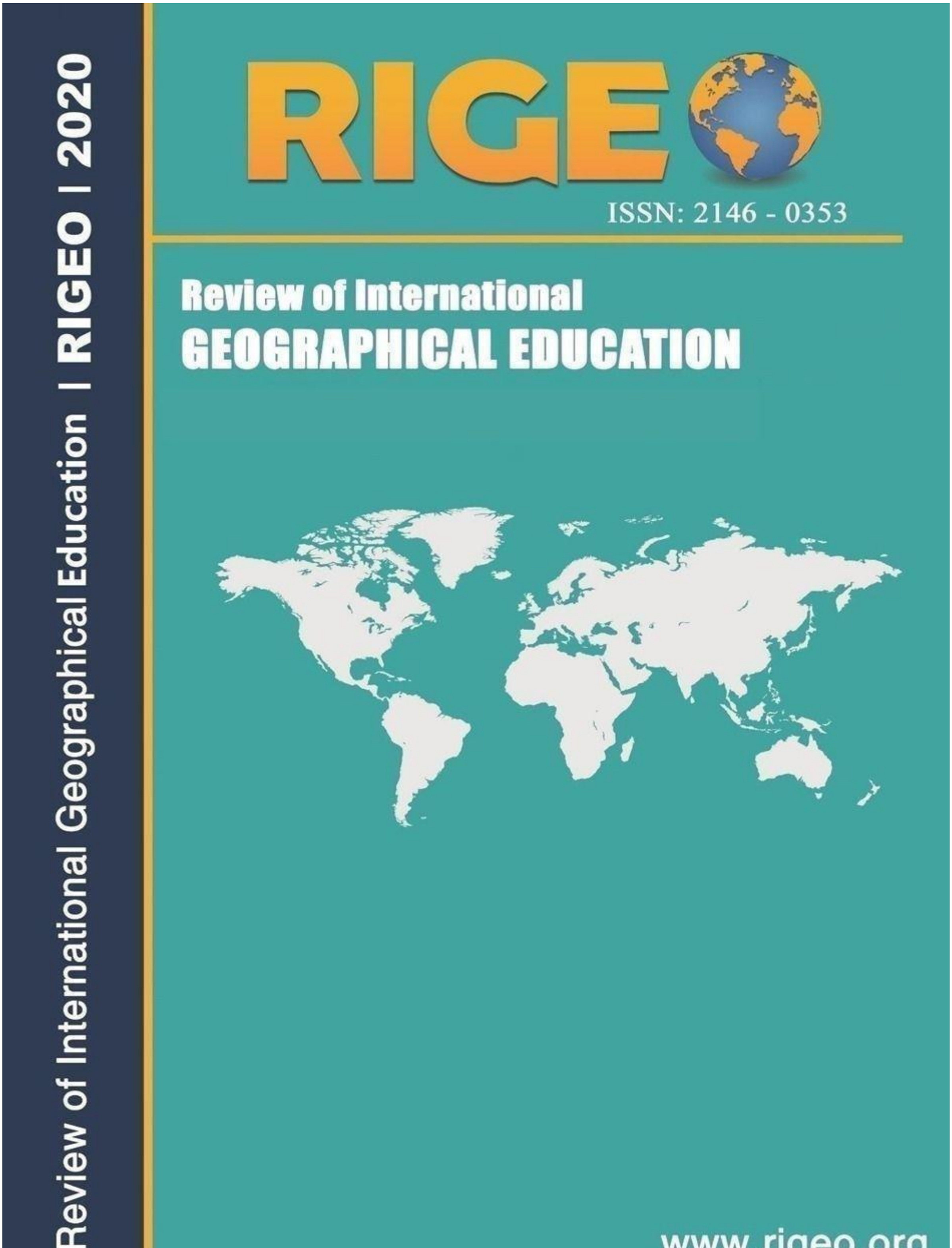
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Transforming Product Design, Manufacturing, and Service with Digital Twin and Big Data Insights

