual models to the physical entity will be higher than ever before.

Intelligent manufacturing is challenged by limited data, while DT dynamically and comprehensively collects data from abundant sources. In PE, DT records real-time data from physical products, environments, peer products and users. In VE, DT extracts data from virtual simulations and models. In TD Center, DT generates data via analysis and learning. Also, different DTs can interact and exchange data with each other, which allows DT to obtain data beyond systems of attached products. Besides, developers can deliberately input data to intervene in the work of DT.

In summary, Figure 3 shows how DT will enhance complexity in the era of intelligent manufacturing. This paper focuses on manufacturing complexity introduced by product design, production lines and supply chains. Manufacturing complexity has been rapidly increasing due to more product design features, market competitions and global productions. In this condition, conventional strategies of complexity management are becoming incompetent. Such a strait is expected to overturn in the era of intelligent manufacturing. However, three challenges of intelligent manufacturing will hinder complexity management, including insufficient quality of virtual models, gaps within physical-virtual communications, and limited data. DT can overcome these challenges by synchronizing physical and virtual spaces, dynamic and comprehensive data collections, and high-fidelity virtual modeling. Hence, DT can promote a more autonomous, analytical and comprehensive manner of complexity management. Here, “autonomous” represent a human-neutral status with self-awareness, self-decision, and self-reaction; “analytical” represents decision-making driven by data contextualization and mathematical processing; “comprehensive” represents the coverage of a whole product lifecycle.

It should be noted that DTs still face several technical and ethical challenges. For example, the limited capability of data processing is a typical technical challenge. Many core functions of DTs heavily consume computing power, such as virtual simulations, model renderings and environment awareness. To date, very limited hardware can afford such enormous computing power consumption. Meanwhile, it is widely agreed that communication capability is constraining DTs. Due to the synchronization between physical and virtual spaces, data transmissions within DTs are tremendous with critical latencies. Both academia and industry believe that reducing data transmission latency via new technology is the key to realize DTs. In terms of ethical challenges, the contradiction between data collections and privacy protections is a controversial example. Theoretically, DTs aim to monitor the physical world dynamically, collect data from PE and VE, and exchange data with peer products. However, these functions enable DTs to extract privacy from stakeholders (engineers, users, business partners, etc.). Thus, the growing concern of privacy protection becomes a barrier to apply DTs. Despite these, investigations on DTs are rapidly growing in recent years, more and more researchers are contributing their efforts into realizing DTs.

![Figure 3. Importance of digital-twin driven complexity management in intelligent manufacturing. DT, digital twin; IIOT, industrial internet of things.](image-url)
The proposed framework for digital twin-driven complexity management in manufacturing

As shown in Figure 4, this section proposes the framework of DT-driven complexity management for intelligent manufacturing. The framework was innovated based on combinations between complexity management problems and functions of DTs in intelligent manufacturing. One important hypothesis of this framework is that DT is widely deployed to manufacturing equipment and products.

Services of digital twins for complexity management

Motivations of complexity management vary in adaptable and unadaptable manufacturing systems. In terms of an adaptable manufacturing system, complexity management aims to minimize dependencies and uncertainties. In an unadaptable manufacturing system, complexity management seeks to control risk and cost caused by dependencies and uncertainties. Although manufacturing complexity appears in different scenarios, DT generally provides three important SVs for complexity management.

Real-time monitors and data collections. Enabled by sensing technologies and IoT, DT can monitor its products and environments in physical and virtual worlds. During this process, data will be collected in real-time. Data can be collected from PE, VE, historical investigations, online resources and peer products. Those data will support the analysis of complexity in manufacturing systems. Besides, such data also assist users and developers in evaluating uncertainties in manufacturing systems. As Formula (1) and (2) indicate, states and information contents of manufacturing systems represent complexity. Thus, data related to states and information contents help users understand complexity. Table 2 provides some examples of data that can be collected for this purpose.

Identifications, diagnoses and predictions of manufacturing complexity. Conventional methods for identifying, diagnosing and predicting manufacturing complexity due to limited knowledge, experience and cognitions. Enabled by tremendous data and analytical methods, DT will transform these objectives into a more objective and rational manner. Complexity appears in manufacturing systems as couplings and system failures. As DT monitors manufacturing systems dynamically, states of all engaged parts will be captured as recordings of couplings and system failures. Then, by tracking and checking these states, DT can rapidly sort out couplings and system failures. Thus, complexity can be identified. As for complexity diagnoses, DT will incorporate data of target system, recorded systems and previous decision-making. The fusion of those data will enable DT to compare and learn from existing samples to highlight complexity causes. Based on training models, DT will learn patterns of complexity dataset and thus predict trends in terms of complexity predictions. Besides, developers can customize training models by editing and filtering out specific data. Except for training models, predictions can also be conducted by simulation and verify in VE. Similar to training models, virtual models in VE can also be customized to improve simulation accuracies.

Fortification of human-machine interaction. Although intelligent manufacturing aims to promote a more autonomous production, flexibility and knowledge of human interventions are still essential to deal with intricate problems. DT provides emerging approaches to engaging human interventions. Enabled by AR and VR, users can flexibly modify virtual models of VE. As VE is synchronized to PE, PE will react in correspondence to changes in VE. Thus, users also control the physical manufacturing system remotely and conveniently. Meanwhile, as VE is a digital mirror of PE, users can flexibly observe...
The number of connections joints, deviations of surface-cutting operations, assembly accuracy of defect identifications, cyclic loads, on-site test recordings, etc.

