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# Digital Twin Bionics: A Biological Evolution-Based Digital Twin Approach for Rapid Product Development

LINLI LI<sup>1,2,3,4</sup>, FU GU<sup>1,3,4,5</sup>, HAO LI<sup>6</sup>, JIANFENG GUO<sup>7</sup>, AND XINJIAN GU<sup>1,2,3,5</sup>

<sup>1</sup>State Key Laboratory of Fluid Power and Mechatronic Systems, School of Mechanical Engineering, Zhejiang University, Hangzhou 310027, China

<sup>2</sup>Zhejiang Key Laboratory of Advanced Manufacturing Technology, School of Mechanical Engineering, Zhejiang University, Hangzhou 310027, China

<sup>3</sup>Department of Industrial and System Engineering, Zhejiang University, Hangzhou 310027, China

<sup>4</sup>Center of Engineering Management, Polytechnic Institute, Zhejiang University, Hangzhou 310015, China

<sup>5</sup>National Institute of Innovation Management, Zhejiang University, Hangzhou 310027, China

<sup>6</sup>Henan Provincial Key Laboratory of Intelligent Manufacturing of Mechanical Equipment, Zhengzhou University of Light Industry, Zhengzhou 450002, China

<sup>7</sup>Institutes of Science and Development, Chinese Academy of Sciences, Beijing 100190, China

Corresponding author: Fu Gu (gufu@zju.edu.cn)


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**ABSTRACT** With intensified market competition, product development procedure is accelerated, requiring rapid product innovation and efficient collaboration between design and manufacturing. However, there still exist information islands, prohibiting integration of product life cycle processes. To address this issue, bionics and digital twin (DT) are combined as a potential solution. The concepts, framework, and features of digital twin bionics (DTB) is originally proposed, with co-evolution mechanism of product-twins (including virtual and physical products) and production-twins (including virtual and physical production) elaborated. A symbiotic co-evolution mechanism is presented to integrate the processes of product development and manufacturing. In detail, the supporting technologies, such as industrial internet of things, cloud edge computing, big data, and artificial intelligence, as well as the potential key technologies, are illustrated. A case study for rapid development of automotive body-in-white in an industrial robotics welding production line is investigated to verify the applicability of the proposed framework. The results suggest that the integration of bionics and DTs can accelerate the innovations and developments of new products and also help to achieve efficient management of production construction.

**INDEX TERMS** Digital twin, bionics, product development, co-evolution, product life cycle.

## I. INTRODUCTION

With increasing market competition, there is an urgent need for the manufacturing companies to turn to smart manufacturing production paradigm for rapid product development [1]. State-of-the-art of information and communication technologies (ICTs), e.g., internet of things (IoT), cloud computing, big data analysis, artificial intelligence (AI) [2], [3], are applied in manufacturing industry so that innovative products with stable qualities can be developed rapidly and efficiently through the digital transformation [4]. However, the core problem of rapid product development is rapid innovation design of product [5] and the efficient collaboration manufacturing with design [6]. To address this problem, the concept of bionics has been introduced in product design to solve

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these problems [7]. Bionics is a frontier in manufacturing industry; it is an interdisciplinary science that combines biological features and evolutionary principles with design and manufacturing engineering technologies [8]. Although progresses have been achieved in bionics-based product design, e.g., theoretical modeling [9], [10], product design [11], [12], product evolution [13]–[15], and product optimizing algorithms [10], [15], yet information islands persist. This leads to an emerging problem: the bionic design cannot be quickly applied and verified in manufacturing [16] due to the absence of integration of design and manufacturing. Consequently, multiple design revisions are needed, thereby compromising the overall efficiency of innovative product development [17].

Digital twin (DT) is considered as a key pillar of cyber-physical integration [3] and an enabler of smart manufacturing paradigm [18]. DT is an equivalent digital virtual model of a physical entity established in cyber world [19],

bridging the cyber world and physical world. It has been applied in product design [20], [21], manufacturing [18] and services [22]–[24] for aerospace, automotive, machine tools, medical, and machinery manufacturing [25], [26]. It breaks the barriers between product design and manufacturing [18] through simulation and interaction. It has also been applied to optimize production in a digital twin shop-floor [27]. The core problem is that product has not been deeply integrated and co-evolved with production system in the product life cycle, thus leading to lots of reworks. Therefore, there is an urgent need to combine the bionics and DT to promote rapid product development.