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Abstract

The big data-driven manufacturing age is here, ushering in next generation information technology into industry and production. Product lifecycle data may be acquired during the whole product lifetime, including design, production, and service. However, much of the study on this topic focuses on actual items rather than virtual models. Furthermore, manufacturing firms are left with meaningless, fragmented, and isolated data throughout the product lifecycle as a result of the absence of convergence between the physical and virtual spaces of products. In the design, production, and servicing stages of a product, these issues cause a lack of intelligence, efficiency, and sustainability. To back up product design, production, and service, however, you'll need data on the physical product, data on the virtual product, and data that links the two. Based on our previous research on big data in PLM, we are now investigating and emphasizing ways to create and utilize converged cyber-physical data to improve product lifecycle. This will drive smarter, more efficient product design, manufacturing, and service. An innovative approach to product design, production, and service delivery based on digital twins is put forward in this study. The study delves into the specific ways and frameworks for using digital twins in product design, production, and service. In addition, we provide three examples to show how digital twins may be used in the future at different stages of a product's lifecycle.

Keywords: Digital twin · Product lifecycle · Design · Manufacturing · Service · Big data · Cyber and physical convergence

1 Introduction

From the initial concept of a product all the way through to its retirement and disposal, product lifecycle management (PLM) is the process by which a company's goods are managed in the most efficient manner possible. Product Lifecycle Management (PLM) is the process that helps businesses increase their income by enhancing innovation, decreasing new product launch times, and delivering exceptional support, new services, and greater customer use of their current goods [1]. We are entering an era of big data-driven manufacturing as a result of the widespread adoption of next-generation information technologies in manufacturing and industry. These technologies include the internet of things (IoT) to gather data from all stages of a product's lifecycle, cloud computing to store and process that data, and artificial intelligence to mine that data for insights. Data management for products[5], modeling of products[6], tracking of products[7], integration framework[8], knowledge management[9], supply-demand matching on product manufacturing[10], product assembly [11], and many more topics have been extensively studied in relation to product lifecycle management (PLM). Several research gaps in product lifecycle management (PLM) remain, despite the availability of varied big data across the full product lifetime (design, manufacture, and service).

1. The current research on product lifecycle data mainly fo- cuses on physical products rather than virtual models.
2. Even if concerned with data from virtual models, there is lack of convergence between product physical and virtual space. Besides, due to the lack of the convergence, the data in PLM is usually isolated, fragmented and stagnant.
3. On one hand, it is difficult for a company to keep control when a product is at a customer location, on the other hand, even realized control, it is difficult to response for the upcoming demand or failure in advance and to guide product design, manufacturing, and maintenance.

As a result of these issues, the product design, production, and service stages are not very intelligent, efficient, or sustainable. Hence, novel approaches are required to address the aforementioned issues. Using state-of-the-art physical models, sensor updates, etc., a digital twin mimics the behavior of its real-life counterpart via an integrated multi-physics, multi-scale, and probabilistic simulation of a complicated product. The concept of a digital twin—a product with a physical and virtual counterpart as well as the data connections between the two—can bring about this merging of the real and virtual worlds. Based on our previous study on big data in product lifecycle management [5], we are now investigating how to create and utilize converged cyber-physical data to enhance product lifecycle services, leading to smarter, more efficient product design, manufacturing, and service. What follows is an outline of the rest of the paper. Part 2 introduces the product lifecycle and associated data in PLM, while Part 3 discusses the current shortfall in PLM. The term "digital twin" and its practical uses in industry are defined in Section 3. In Section 4, we examine the cases in each of the three stages of a product lifecycle—digital twin-driven product design, digital twin-driven product manufacturing, and digital twin-driven product service—to see how digital twins may be used. Section 5 wraps up the research and highlights the efforts to come.