The smoothness of surfaces, tolerance of edge-cutting tools, the strength of tolerances of drillings, deviations of robot pose positioning, operation conformity, etc.

Examples of data

<table>
<thead>
<tr>
<th>Source of manufacturing complexity</th>
<th>Secondary sources</th>
<th>Examples of data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product design</td>
<td>Design of physical feature</td>
<td>The smoothness of surfaces, tolerance of edge-cutting tools, the strength of materials, etc.</td>
</tr>
<tr>
<td></td>
<td>Segmentation design</td>
<td>The number of connections joints, deviations of surface-cutting operations, assembly speeds on production lines, etc.</td>
</tr>
<tr>
<td>Production line</td>
<td>Product variety</td>
<td>Number of products, number of production processes, number of production operations, etc.</td>
</tr>
<tr>
<td></td>
<td>Deviation of operation</td>
<td>Tolerances of drillings, deviations of robot pose positioning, operation conformity, etc.</td>
</tr>
<tr>
<td>Supply chain</td>
<td>Quality inspection</td>
<td>Accuracy of defect identifications, cyclic loads, on-site test recordings, etc.</td>
</tr>
<tr>
<td></td>
<td>Fluctuating market demands</td>
<td>Supply of substitute goods, change of customers' incomes, cost of raw materials, etc.</td>
</tr>
<tr>
<td></td>
<td>Uncertainties of supply chain units</td>
<td>Frequency of power cut, change of tax, number of available infrastructures, etc.</td>
</tr>
</tbody>
</table>

every aspect of PE. Besides, DT also enables users to control the manufacturing system by simply editing settings, commands and data. In these ways, users can rapidly, remotely and conveniently guide complexity management when DT cannot autonomously handle problems.

Digital twin-driven management of manufacturing complexity in product design

As aforementioned, complexity in product design is introduced by the segmentation of parts and physical features of products. For the former, it is arguable to say that products have infinite ways to be segmented. Despite this, one ubiquitous principle is the reduction in the number of parts. Thus, designers tend to apply sophisticated shapes and composite parts. Consequently, variations in segmentation design, shape design and composite parts result in capricious manufacturing processes. For the latter, similarly, manufacturing processes ought to be highly adaptable to produce products with whimsical feature design. Besides, even for one single manufacturing process, various combinations of tools, control systems and networks can be deployed, which is defined as station level complexity by Zhu et al. Those altogether result in combinatorial complexity. Generally, manufacturing complexity caused by product design can be resolved in two ways: optimizing product design for easier productions or improving manufacturing plans to match product design.

Figure 4 shows DT-enabled approaches to complexity management. DT aims to reduce dependencies and uncertainties to manage complexity from product design.

To reduce dependencies, DT will diagnose the causes of dependencies by dissecting manufacturing systems and analyzing previous cases. At first, DT identifies dependencies by analyzing couplings. When manufacturing systems have couplings, engaged workpieces will interact with each other inevitably. Hence, couplings among these workpieces can be detected by tracing their interactions. Then, DT will check the logic relations behind these couplings. Couplings among workpieces with clear logic relations can be classified as dependencies. If a candidate manufacturing plan has massive dependencies, DT will sort out production procedures that generate dependencies. Procedures with plentiful dependencies will be recommended for removal. If highlighted procedures are necessary for the manufacturing system, DT will analyze previous similar cases to explore a simplified structure. Alternatively, engineers can manually edit manufacturing plans and verify their feasibilities via simulations in VE.

DT analyzes manufacturing data and makes predictions to reduce uncertainties. In the proposed framework, based on dependency analysis, uncertainties of manufacturing systems can be calculated with relevant data. Figure 5 illustrates a dissected manufacturing plan. In a manufacturing plan, parts will be produced through several processes, and the combination of these processes is defined as a “set” here. For example, if a part can be produced via die casting, welding, grinding and inkjet painting, these four processes and the sequence will be recorded as “Set I”. The part may also be produced via additive manufacturing, molding and casting, and then these can be recorded as “Set II”. By analyzing production machines and product inspections data, DT can collect uncertainties of each process (number of defects, conformity, operation deviations, etc.). Then, with the sequence and couplings of processes, a probability can be calculated to represent uncertainties to produce these parts in a specified set. This probability will be recorded as an entry. Similarly, applying the same approach in an assembly plan, the uncertainty to produce a product can also be calculated. Besides, different sets of processes sometimes are adopted simultaneously in a factory. Uncertainty of a factory contains uncertainties of all deployed sets. Finally, the overall uncertainty of a manufacturing plan can be evaluated after analyzing the uncertainties of all engaged factories. DT can calculate those entries of uncertainties through three phases. The first
phase is the accumulation of manufacturing data. DT will keep collecting data from each factory. As DTs are deployed to all machines and products, manufacturing data can be rapidly and comprehensively collected. Thus, uncertainties of each process can be obtained with data like the number of defects, conformity of parts and operation deviations to fill in each entry. As DT collects data dynamically, the accuracy of uncertainties tends to increase over time gradually. In the second phase, when data is has been accumulated sufficiently, they can be used for self-planning. Theoretically, the manufacturing plan with minimum uncertainties is the optimal solution in terms of manufacturing complexity. DT can automatically generate the manufacturing plan with minimum uncertainties by continuously adjusting processes, production sequences, and production distributions to each factory. Besides, the developed plan can be verified in VE. The third phase is calibration. There is always a difference between anticipations and practical performances. Thus, users and DT will collaborate to improve accuracies. Accuracies can be enhanced via several approaches such as optimizing anticipation models, cleansing manufacturing data and deploy more DTs in factories.