In this paper, the concept and framework of digital twin bionics (DTB) is introduced firstly by combining bionics and DT to solve the problems of innovative product rapid development. And then the co-evolution mechanism of product-twins (including virtual and physical products) and production-twins (including virtual and physical productions) is proposed separately with the conceptual framework of DTB and to their symbiotic co-evolution mechanism. Furthermore, the application of supporting technologies of DTB in the innovation and evolution of product twins are explained.

The main contributions of this paper are as follows. (1) The concept of DTB is introduced for products bionics design to address information islands in product life cycle processes. (2) The symbiotic co-evolution mechanism of product-twins and production-twins mentioned above will push the progress of product integrating and co-evolving with production system in the product life cycle, and help to speed up the construction of a more suitable production system for rapid product development. (3) The key technologies for the evolution of digital-twins, such as multidisciplinary collaborative simulation and virtual commissioning, are illustrated for the integration between design and manufacturing.

The rest of this paper is organized as follows. Section II reviews related works. Section III introduces the concept, features, and framework of DTB. Section IV illustrates the related co-evolution mechanisms of DTB. Section V presents the supporting technologies for DTB. Section VI relates to a case study, and Section VII makes a conclusion.

## II. RELATED WORKS

### A. BIONICS IN PRODUCT DEVELOPMENT

The extant literature on bionics in product development mainly focuses on product design, optimizing algorithms, and bionics manufacturing system, as shown in Table 1.

Still, the gap between product design and manufacturing inevitably results in information islands, which prevents the bionic models to accurately depict the characteristics of product. This would lead to product defects. In addition, the results of bionic design cannot be directly applied to manufacturing process and cannot be verified. This would increase reworks and reduce product design efficiency.

### B. DIGITAL TWIN IN PRODUCT DEVELOPMENT

There has been a hot discussion on DT in the context of industry 4.0 [19], [26]. Since 2017, a lot of research has

**TABLE 1. Categories of bionics in product development.**

Reference	Contents
Zhao <i>et al.</i> [11] Maier <i>et al.</i> [12] Chen <i>et al.</i> [14] [28]	Theory: product structure bionic design, product bionic innovation design. Methods: genetic engineering, product virtual chromosomes. Application: clone products by computer-aided design/computer-aided manufacturing.
Altshuller [29] Holland [30] Neugebauer [31] Hao [32] Yang [33] Chen <i>et al.</i> [34]	Theory: product evolutionary design and evolutionary gene process. Methods: evolutionary algorithms, genetic modeling, and coding of product functions. Application: machine tools, 3D printing, notebook product line.
Chen [35] Yang [13]	Theory: product gene and growth design. Methods: definition of product gene and automatic “growth” mechanism, expression of product genetic engineering. Application: product design.
Ueda [36][37]	Theory: decentralized biological manufacturing system. Methods: a bionic manufacturing system model based on DNA type information. Application: Production systems.
Gong <i>et al.</i> [38] Chen <i>et al.</i> [35] Zhou <i>et al.</i> [15] Zhao <i>et al.</i> [10] Sun <i>et al.</i> [39] Leirimo <i>et al.</i> [40]	Theory: evolutionary computation, evolutionary algorithms for product design, genetic algorithm for production scheduling. Methods: product gene and evolutionary algorithm, genetic algorithm. Application: product design, additive manufacturing, production scheduling.

been made on many areas of DT, such as product design and development [20], [21], [41], production planning design [42]–[44], services [24], [45], application [46], and standards [47]. Tao *et al.* [25] proposed a 5D model of DT, consisting of physical models, cyber models, data, service, and connections of them. Li *et al.* [16] presented a collaborative symbiosis framework model for product DT, production DT, and their performance DT, and introduced technologies of DT modeling and virtual commissioning for product development to solve the problem of multidisciplinary integrated modeling design of complex mechanical products. However, the problem of integration and co-evolution mechanism between product and production system still has not been solved yet, which will further result in less coordinated development of design and manufacturing, thus leading to inefficient manufacturing.

In sum, it seems that DT technology could solve the problems of information islands in bionics design, and the biological evolutionary principle may explain the co-evolution mechanism between product and production.

**C. FUSION OF DIGITAL TWIN AND BIONICS**

Bionics has inspired engineers to design innovative products with good structure and material performance, but the gap between bionic design and manufacturing leads to information islands, preventing bionic design to be applied, verified, and optimized in time.