2 Product lifecycle and related data

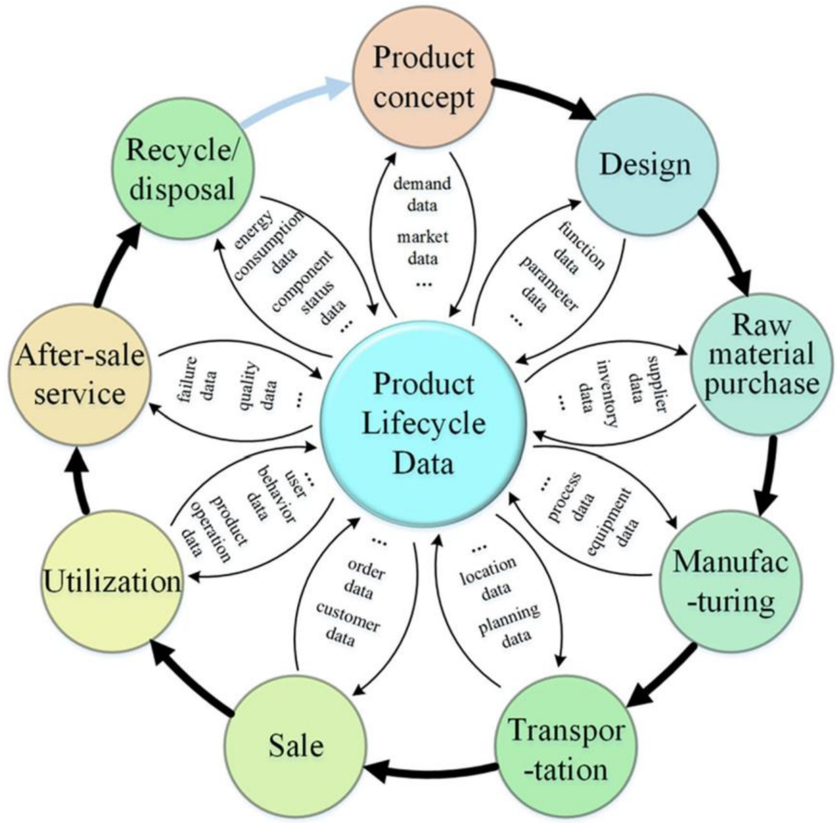
2.1 Product lifecycle and data

The concept of product lifecycle was proposed by Dean [12] in 1950 and was used in product marketing strategy research by Levitt [13]. The product lifecycle initially referred to the process from acceptance by the market to the final elimina- tion. A biologically inspired lifecycle of the product was di- vided into four stages, i.e., introduction, growth, maturity, and decline [14]. With the rise of concurrent engineering [15], the product lifecycle was extended to the engineering field. And the product lifecycle was redefined to cover the entire process from product demand analysis, design, manufacturing, sales, and after-sales service to recycle [16].

When a specific product lifecycle is understood from the perspective of the manufacturer [17], it refers to the whole process from concept generation, design, procurement, manufacturing to use, and recycle. As shown in Fig. 1, each stage of the product lifecycle has its specific activities, in- volves the relevant staff and departments, and generates large amount of data [5].

1. Concept generation: Based on customers' demands, mar- ket information, investment planning, and other data, the concept of new product or product design improvements is defined, as well as the esthetics and main functions of the product. At this stage, a variety of data needs to be processed, such as various forms of customers' demands including comments, complaints and videos on the Internet, market information including volume of product sales, customer satisfaction, investment planning, and so forth.
2. Product design: Product development team completes product design work collaboratively through exchanging and sharing design data and ideas. The data involved in product design includes description of product function and appearance, product configurations, design parameter and test data, etc. And even historical fault data of similar products will improve the product design.
3. Raw material procurement: At this stage, appropriate procurement plan is drawn up for the purchasers by analyzing the availability, quotations, substitutes, po- tential suppliers of materials, or parts. The data consid- ered at this stage includes manufacturer's data, such as the type, quantity, performance of raw materials, as well as supplier data such as price, distance, inventory, and so on.
4. Manufacturing: According to design specifications, the raw materials or components are processed or assembled into products, and then products are inspected through quality testing. At this stage, the dynamic manufacturing execution process needs to be monitored and managed. Therefore, the attributes, performance, parameters, and process conditions of production factors (e.g., human-ma- chine-material-environment) are collected in real-time and recorded to monitor the production process.
5. Transportation: After finishing the production, products are transported to the point of sale in accordance with market demand and orders. At the same time, after the product is sold, delivery services are provided to users. In order to transport products accurately and timely, logis- tics arrangements must be optimized based on inventory data, order data, location data, etc.