Despite the autonomy of DT, users’ engagement is still meaningful in many situations. DT can also benefit users’ engagement. For example, professional users may quickly notice and correct problems with manufacturing plans. They can prototype and verify their manufacturing plans via simulations in VE. During simulations, users can intuitively observe their manufacturing plans to identify potential problems. Alternatively, DT can forward outcomes of simulations to engineers for evaluations. Besides, DT can also quickly extract existing samples of manufacturing plans to compare with new plans. Differences will be highlighted in virtual models for users to inspect. Also, users’ engagement serves as a learning resource to train DT.

Digital twin-driven management of manufacturing complexity in production lines
Product varieties, operation deviations and quality inspections in production lines appear in different forms and result in different manufacturing complexity. Production varieties require adaptable production lines and thus introduce dynamic complexity. Besides, compared to single-model production lines for mass productions, adaptable production lines have less reliability and productivity. As for operation deviations caused by machine precisions and human operators’ skills, they introduce static complexity to production lines. With regard to quality inspections, they are caused by differences between inspections and practical usages. Besides, every product has a service life and its statistical distribution ($R$ in Formula (3)) over time. Hence, it introduces time-dependent complexity. As the three causes in production lines result in different manufacturing complexity, goals of complexity management thus vary.

With regard to product varieties, the goal of complexity management is balancing among adaptability, reliability and productivity for production lines. The key to such a balance is satisfying the production demands of varieties while preventing redundant adaptability. DT can manage complexity caused by adaptability via diagnosis and virtual simulations. To diagnose causes of complexity in production lines, Zhu et al. proposed an analytic model:

$$C_j = \sum_{k=1}^{K} a_j^k H_j^k, \quad a_j^k > 0, k = 1, 2, \ldots, K$$

(4)

$$\begin{bmatrix} C_1^{n/a} \\ C_2 \\ \vdots \\ C_n \end{bmatrix} = \begin{bmatrix} a_{01} & 0 & \cdots & 0 \\ a_{02} & \cdots & \cdots & 0 \\ \vdots & \cdots & \cdots & \cdots \\ a_{0n} & a_{in} & \cdots & a_{n-1,n} \end{bmatrix} \times \begin{bmatrix} H_0 \\ H_1 \\ \vdots \\ H_{n-1} \end{bmatrix}$$

(5)

$$\begin{bmatrix} C_1^{n/a} \\ C_2 \\ \vdots \\ C_n \end{bmatrix} = \begin{bmatrix} a_{01} & 0 & \cdots & 0 \\ a_{02} & \cdots & \cdots & 0 \\ \vdots & \cdots & \cdots & \cdots \\ a_{0n} & a_{in} & \cdots & a_{n-1,n} \end{bmatrix} \times \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \cdot *[H_0, H_1, \ldots, H_{n-1}]^T$$

(6)
In Formula (4), $a_j^k$ represents weights related to the task difficulty of the $k^{th}$ assembly activity at station $j$. The greater difficulty of assembly results in a higher $a_j^k$. The difficulty of assembly is determined by feature variants, choice of fixtures, tools, and assembly procedures. $H_j^k$ represents the entropy computed from the variant mix ratio relevant to the $k^{th}$ assembly activity at station $j$, which can be calculated via Formula (1). Derived from Formula (4), Formula (5) and (6) represent the incoming and outgoing complexity of each station, respectively. Hence, each station’s incoming and outgoing complexity can be calculated and plotted against station positions in a multistage assembly system. Besides, the manufacturing stations with high incoming complexity should be replaced. Enabled by DTs of stations, data of assembly activities at a station ($k^{th}$), frequencies of station states during a period (to calculate $P_j$ in Formula (1)), the number of resources ($M$) and the number of all station states ($N$) will be collected. Besides, weights related to task difficulty $a_j^k$ can be automatically assigned by extracting samples from existing cases of production line models. Hence, DT can automatically sort out the complexity of each station. Stations with high incoming complexity will be forwarded to users for modifications. Modified models of production lines will be sent back to DT to verify their adaptability and productivity via virtual simulations. Meanwhile, DT also makes it more convenient to build production lines in the physical world. Production lines are characterized as modular systems. Their creations are assemblies of function modules in specific sequences. If DTs are deployed to function modules, the conveyance system will shift function modules to synchronize with users’ redesign in VE. In other words, users can conveniently restructure models of production lines by controlling their virtual twins.