DT enables the integration of bionics design and manufacturing, and remove the information island. But DT, as a tool technology, cannot solve the problems of the integration and co-evolution mechanism between product and production system. Thus, the design results of product cannot be quickly imported to production because of lacking a suitable production on the condition of product changing at any time. However, the papers on growth design and evolutionary design will inspire us to explore the co-evolution mechanism between product and production system from a bionics perspective.

In sum, bionics and DT are complementary, as their integration will break the information integration barriers between product design and manufacturing, and it further promotes the symbiotic co-evolution between product-twins and production-twins. They work together to achieve the promotion of rapid product development and realization of smart manufacturing.

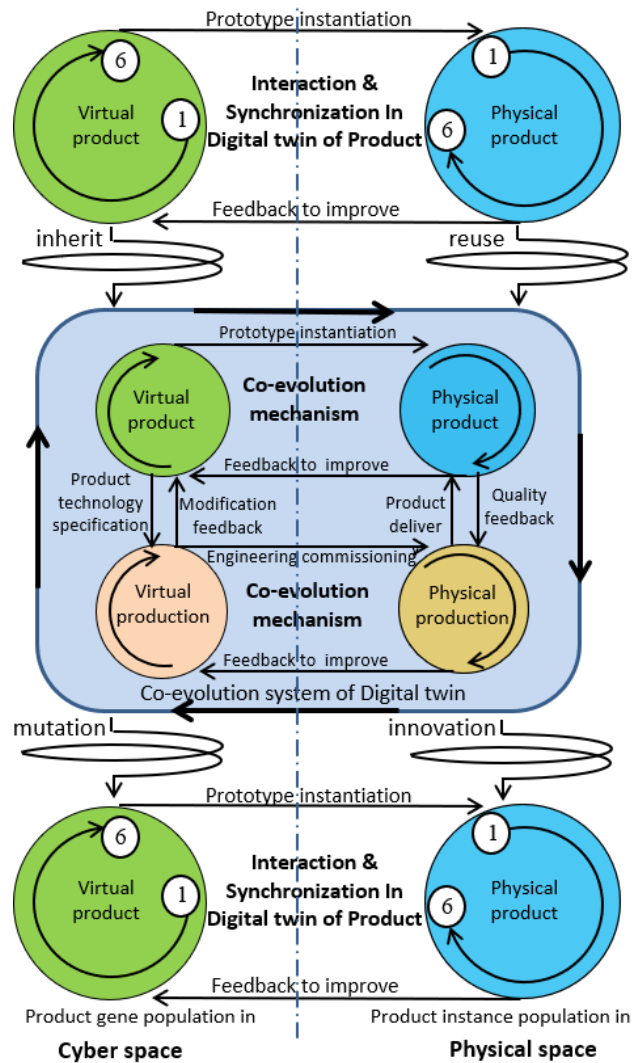
**III. CONCEPT, FRAMEWORK, FEATURES OF DIGITAL TWIN BIONICS**

**A. CONCEPT OF DIGITAL TWIN BIONICS**

Based on what is illustrated in previous part, the co-evolution conceptual framework of DTB is proposed by combining bionics and DT, as is shown in Figure 1.

(1) In the top of Figure 1, two circles represent the virtual and physical products respectively. The first-generation virtual product co-evolves with the physical product during the product life cycle. The evolution of virtual product undergoes six stages: (a) conceptual design, (b) detail design, (c) multi-disciplinary simulation, (d) problem discovery and analysis, (e) improvement, and (f) verification. As is shown in the right of Figure 1 at the top, the virtual product is instantiated to be a physical product, which evolves according to the simulation results. The physical product also undergoes six stages: (a) operation, (b) problem discovery and analysis, (c) improvement, (d) test and verification, (e) problem discovery and analysis, and (f) improvement. During the evolutionary process of first-generation product, the virtual product and the physical product keep continuous interaction and real-time synchronization to finish the co-evolution process, when they are internal self-circulation and self-evolution separately.