Fig. 1 The product lifecycle and related data



6. Sales: At this stage, product launch and marketing are carried out based on orders data, customers' data, inven- tory data and suppliers' data. In the sale process, cus- tomers' preferences, preferences crowd, location distribu- tion of orders and other information can improve product design, production, logistics, and sale progress.
7. Utilization: Based on the information from user manual, customer can operate product normally. During use- phase, a large amount of data is generated, such as product status data, operational environment data, user behavior data. These data can be used not only for product mainte- nance and repair but also to improve product design.
8. After-sales service: This stage is responsible for product maintenance, service, and repair. According to the data acquired from products, appropriate maintenance and ser- vice solutions are generated and transmitted to manufac- turers. As a result, efficient and accurate services are pro- vided to users. In this process, failure data and causes, maintenance data, component quality, and status data are recorded and managed to predict product lifetime and other product failures.
9. Recycle/disposal: When a product is recycled, the remain- ing value of individual components are analyzed to deter- mine when, how, where, and what to recycle or disposal based on product status data and historical maintenance data. In order to maximize product recycling benefits, the cost of recycling and disassembly, the reusable state, val- ue, and remaining time of components, needs to be considered.

Product lifecycle engineering is an iterative process. At any stage of the product lifecycle, a large amount of data is col- lected, processed, and used, thus big data is formed [5].

2.2 Problems about product lifecycle data

The advances in information technology are driving the manufacturing industry toward big data era. Data analysis and mining are gradually playing a more and more significant role in manufacturing enterprise management. Big data can provide systematic guidance for related production activities through effectively collecting and analyzing a variety of data generated in the entire product lifecycle [5]. Furthermore, it can help enterprises' managers to solve the problems related to operation and decision-making. The value of manufactur- ing big data can be explored adequately to enhance the manufacturing efficiency. At present, smart manufacturing is driven by big data through three steps, which are association, forecast and control [18]. It is to find the new value from relationship and statistical characteristics of various data.

However, some problems affecting product data manage- ment and application in PLM still exist as follows: (1) Due to the different purposes and tasks, the data generated in various phases of the entire product lifecycle may form the informa- tion island between different phases of product lifecycle. (2) There is a lot of duplicate data in different phases of product lifecycle. These duplicate data may cause a lot of waste of resources and data sharing problem. (3) The interaction and iteration between big data analysis and various activities in the entire product lifecycle are relatively absent. Therefore, the big data analysis and the actual manufacturing process cannot be compared in parallel. (4) The current applications of big data prefer to put emphasis on the analysis of physical product data rather than the data from virtual models.

In response to the above problem, digital twin is viewed as an effective approach. The implementation of digital twin is a mutual promotion process between virtual and physical space of product lifecycle. Digital twin can directly compare and analyze the theoretical values of big data and the real values of product lifecycle activities. As a result, it can optimize iteratively various activities in the entire product lifecycle. In the virtual space of digital twin, various activities in the entire product lifecycle can be simulated, monitored, optimized, and verified. As well as, the seamless coordination of the entire product lifecycle can be realized. Therefore, information islands and data duplication can be effectively avoided.

3 Digital twin and its applications

3.1 Concept of digital twin

The concept of digital twin was firstly presented by Grieves at one of his presentation about PLM in 2003 at University of Michigan [19]. Up to now, several explanations and defini- tions of digital twin have been proposed.

For example, Hochhalter et al. [20] believe that digital twin is a life management and certification paradigm whereby models and simulations consist of as-built vehicle state, as- experienced loads and environments, and other vehicle- specific history to enable high-fidelity modeling of individual aerospace vehicles throughout their service lives. Reifsnider and Majumdar [21] hold the view that the digital twin is a kind of ultra-high fidelity simulation integrating with an on-board health management system, maintenance history, and histori- cal vehicle and fleet data. It can mirror the whole life of a specific flying physical twin (or tail number), which enables significant gains in safety and reliability.

A general definition of digital twin which has been recog- nized and used by most people till now was given by Glaessegen and Stargel in 2012 [22]: digital twin is an inte- grated multi-physics, multi-scale, probabilistic simulation of a complex product and uses the best available physical models, sensor updates, etc., to mirror the life of its corresponding twin. Meanwhile, digital twin consists of three parts: physical product, virtual product, and connected data that tie the phys- ical and virtual product.