With regard to operation deviations, the goal of complexity management is replacements of workpieces with high uncertainties. DT can achieve this goal via dynamic monitors and statistical analytics. DTs deployed to workpieces will continuously collect their operation data. Simultaneously, collected data will be plotted by DT to compare with design expectations. As data accumulate, plots will appear in the forms of normal distributions and intersect with design ranges. According to Formula (3), uncertainties of operations can be calculated. Besides, DT can also use these data to evaluate the significance of uncertainties based on mathematical methods. For example, with the number of defective products from each workpiece, DT can analyze variance (a statistical technique to tell differences between two data groups) tests to evaluate their differences. Workpieces with significantly higher defective rates will be maintained and replaced.

With regard to quality inspections, the goal of complexity management is predicting the uncertainties of products through their lifecycles. Such predictions will be based on dynamic monitors, data retrievals and virtual simulations of DT. As shown in Figure 6, according to the theory of Information Axiom, product performances can be plotted as probability density functions and intersect with design expectations. Their cross-section areas can be used to describe uncertainties in achieving corresponding functional requirements (as Formula (3)). However, different product states (working environments, ways of usages and life stages) can shift these plots. As shown in Figure 6 either, one state will correspond to one unique plot. In the beginning, the main objective of DT is accumulating data of target products through their lifecycles. As DTs are deployed to all products, data coverage will

![Figure 6](https://example.com/figure6.png)

**Figure 6.** Changes in product performance over time in certain conditions.
rapidly expand from sundry product states. Collected data will be classified, cleansed, packed and stored in the TD Center. When datasets are large enough, DT can then predict uncertainties of products via data retrievals. For a specified product, DT can mobilize data of all its peers to reflect its uncertainties through the lifecycle. States with possible risks will be highlighted to guide future optimizations. Alternatively, enabled by datasets of different scenarios, users can customize virtual models to simulate uncertainties of products in various working environments, ways of usages and product life stages.

Digital twin-driven management of manufacturing complexity in supply chain

Complexity in supply chains is caused by fluctuating market demands and uncertainties of supply chain units. Although external factors often generate complexity in supply chains, it is still feasible to reduce costs and risks by implementing management strategies.

To handle fluctuating market demands, DT will predict supply changes and intelligently plan productions and logistics. As DTs are deployed to products, factories and warehouses, dynamic flows of products can be monitored through the whole supply chain. Hence, DT can capture and record supplies and inventories in each site. Thus, short-term demands can also be derived. Besides, such monitors and data collections also enable DT to plan productions and logistics. For example, if DT notices that the turnover of a warehouse is far below others, DT will then check data of supplies and logistics related to this warehouse. Based on the diagnosis, DT will re-plan supply chains to balance the loads of each supply chain unit. Compared to human-lead planning, real-time monitors enable DT to react instantly and thus reduce risks and costs. Meanwhile, high-fidelity supply chain models of DT enable virtual simulations, which help users make long-term plans for supply chains.

To handle uncertainties of supply chain units, DT will evaluate risks, predict losses and make emergency plans. With regard to risk evaluations, the risks of supply chain units can be internal or external. Internal risks are introduced by management issues such as safety management, power management and equipment management. External risks are introduced by local environments, infrastructures and economic policies. Internal risks can be identified by monitoring systems, analyzing previous cases and exchanging data with peer DTs. External risks can be identified via crowdsourcing. For example, to identify risks related to equipment management, DT firstly extracts data recordings of previous cases (states of equipment when hazards occur). Then, DT analyzes those recordings and compares them with data of standard equipment. Hence, differences in data will highlight indications of risks. Afterward, DT will use data of such indications as a reference to check the states of current equipment and thus identify potential risks. Besides, DTs of different factories can exchange their datasets to verify and improve risk identifications. These data are also essential to predict losses. Enabled by high-fidelity virtual models, users can input data of risks to simulate hazards. Simulation outcomes will predict losses when risks occur. Based on those simulation outcomes, feedbacks will be sent back to engineers and managers. Subsequently, these simulation outcomes support DT to generate emergency plans such as back-up inventories, reallocations of supplies and replacements of equipment. Users or virtual simulations can verify these plans.

Use case: complexity management for airplane manufacturing

This section will present a use case of airplane manufacturing to illustrate the proposed framework of DT-driven complexity management. As airplane manufacturing is arguably the most sophisticated manufacturing project, this section will select some typical scenarios of airplane manufacturing for illustration. Figure 7 shows a simple summary of the use case.

A simple background of airplane manufacturing

Complexity exists in each corner of airplane manufacturing. Airplane design is a complex of multiple disciplines such as aerodynamics, thermodynamics, mechatronics and material science. Aviation equipment enabled by different techniques coordinate with each other to support flights. Meanwhile, as one of the most sophisticated engineering products, the design for airplane production is particularly challenging for engineers. Not only because airplane structures often contain composite materials and intricate geometric shapes, but also an airplane contains massive parts for assembly. Besides, in terms of product features, aviation equipment has a much stricter requirement towards integration, stability, environmental adaptability, size and weight (especially for avionic equipment) compared to ground equipment. Those introduce much complexity to the airplane manufacturing plan.