(2) In the middle of Figure 1, the rectangle represents the big circulation of the co-evolution between product-twins and production-twins. Firstly, when the first-generation



**FIGURE 1.** Co-evolution conceptual framework of DTB.

product matures, it will evolve to the next generation product. The virtual model of second-generation product will experience the process of incubation through inheriting the desirable characteristics of first-generation product, as well as the process of crossover and mutation. In the whole process of incubation, the product-twins will always keep co-evolving, and experience the process of internal self-circulation and self-evolution. Secondly, this process will promote the internal self-circulation and self-evolution of production-twins at the same time. Furthermore, the product-twins interact with the production-twins through two channels in virtual and real spaces separately. On the left side, the virtual product sends product technology parameters and processing specification to virtual production when the virtual production sends the simulation results to the virtual product for product improvement. On the right side, physical production delivers products and gets quality feedback from the product quality system to improve the production continuously. Thirdly, the production-twins undergo an evolutionary process like product-twins, and production-twins continue

TABLE 2. Features of DTB.

Features	Explanations	Advantages compared with current DT
Smart	(a) smart units: self-sensing, self-adaptation, and self-evolution. (b) smart groups: interactive, self-healing, self-circulation. (c) smart ecosystems (e.g., design, production, and supply chain ecosystem): self-organization, self-circulation, and self-evolution.	Based on big data and AI, the intelligent design and manufacturing of product DT will be accelerated to promote the implementation of smart manufacturing paradigm.
Self-evolutionary	Product families multiply and evolve across generations through inheritance and mutation. The evolutionary laws of product-twins and production-twins are explored deeply through big data and AI, separately, as well as the symbiotic co-evolution of them.	The evolutionary laws are studied between children generation products and parent generation products for knowledge sharing and rapid innovation through extending the research scope of time and space dimensions (e.g., from molecule to individuals, from individuals to groups, from groups to ecosystem).
Collaborative	In a biological smart manufacturing system, smart units (products, equipment) are competitive and cooperative. The cross-regional, cross-industry, large-scale collaboration are achieved through cloud-based digital services.	A distributed ecological manufacturing system is formed through self-organization and self-coordination of smart units DT to complete the target tasks through free competition and division of labor collaboration.
Shared	The fusion and sharing of multidisciplinary and cross-domain knowledge are realized through the application of biological technologies in design, manufacturing, operation management, and service.	The DTs of smart units carry out self-calculation, self-decision, and self-adjustment through perceiving self-states and external environments, spread and share knowledge acquired among the target group.
Self-innovating	Self-innovation of products will be accelerated through new processing (e.g., additive manufacturing) and IT technologies (e.g., big data, AI), to optimize the design and processing paths without involvement of human experts.	Individuals (or systems) are endowed with some biological features (e.g., selection, mutation, and adaptation) to complete its self-innovation through natural competition, survival of the fittest, re-selection and integration innovation.
Ecological	With IoT and cloud computing, a smart, virtualized, and digital manufacturing ecosystem is established to achieve the self-evolution, collaboration, sharing, and self-innovation driven by big data and AI.	DT of smart units has clear self-positioning and clear task objectives in the ecosystem, and they compete and cooperate freely with each other to complete the target task in each project.

keeping co-evolving with product-twins in real time. Therefore, they experience the process of symbiotic co-evolution as well as the process of self-circulation and self-evolution separately. They work together to realize virtual-real synchronization, mutual adaptation, iterative optimization, and dynamic balance during the co-evolution process. This will be introduced in SECTION IV.

(3) In the bottom of Figure 1, the second-generation product is incubated through mutation and innovation, and the new second-generation product-twins would experience the same evolutionary process as the first-generation product, and it also experiences the process of co-evolution with production-twins.

## B. FEATURES OF DIGITAL TWIN BIONICS

The combination of DT and bionics endues DT with some features of intelligent living beings, which urges engineers and users to develop, use and manage DT from the perspective of bionics. DTB is different from the current DT

in that it not only has basic features of DT, but also has some features of biological living beings which current DTs do not possess, for example, the intelligence, self-evolution of individual, and collaboration of group. Therefore, there are six features of DTB, namely self-evolutionary, collaborative, shared, self-innovating, and ecological, as shown in Table 2.

## IV. THEORIES OF DIGITAL TWIN BIONICS FOR PRODUCT RAPID DEVELOPMENT

### A. DTB-DRIVEN PRODUCT-TWINS CO-EVOLUTION FOR PRODUCT RAPID DEVELOPMENT

#### 1) DTB-DRIVEN PRODUCT RAPID BIONIC DESIGN

Both Bionic design and bionic manufacturing are important topics in bionics for product development. First, to obtain desirable product structure and properties [11], DT technologies are applied to extract bionic structure and functions from biological structural features in nature to a machinable product part model, and they include bionics evolutionary



design, finite element simulation analysis and evolutionary algorithm [12].