According to these explanations and definitions of digital twin, the following characteristics of digital twin are summa- rized: (1) Real-time reflection. Two spaces exist in digital twin, physical space and virtual space. The virtual space is the real reflection of the physical space, and it can keep ultra-high synchronization and fidelity with the physical space. (2) Interaction and convergence. This characteristic can be explained from three aspects. (a) Interaction and con- vergence in physical space. Digital twin is a kind of full-flow, full-element, and full-service integration. So the data generat- ed in various phases in physical space can connect with each other. (b) Interaction and convergence between historical data and real-time data. Digital twin data is more comprehensive. It not only depends on expert knowledge but also collects data from all deployed systems real-timely. Therefore, the data can be mined deeply and used more fully through the conver- gence. (c) Interaction and convergence between physical space and virtual space. The physical space and virtual space are not isolated in digital twin. There exit smooth connection channels between the two spaces, which makes them interact easily [23]. (3) Self-evolution. Digital twin can update data in real time, so that virtual models can undergo continuous im- provement through comparing virtual space with physical space in parallel [24].

3.2 Applications of digital twin

Since the concept of digital twin was proposed, it has been applied in many industrial fields and has demonstrated its great potential.

Structural Sciences Center at US Air Force Research Laboratory employed digital twin to build a realistic high- fidelity flight model and combine virtual model data with physical data to make a more accurate fatigue life predic- tion [24]. The Air Force Research Laboratory created a framework, in which the model integrates various data and has a high fidelity to physical space to simulate and assess the confidence in aerothermal model predictions for the coupled aero thermoelastic problem [25]. Bielefeldt et al. [26] also established a model based on digital twin to detect and monitor the damage in aircraft structure, and they used the case of aircraft wings to prove that the model was more effective. Hochhalter et al. [27] proposed to combine digital twin with sensory particles technology to realize real-time detection and aerospace vehicles' in- spection, repair, and replacement as necessary. Based on digital twin, Tuegel [28] put forward the concept of Airframe Digital Twin (ADT) to achieve the goal of de- creasing aircrafts' maintenance costs. And he also pointed out the challenges during realization process. Cerrone et al. [29] built the model of digital twin specimens and

made the simulation implementation to solve crack path ambiguity. Simulation result shows using digital twin can reduce the inaccurate prediction under shear loading. Besides, PTC is trying to establish a virtual space as one-to-one representation of a unique physical product to be used in the product design process. And many other global famous companies (e.g., Dassault Systèmes, Siemens PLM Software) also express great interests in application of digital twin [30].

According to the applications of digital twin mentioned above, digital twin currently is primarily applied to the field of aeronautics and astronautics for failure prediction and is mainly applied to product service and maintenance phase. With the concluded characteristics of digital twin, especially synchronous linkage and ultra-high fidelity be- tween physical product and corresponding virtual product, digital twin has high potential to solve above problems existing in PLM. This paper will emphasize its potential applications in product design, product manufacturing and product service.

4 Conclusion and future works

Many new technologies, such the internet of things (IoT), big data, and the advent of the big data age in manufacturing,

PLM has made use of cloud computing and service-oriented technologies. But rather than data from virtual models, existing solutions mostly concentrate on data from actual products. One possibility is that data created at different points in the product lifecycle can serve as an information island that spans the whole product lifetime. On the other side, data duplication is common throughout product lifecycle stages, which causes inefficient data exchange and wastes resources. Aside from that, there is a noticeable lack of interaction and iteration between big data analysis and the other activities that make up the whole product lifecycle. Digital twins have great promise for use in product design, production, and service because they can address issues with ultra-high synchroni-zation and fidelity, as well as with the convergence of physical and virtual products.

The paper's key contributions are as follows: (1) A novel approach for digital twin-driven product design, production, and service is suggested to address data-related issues throughout the product lifecycle. (2) The framework and methodologies for digital twin-driven product design, production, and service are examined in depth. (3) The three stages of a product lifecycle are shown via three examples to demonstrate the real-world uses of digital twins.

The approaches and frameworks for using digital twins in product design, production, and service were first explored in this study. The study is still in its early stages and requires more investigation. In the next years, researchers will be focusing on four main areas: (1) technology for intelligent perception and connection; (2) methods for building and managing digital twin data; (3) a smart service analysis approach that uses digital twin data; and (4) more applications of digital twin-driven product lifecycle management (PLM).

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