The complexity of airplane production lines is one popular topic in aviation and manufacturing fields. Due to different purposes and usage scenarios, airplanes have significant varieties. For example, in terms of categories, aerospace engineers develop families of airliners, small fixed-wing airplanes and military airplanes. A fixed-wing airplane family shows varieties in wings, tails, fuselages, and propulsion systems in terms of design configurations. Therefore, adaptability is essential for airplane production lines. Meanwhile, due to sophisticated design and precisions, fabrications of some parts can contain a number of different processes. Besides, airplanes usually have long service lives, while predictions of lifecycle performances are particularly challenging during quality inspections.

Airplane manufacturing is arguably the most typical example of global production. Parts of airplanes (especially airliners) are usually produced in different countries. For example, for one airliner, its middle fuselage can be produced in Japan, its trailing edge of the wing can be produced in France, its tail can be produced in Canada, and its stabilizer can be produced in Italy. Finally, all parts will be transported to the same workshop for assembly. Complexity is thus introduced to supply chains of airplane manufacturing.

Digital twin-driven management of manufacturing complexity in airplane design

As aforementioned, composite materials and sophisticated geometric shapes of parts introduce complexity to airplane
manufacturing. For example, for an airframe of a fuselage, its cross-section shape along the longitude direction is inconsistent due to the payload space, taper of tail and locations of wings. Besides, composite materials are often deployed on circular frames and longitude beams to balance weight and strength. Each circular frame or longitude beam is produced independently and is then finally assembled. Thus, the management of the manufacturing plan becomes essential.

In this new framework, DTs can analyze relevant cases of airplane manufacturing and reorganizes manufacturing plans to reduce dependencies and uncertainties. Take the middle circular frame made of aluminum alloy as an example. Hypothetically, in an aluminum frame factory, users notice that the current manufacturing plan for circular frames of an airliner should be updated for fewer uncertainties. To help users update this manufacturing plan, DTs of workpieces begin with data uploading to trace manufacturing processes. The tracing outcome indicates that the “forming press” can only be executed after the “punch press” on Workpiece P, Q and M. After identifying such dependencies, DTs will reorganize the manufacturing plan by analyzing relevant cases. Via data exchanging with DTs in a peer factory, it is recognized that “punch press + forming press” can be done merely by Workpiece K and L. Besides, it is also identified that hollowing cuttings and edge bendings can also be done via other manufacturing processes. Consequently, as shown in Table 3, new manufacturing plans with fewer dependencies are generated as “Set I, Set II and Set III”. Afterward, DTs will compare the uncertainties of each new manufacturing plan. Set I consists of seven procedures: shearing, punch press, forming press, rolling, spot welding, frame welding, and grinding. Each procedure has specific inspection standards. For example, the quality of the punch press can be evaluated based on its hollow cut, springback effect and burst effect. DTs of workpieces can output uncertainties of corresponding inspection standards via dynamic work monitoring and data collections. Compared to Set I, Set II consists of six procedures, including shearing, punch press, rolling, forming press, pierce riveting.
and blasting. Set III is based on additive manufacturing. It thus merely consists of directed energy deposition and blasting. Similarly, uncertainties of each procedure can be obtained via DTs of engaged workpieces. Although different manufacturing plans vary in procedures, standards for the quality inspection of circular frames are the same, such as the diameters of hollows, heights of beams and radius of curvatures. Uncertainties of manufacturing plans can thus be calculated based on uncertainties of each inspection standard. All relevant data during this process will be forwarded to users. Uncertainties of manufacturing plans and their procedures will help users optimize and build manufacturing systems.