Second, for the rapid design in the product evolutionary process, a bionic design is proposed to accelerate the innovation cycle of machine tool development in literature [31]. However, the process is impossible to be controlled and verified. Therefore, DT is integrated with bionic design to optimize the bionics structure and verify the reliability of design through virtual simulation. Furthermore, the manufacturing process can also be simulated, predicted and optimized through virtual simulation. While the manufacturing starts, the process will be dynamically monitored and even controlled by virtual manufacturing model through real-time interaction between the virtual and real-time manufacturing. Besides, the design data, virtual manufacturing data and even real manufacturing data will be fused to optimize the design and manufacturing process, and this process will be iterated. In the whole process of design and virtual manufacturing, all the data are in the same database and the version is exclusive and consistent. On basis of this, the data are valued to further data analyzing, and the results of analysis will guide the improvement of design and optimize manufacturing process to reduce time and cost. In other words, the integration of DTs and bionic design will push the process of product-twins evolution and accelerate the development of new products.

## 2) DTB-DRIVEN PRODUCT RAPID BIONIC MANUFACTURING

DTB-driven product bionic manufacturing aims to integrate the principles of bionics and DT technology in the product manufacturing to improve processes and quality and reduce manufacturing time and overall cost. In this paper additive manufacturing will be introduced as a special application of bionic manufacturing. Emerging in recent years, bionic additive manufacturing, as an advanced bionic manufacturing technology, aims to process special bionic components through product bionic structural design and additive manufacturing [48]. In literature [7], several versatile metal-based parts and molds are designed and manufactured with the combination of biological principles with digital technology, biomaterials and additive manufacturing as a new process. However, there are still many difficulties in the industrialization of additive manufacturing, for example, unstable product quality (dimensional accuracy and mechanical properties), long processing time, and high cost.

DT enables the realization of the integration of design and manufacturing through the fusion of cyber and physical system. First, the problems of temperature field controlling in additive manufacturing can be solved through multi-physics simulation and in-time virtual-real information interaction. Second, the processing speed can be effectively controlled through simulating the scanning path. Third, virtual commissioning and virtual machining can be used to predict, optimize and verify the actual machining process to reduce errors and commissioning time as well as the pilot production time. Additionally, the machining parameters can be adjusted and optimized dynamically to achieve high-quality and rapid

processing of products through in-time information interaction between the virtual machining and actual machining. Hence, the coupled application of bionics manufacturing and DT will improve the manufacturing process quality, accelerate product development and reduce the manufacturing time and cost.

## 3) DTB-DRIVEN PRODUCT-TWINS CO-EVOLUTION FOR PRODUCT RAPID DEVELOPMENT

The co-evolution of product-twins is realized in the product life cycle. The evolutionary process of product, including inheritance and mutation and undergoing self-evolution and co-evolution, is controlled by product gene carried in the DT models and data.

There are three types of inheritance. (a) Product genes are inherited during the instantiation process from virtual products to physical prototypes. (b) Gene is replicated during the population instantiation process from product prototypes to mass production. (c) The new child products inherit the genes from the old parent ones. To meet the customized requirements, mutations of product genes must be controlled to occur in a certain direction while the simultaneous co-evolution of both virtual and physical products is maintained until entering the next-generation iteration cycle.

Therefore, inheritance and mutation must be controlled. The product bionic evolutionary process is recorded in DT data. Based on the data analysis results through big data and AI algorithms, the product evolutionary laws that are recessive genes of product DT can be represented by the evolutionary algorithms and can be controlled to accelerate product evolution and innovation.

## B. DTB-DRIVEN PRODUCTION-TWINS CO-EVOLUTION FOR RAPID PRODUCT DEVELOPMENT

Production-twins have a similar co-evolution mechanism with product-twins. The co-evolution of production-twins is realized during their life cycle through real-time interaction and dynamic adjustments, ensuring the consistency of their data and behavior states. The co-evolution is influenced by evolutionary laws, emerging technologies, and social environment.

For continuous adapting to the requirements of product development, both of virtual and physical production experience incubation (e.g., production planning and design), growth (e.g., engineering construction, renovation, and innovation), and service (e.g., operation and Maintenance, Repair and Overhaul, MRO) in the production life cycle.

In the incubation phase, a production DT model (including all elements, all businesses, and all processes) is established and various key performance indicators (e.g., capacity, efficiency, energy consumption, quality, etc.) of the production system are optimized through simulation. Finally, a relatively perfect production DT model is transferred to the EPC company (Engineering Procurement Construction) and end user in a digital way to guide the production engineering construction and manufacturing operation services.

In the growth phase, the production DT model is strictly followed to construct factory and organize production. The production planning is dynamically revised and improved in accordance with the feedback of actual construction. Then both virtual and physical production will be combined and digitally delivered to the end user by EPC. Simulation and offline virtual commissioning will be carried out in virtual world with the virtual models of the production lines and equipment before real construction. By this way, more than 85% of the PLC (programmable logic controller) programming and on-site commissioning work are completed before the equipment and production line are installed in the factory, which will greatly accelerate the construction cycle. Besides, all the data of the construction process and even the company and engineer's name can be recorded in the model of production DT. These data and optimized production DT model will be digitally handed over to end user, who is no longer presented with a collection of computerized CAD drawings, equipment lists and PLC programs, but with a digital production system model that consists of various interrelated objects, elements, business and processes.

In the operation phase, production simulation is performed on basis of the virtual production model delivered by EPC to optimize resource allocation, takt time and logistics paths through production planning and scheduling. The simulation data and historical production data (e.g., production data, equipment operation data, and energy consumption data) are integrated for data analysis. The results of data analysis will be used to guide and promote the manufacturing execution of physical production. The virtual production is adjusted in real-time in accordance with the physical production conditions to continuously optimize production efficiency, equipment utilization and energy utilization.

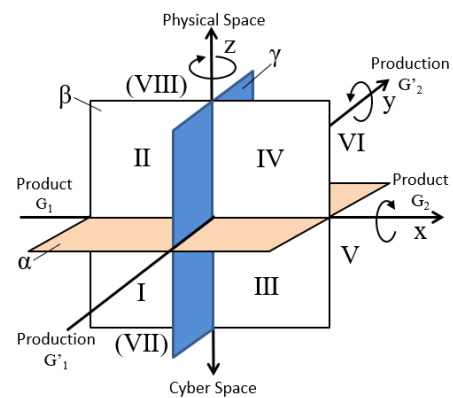
In the service phase, the service process may be simulated and then optimized in advance in the virtual system before addressing emergencies such as demand changes and equipment failures. The actual changed process and data are updated in the virtual production model after the real services are completed to improve the service process next time. Furthermore, the virtual production model will ensure real-time synchronization and data consistency with physical production status.

The optimization iteration and the co-evolution of production-twins are realized through inheritance and mutation during the production life cycle. The production evolutionary process is recorded in production DT data and can be studied through big data analysis and artificial intelligence to achieve precise process control of production. The evolutionary laws of production are the recessive gene of production DT and can be represented by the production evolutionary algorithms. They can be developed to plan production, manufacturing operation, and production improvement (including old factory transformation and new factory replication) in the production life cycle. Therefore, the production-twins enable the realization of digital transparent management of equipment and factory.

The evolution of production-twins supports and provides a suitable production system to match the needs of rapid product development. Next, the synchronizing symbiotic co-evolution of product-twins and production-twins will be realized in virtual and physical spaces.

**C. DTB-DRIVEN SYMBIOTIC CO-EVOLUTION OF PRODUCT-TWINS AND PRODUCTION-TWINS**

The co-evolution mechanism of product-twins and production-twins in both the cyber and physical spaces is shown in Figure 2, explaining the relationship of product and production system.



**FIGURE 2. Symbiotic co-evolution relationship of product twins and production twins in eight quadrants.**

First, the x-axis, y-axis, and z-axis cross each other. The intersection of x-axis and y-axis forms a horizontal plane  $\alpha$  (top view). The intersection of x-axis and z-axis forms a vertical plane  $\beta$  (front view), and the intersection of y-axis and z-axis forms another vertical plane  $\gamma$  (side view). The x-axis is a time axis and represents the product life cycle value chain. The direction of x-axis represents the evolutionary direction of product twins. The left and the right ends of x-axis represent the first-generation product  $G_1$  ( $PG_1$ ) and second-generation product  $G_2$  ( $PG_2$ ), respectively. The evolutionary process from  $PG_1$  to  $PG_2$  is a spiral process. The y-axis is also a time axis and represents the production life-cycle value chain. The arrow direction of y-axis represents the evolution direction of production twins. The front and the back ends of y-axis represent the first-generation production  $G'_1$  ( $P_nG'_1$ ) and second-generation production  $G'_2$  ( $P_nG'_2$ ), respectively. The evolutionary process from  $P_nG'_1$  to  $P_nG'_2$  is spiral. The z-axis is a spatial axis. The horizontal plane  $\alpha$  divides the z-axis into upper physical space and lower cyber space. The upper and the lower directions of z-axis indicate that the cyber and physical spaces can be expanded and integrated freely.