**Table 3. Manufacturing plan evaluations of circular frames for illustration.**

<table>
<thead>
<tr>
<th>Properties of raw materials</th>
<th>Ultimate tensile strength: $A_1$ Mpa; Yield tensile strength: $A_2$ Mpa; Elongation at break: $A_3$%, etc.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standards of circular frames</td>
<td>Diameter of hollows: $B_1$ IN; Height of beams: $B_2$ IN; Radius of curvatures: $B_3$ IN, etc.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Production procedures and uncertainties</th>
<th>Set I</th>
<th>Set II</th>
<th>Set III</th>
</tr>
</thead>
<tbody>
<tr>
<td>Procedure 1</td>
<td>Shearing: $C_1$% Straight edge</td>
<td>Shearing: $E_1$% Straight edge</td>
<td>Directed energy deposition</td>
</tr>
<tr>
<td></td>
<td>Tearing: $C_2$%</td>
<td>Tearing: $E_2$%</td>
<td>Unequal height build: $Q_1$%</td>
</tr>
<tr>
<td></td>
<td>Wrinkling: $C_3$%</td>
<td>Wrinkling: $E_3$%</td>
<td>Internal cracking: $Q_2$%</td>
</tr>
<tr>
<td>Procedure 2</td>
<td>Punch press: $D_1$% Hollow cut</td>
<td>Punch Press: $F_1$% Hollow cut</td>
<td>Blasting &amp; Painting</td>
</tr>
<tr>
<td></td>
<td>Springback: $D_2$%</td>
<td>Springback: $F_2$%</td>
<td>Surface roughness: $P_1$%</td>
</tr>
<tr>
<td></td>
<td>Burst: $D_3$%</td>
<td>Burst: $F_3$%</td>
<td></td>
</tr>
<tr>
<td>Procedure 3</td>
<td>Forming press: $G_1$% Bending angle</td>
<td>Rolling: $J_1$% Line width</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Edge height: $G_2$%</td>
<td>Longitudinal twist: $J_2$%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Edge gap: $G_3$%</td>
<td>Curvature diameter: $J_3$%</td>
<td></td>
</tr>
<tr>
<td>Procedure 4</td>
<td>Rolling: $H_1$% Line width: $M_1$%</td>
<td>Forming press: $H_1$% Bending angle</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Longitudinal twist: $M_2$%</td>
<td>Edge height: $H_2$%</td>
<td>Edge gap: $H_3$%</td>
</tr>
<tr>
<td></td>
<td>Curvature diameter: $M_3$%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Procedure 5</td>
<td>Spot welding: $J_1$% Welding crack</td>
<td>Pierce riveting: $L_1$% Rivet fracture</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Welding size: $J_2$%</td>
<td>Riveting crack: $L_2$%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Unfused area: $J_3$%</td>
<td>Misplacement: $L_3$%</td>
<td></td>
</tr>
<tr>
<td>Procedure 6</td>
<td>Frame welding: $K_1$% Welding crack</td>
<td>Blasting &amp; Painting</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Welding size: $K_2$%</td>
<td>Surface roughness: $N_1$%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Unfused area: $K_3$%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Procedure 7</td>
<td>Grinding: $O_1$% Surface roughness</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall evaluations</td>
<td>Diameter of Hollows: $R_1$%</td>
<td>Diameter of Hollows: $S_1$%</td>
<td>Diameter of Hollows: $T_1$%</td>
</tr>
<tr>
<td></td>
<td>Height of Beams: $R_2$%</td>
<td>Height of Beams: $S_2$%</td>
<td>Height of Beams: $T_2$%</td>
</tr>
<tr>
<td></td>
<td>Radius of curvatures: $R_3$%</td>
<td>Radius of curvatures: $S_3$%</td>
<td>Radius of curvatures: $T_3$%</td>
</tr>
<tr>
<td></td>
<td>Overall uncertainties: $R_4$%</td>
<td>Overall uncertainties: $S_4$%</td>
<td>Overall uncertainties: $T_4$%</td>
</tr>
</tbody>
</table>

Digital twin-driven management of manufacturing complexity in airplane production lines

In this new framework, based on dynamic monitoring and virtual simulations, DTs can evaluate complexity from airplane production lines while maintaining adaptability. Take the fuselage
assembly as an example. Although the fuselage assembly is a typical modularized production, its adaptability is still essential to customize fuselages. Besides, fuselage assembly consists of abundant procedures such as weldings, pierce rivetings and blastings. In correspondence, there are abundant tools for assembly such as fasteners, drillers and welding machines. According to Formula (4), as difficulties of assembly and feature variants are constant, the complexity of an assembly station is determined by choices of fixtures, tools, assembly activities and resources. Meanwhile, according to Formula (6), the complexity of a production line is determined by the number and complexity of consisted assembly stations. Hypothetically, users input multiple candidate designs of fuselage assembly lines for complexity evaluations. Enabled by high-fidelity models and recordings of assembly cases, DTs begin with simulating candidates. Those incompetent designs will be removed. Afterward, candidate designs with clearly excessive complexity will be removed either. Table 4 shows some examples of the rest designs, which will come to the complexity comparison. Based on dynamic data recordings of workpieces, users’ settings and statistics of previous cases, different fixtures, tools, assembly activities and resources, weight contributions towards task difficulties and station entropies can be estimated by DTs. The outcome will be forwarded to users for selections and optimizations.

DTs help users replace workpieces with high uncertainties. Operation deviations exist in every workpiece, while operation accuracy is arguably the most essential issue in airplane production lines. Timely replacement of worn workpieces is necessary to reduce production uncertainties. Take the compressor of an airplane engine as an example. Production precision significantly affects the aerodynamic performance of an engine compressor, while its intricate structure challenges conventional production techniques. Nowadays, additive manufacturing has become a popular approach to fabricating engine compressors due to its flexibility of structure shaping. Table 5 shows some important parameters of powder bed fusion (a typical additive manufacturing technique to produce metal products) to produce a compressor\textsuperscript{11}. Any deviations of those parameters can cause defective compressors. DTs can be deployed to workpieces on a powder bed fusion machine, such as the substrate, leveling roller and laser shooter. Thus, DTs can dynamically monitor the states of workpieces and record operating parameters. Based on production standards, DTs of workpieces can automatically adjust those operating parameters.