Second, horizontal plane  $\alpha$  indicates the relationship between the product and its production system in the evolution process. It reveals the value-added processes of the product life cycle value chain and the production life cycle value chain. Manufacturing operation (Manufacturing Execution)



FIGURE 3. Interaction process of product-twins and production-twins in eight quadrants.

is the intersection of the two value chains and is the core of product value added. Vertical plane  $\beta$  indicates that the product co-evolves along the x-axis in the cyber and physical spaces. Vertical plane  $\gamma$  indicates that the production co-evolves along the y-axis in the cyber and physical spaces.

Third, horizontal plane  $\alpha$ , vertical plane  $\beta$ , and vertical plane  $\gamma$  intersect each other and divide the entire space into eight quadrants: I, II, III, IV, V, VI, VII, and VIII.

In figure 3, the interaction process of product-twins and production-twins is illustrated in the eight quadrants. There are four types of relationship between the product-twins and production-twins, namely cyber-cyber interaction, physical-physical interaction, cyber-physical interaction and cyber-physical interaction only in the cyber space.

The co-evolution process model of product-twins and production-twins are expressed below.

**Product gene:**

$$PG_1 = \{P = (g_1, \dots, g_i), g_i \in G_i\} \quad (1)$$

In Equation 1,  $g$  is product meta gene. All the genes ( $g_i$ ) are combined into product gene  $P$ .  $G_i$  is gene population of  $PG_1$ .  $i$  is the number of product meta gene.

**Production gene:**

$$P_nG'_1 = \{P_n = (g'_1, \dots, g'_j), g'_j \in G'_j\} \quad (2)$$

In Equation 2,  $g'_j$  is production meta gene. All the genes ( $g'_j$ ) are combined into product gene  $P_nG'_j$  is gene population of  $P_nG'_1j$  is the number of production meta gene.

**External environment:**

$$E = \{E_1, \dots, E_k\} \quad (3)$$

In Equation 3,  $E_k$  is the external impact factor. All the  $E_k$  are combined into external environment  $E$ .  $k$  is the number of external impact factor.

**Production environment:**

$$EP = \{(\sum E_k \cup \sum g'_j), k = (1, \dots, k), j = (1, \dots, j)\} \quad (4)$$

In Equation 4, production environment  $EP$  is composed of all the related  $E_k$  and  $g'_j$ . Symbol  $\cup$  represents the fusion relationship of  $E_k$  and  $g'_j$ .

**Transfer function:**

$$f' : P_nG'_1 \times E \rightarrow P_nG'_2 \quad (5)$$

$$P_n = f'(\sum g'_j, E) \quad (6)$$

TABLE 3. Symbiotic co-evolution process of product-twins and production-twins in eight quadrants.