### Table 4. Examples of fuselage assembly line for complexity evaluations.

<table>
<thead>
<tr>
<th>Assembly Line 1</th>
<th>Fixtures</th>
<th>Tools</th>
<th>Activities</th>
<th>Resources</th>
<th>Task difficulty ($a_j^k$)</th>
<th>Station Entropy ($H_j^k$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Station 1</td>
<td>F1</td>
<td>T1, T2</td>
<td>$k^1$</td>
<td>R1, R2, R3</td>
<td>$a_1$</td>
<td>$H_1$</td>
</tr>
<tr>
<td>Station 2</td>
<td>F2</td>
<td>T3, T4, T5</td>
<td>$k^2$</td>
<td>R2, R4</td>
<td>$a_2$</td>
<td>$H_2$</td>
</tr>
<tr>
<td>Station 3</td>
<td>F3</td>
<td>T6</td>
<td>$k^3$</td>
<td>R3, R5, R6, R7</td>
<td>$a_3$</td>
<td>$H_3$</td>
</tr>
<tr>
<td>Station 4</td>
<td>F4</td>
<td>T7</td>
<td>$k^4$</td>
<td>R5, R7, R8</td>
<td>$a_4$</td>
<td>$H_4$</td>
</tr>
<tr>
<td>Overall complexity: $C_1$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Assembly Line 2</th>
<th>Fixtures</th>
<th>Tools</th>
<th>Activities</th>
<th>Resources</th>
<th>Task difficulty ($a_j^k$)</th>
<th>Station Entropy ($H_j^k$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Station 1</td>
<td>F5</td>
<td>T6</td>
<td>$k^5$</td>
<td>R3, R5, R6, R7</td>
<td>$a_5$</td>
<td>$H_5$</td>
</tr>
<tr>
<td>Station 2</td>
<td>F6</td>
<td>T2, T4, T5</td>
<td>$k^6$</td>
<td>R4, R9</td>
<td>$a_6$</td>
<td>$H_6$</td>
</tr>
<tr>
<td>Station 3</td>
<td>F7</td>
<td>T7, T8</td>
<td>$k^7$</td>
<td>R5, R7, R10</td>
<td>$a_7$</td>
<td>$H_7$</td>
</tr>
<tr>
<td>Station 4</td>
<td>F8</td>
<td>T9</td>
<td>$k^8$</td>
<td>R2, R11, R12</td>
<td>$a_8$</td>
<td>$H_8$</td>
</tr>
<tr>
<td>Overall complexity: $C_2$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Assembly Line 3</th>
<th>Fixtures</th>
<th>Tools</th>
<th>Activities</th>
<th>Resources</th>
<th>Task difficulty ($a_j^k$)</th>
<th>Station Entropy ($H_j^k$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Station 1</td>
<td>F9</td>
<td>T3, T4, T10</td>
<td>$k^9$</td>
<td>R2, R4</td>
<td>$a_9$</td>
<td>$H_9$</td>
</tr>
<tr>
<td>Station 2</td>
<td>F10</td>
<td>T6</td>
<td>$k^{10}$</td>
<td>R3, R5, R6, R7</td>
<td>$a_{10}$</td>
<td>$H_{10}$</td>
</tr>
<tr>
<td>Station 3</td>
<td>F11</td>
<td>T9</td>
<td>$k^{11}$</td>
<td>R2, R11, R12</td>
<td>$a_{11}$</td>
<td>$H_{11}$</td>
</tr>
<tr>
<td>Station 4</td>
<td>F12</td>
<td>T11</td>
<td>$k^{12}$</td>
<td>R8, R13, R14</td>
<td>$a_{12}$</td>
<td>$H_{12}$</td>
</tr>
<tr>
<td>Overall complexity: $C_3$</td>
<td></td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>
in real-time during the operation. As data accumulate, DTs can also identify worn workpieces on powder bed fusion machines. With standard production parameters as references, DTs can conduct analysis of variance tests for workpieces based on their production data. Tests with significant data differences indicate high defective rates of corresponding workpieces. Finally, outcomes will be forwarded to users for workpiece replacements or maintenance.

DTs can predict the uncertainties of an airplane through lifecycles. Airplanes work in fluctuating environments and working states. Besides, airplanes usually have long service lives. Therefore, working uncertainties of airplane parts shift following accumulations of cyclic loads. Conventional quality inspections are struggled to assure reliabilities of components through lifecycles while DTs have such potentials. Take flaps on airplane wings as an example. Flaps are vital surface control units of airplanes. During airplane landings, flaps deflect to increase stall angle and drag forces, reducing taxi distance and enhancing airplane brakes. Actuators on wings control flaps. Performances of flaps are affected by several environmental factors such as humidity, temperature and wind speed. Besides, flaps tend to get worn out faster than many other airplane components. DTs of flaps can predict performances through their lifecycles. DTs can obtain data of flaps in different states (environments and service time) via three approaches. Firstly, DTs can predict the performances of flaps via relevant mathematics models. Secondly, DTs can monitor flaps in real-time and record working data in different states. Besides, data exchanges among peer DTs enable rapid accumulations of flap datasets. Finally, DTs can simulate performances of flaps in different states via high-fidelity virtual models. Afterward, based on Information Axiom and flap datasets, Figure 8 shows the system distributions of flap drag forces in different states. Thus, uncertainties of each flap state can be calculated according to the design range.

Digital twin-driven management of manufacturing complexity in airplane supply chain
In this new framework, DTs can help users predict supply changes and evaluate risks. Airplane manufacturing is a paradigm of global production. Suppliers, factories and logistic stations vary in local conditions. Take the landing gears of an airliner as an example. A landing gear consists of massive components. Damaged by shocks of airliner landings, landing gears often go through frequent maintenances and overhauls. Besides, landing gears are customized for each airliner.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Laser power($P$)</td>
<td>$P_1$</td>
</tr>
<tr>
<td>Scanning Speed($v$)</td>
<td>$v_1$</td>
</tr>
<tr>
<td>Hatch Spacing($h$)</td>
<td>$h_1$</td>
</tr>
<tr>
<td>Layer sickness($t$)</td>
<td>$t_1$</td>
</tr>
<tr>
<td>Bed temperature($T$)</td>
<td>$T_1$</td>
</tr>
<tr>
<td>Laser spot size($d_{\text{spot}}$)</td>
<td>$d_{\text{spot}}$</td>
</tr>
<tr>
<td>Laser focusability($M$)</td>
<td>$M_1$</td>
</tr>
<tr>
<td>Laser wavelength($\gamma$)</td>
<td>$\gamma_1$</td>
</tr>
</tbody>
</table>

Table 5. Examples of parameters of powder bed fusion.

![Figure 8. Uncertainties of flaps in different states.](image-url)
Thus, different supply chains of airliners have few intersections. Hypothetically, a landing gear factory undertakes maintenance, overhauls and replacements of landing gears for a specific airliner model in a local airport. DTs in the factory can predict required supplies by exchanging data with DTs of landing gears on airliners.

As DTs of landing gears dynamically can collect data from landing gears, the health conditions of each component can thus be retrieved. Afterward, DTs of landing gears will forward data to DTs in the landing gear factory. Therefore, DTs in the factory can calculate required maintenance, overhauls and replacements at a specific moment. Thus, the factory managers can plan component productions and supplies for the airport in the following period. Then, DTs of the factory will evaluate risks from component suppliers. Hypothetically, the factory has three suppliers for trailing arms and shock absorb cylinders, respectively. The risk evaluations will be based on data about local environments, factory management and economic policies related to component suppliers. DTs can collect data of local environments from historical recordings and data release from local environmental management departments. For example, the factory is going to purchase a batch of trailing arms from a supplier during the summer. However, the supplier's factory is located near the equator, and data show a high possibility of floods during this period. Hence, the landing gear factory manager should consider the influence of delivery delay or turn to the other two suppliers. About suppliers' factory management, DTs can obtain data via crowdsourcing. All stakeholders related to component suppliers can be potential data sources, such as suppliers of raw materials, other customers of component suppliers and employees of component suppliers. For example, DTs can source their feedbacks and whitepapers about component suppliers. These can be processed into risk indexes of suppliers’ factory management. Meanwhile, DTs can obtain data of economic policies by analyzing related recordings. For example, by analyzing fluctuations of exchange rates and speed of merchandizes through customs in previous years, DTs can predict these changes in a short term and highlight possible risks.

Conclusions and future work

In conclusion, in the era of intelligent manufacturing, DT enables a new paradigm of complexity management. DT improves the management of manufacturing complexity via its three important SVs: (1) Real-time monitors and data collections; (2) identifications, diagnoses and predictions of manufacturing complexity; (3) Fortifications of human-machine interactions. For manufacturing complexity from product design, DT aims to reduce the dependencies and uncertainties in manufacturing plans. For manufacturing complexity from production lines, DT aims to: (1) balance among adaptability, reliability and productivity. (2) Replace workpieces with high uncertainties. (3) Predict uncertainties of products through lifecycles. DT aims to predict supply changes, evaluate risks, predict losses, and make emergency plans for the manufacturing complexity from supply chains.

This paper proposes an innovative approach for complexity management. Conventionally, complexity management has remained an empirical process in manufacturing and is mainly driven by human efforts. DT enables this process to be more autonomous, analytical and comprehensive. Besides, compared to other cyber-physical systems, DT resolves gaps within physical-virtual communications, insufficient quality of virtual models and limited data. Intelligent manufacturing is characterized by its digitalization, autonomy and flexibility. The DT-driven complexity management will promote this trend. Meanwhile, in terms of the development of DT, as emerging information technology, its concepts, enabling technology and applications are still under investigation. Most existent research about DT concentrates on mega-project developments, production management and health care issues. This is the first proposition that applies DT to complexity management. This innovative framework enables new research about manufacturing design and DT in intelligent manufacturing. In terms of manufacturing design, this framework can be implemented for investigations on verifications and evaluations of manufacturing complexity in different scenarios. Besides, this framework also serves as a piece of puzzle for the research about the future grand manufacturing design together with functional design, process design and verification design enabled by other emerging technology. In terms of DT, this framework extrapolates functions and roles of DTs in future factories. Future research can work on collaborations of DT-driven complexity management with other functions. Also, future research can proceed this framework by completing technical details of DTs in realizing this framework.

There are two important issues for future work. One is the verification of this framework in industry. This paper serves as a proposition, clarification and illustration of DT-driven complexity management in manufacturing. Its practical effect remains pending until verified in industries. However, such verification can be particularly challenging as it consists of abundant designs, resources and human efforts. Besides, several important challenges are to be resolved for its realization, such as communication latencies among systems, capabilities of tremendous data processing, and privacy protections. Therefore, the completion and verification of this framework rely on developments of relevant technologies, such as edge computing, the fifth generation of cellular networks and federated learning.\(^\text{1}\)

The other issue is the investigation on how to manage complexity caused by DT. DT is a sophisticated system that consists of tremendous software and hardware devices. Through the working of DT, massive data flows and couplings get engaged. Therefore, when resolving manufacturing complexity, DT simultaneously introduces complexity to manufacturing. Complexity management of DT will be an essential issue of future research.

Data availability

No data are associated with this article.
References