Quadrants	Product (P) evolutionary process	Production (P <sub>n</sub> ) evolutionary process	Relationship
I	(1) Virtual PG <sub>1</sub> will be designed, simulated, and optimized to come to be a mature product with the co-simulation of Virtual P <sub>n</sub> G' <sub>1</sub> .	(2) Virtual production P <sub>n</sub> G' <sub>1</sub> will also be designed, simulated, tested, and verified to be a suitable production system with the PG <sub>1</sub> design parameters and processing specification.	The digital models of PG <sub>1</sub> and P <sub>n</sub> G' <sub>1</sub> interact with each other and keep co-evolving in Quadrant I (Seen in Equation (1) and (2)).
II	(4) The processing parameters and specification of Virtual PG <sub>1</sub> will be imported to P <sub>n</sub> G' <sub>1</sub> production system to produce physical product PG <sub>1</sub> .	(3) According to Virtual P <sub>n</sub> G' <sub>1</sub> , the physical production system will be constructed to produce PG <sub>1</sub> , and at the same time the real conditions will be fed back to Virtual PG <sub>1</sub> and Virtual P <sub>n</sub> G' <sub>1</sub> for further optimization.	The product-twins of PG <sub>1</sub> and production-twins of P <sub>n</sub> G' <sub>1</sub> keep co-evolving in quadrant I and II separately, and they are also symbiotic co-evolution. (Seen in Equation (6) and (9)).
III	(5) The product PG <sub>1</sub> will evolve to Virtual PG <sub>2</sub> . It will also be designed, simulated, and optimized to be a new mature product.	The Virtual production model P <sub>n</sub> G' <sub>1</sub> is still the old one for 1-generation product PG <sub>1</sub> . It cannot meet the needs for 2-generation product PG <sub>2</sub> , and it needs to be improved to meet the producing requirements of PG <sub>2</sub> .	There is a little interaction between PG <sub>2</sub> and P <sub>n</sub> G' <sub>1</sub> in Quadrant III because P <sub>n</sub> G' <sub>1</sub> cannot match the requirements of PG <sub>2</sub> (Seen in Equation (5) and (7)).
IV	The 2-generaion product PG <sub>2</sub> is needed, but the old production system P <sub>n</sub> G' <sub>1</sub> cannot produce it.	The old production system P <sub>n</sub> G' <sub>1</sub> is not suitable to produce the 2-generaion product PG <sub>2</sub> . It must be rebuilt and improved to adapt product PG <sub>2</sub> .	The old production system P <sub>n</sub> G' <sub>1</sub> and product PG <sub>2</sub> are not matched. They have no interaction in real.
V	(7) Virtual product model PG <sub>2</sub> will be optimized with the co-simulation of Virtual production model P <sub>n</sub> G' <sub>2</sub> .	(6) Virtual production model P <sub>n</sub> G' <sub>2</sub> will be designed, simulated, tested, and verified to be a suitable production system with the PG <sub>2</sub> processing parameters and specification.	The digital models of PG <sub>2</sub> and P <sub>n</sub> G' <sub>2</sub> are matched in Quadrant V, and they interact with each other and keep co-evolving (Seen in Equation (5) and (7)).
VI	(9) The processing parameters and specification of Virtual PG <sub>2</sub> will be imported to P <sub>n</sub> G' <sub>2</sub> production system to produce PG <sub>2</sub> .	(8) According to Virtual P <sub>n</sub> G' <sub>2</sub> , the physical production system of P <sub>n</sub> G' <sub>2</sub> will be constructed to produce the PG <sub>1</sub> , and at the same time the real conditions will be fed back to Virtual PG <sub>2</sub> and Virtual P <sub>n</sub> G' <sub>2</sub> for further optimization.	The product-twins of PG <sub>2</sub> and production-twins of P <sub>n</sub> G' <sub>1</sub> keep symbiotic co-evolving like them in quadrant I and quadrant II (Seen in Equation (6) and (9)).
VII	Virtual product PG <sub>1</sub> is designed.	Virtual production model P <sub>n</sub> G' <sub>2</sub> is designed.	PG <sub>1</sub> and P <sub>n</sub> G' <sub>2</sub> are not matched.
VIII	Product PG <sub>1</sub> is needed.	Real production system P <sub>n</sub> G' <sub>2</sub> is constructed.	PG <sub>1</sub> and P <sub>n</sub> G' <sub>2</sub> are not matched.

In Equation 5 and Equation 6, transfer function  $f'$  shows that the evolution of production  $P_n$  is impacted with external environment  $E$ , and it provides a model for evolution production gene  $P_n$  through the interaction of production genes ( $g'_j$ ) with external environment  $E$ .

**Transfer function:**

$$f : PG_1 \times EP \rightarrow PG_2 \tag{7}$$

$$P = f(\sum g_i, EP) \tag{8}$$

$$P = f(\sum g_i, (\sum E_k \cup \sum g'_j)) \tag{9}$$

In Equation 7 and Equation 8, transfer function  $f$  shows that the evolution of product is impacted with the production

environment  $EP$ , and it provides a model for evolution of product gene  $P$  through the interaction of product genes ( $g_i$ ) with production environment  $EP$ . The product gene  $P$  is determined and impacted by product meta gene  $g_i$ , production meta gene  $g'_j$  and environment impact factor  $E_k$ .

Next, the symbiotic co-evolution process of product-twins and production-twins and the relationship between them in Figure 3 will be illustrated in detail in Table 3 below.

Special attention should be given to Quadrant VII and VIII, and the mismatch and imbalance between the product-twins and production-twins are illustrated separately. In Quadrant VIII, the performance of production system largely exceeds the product manufacturing requirements,



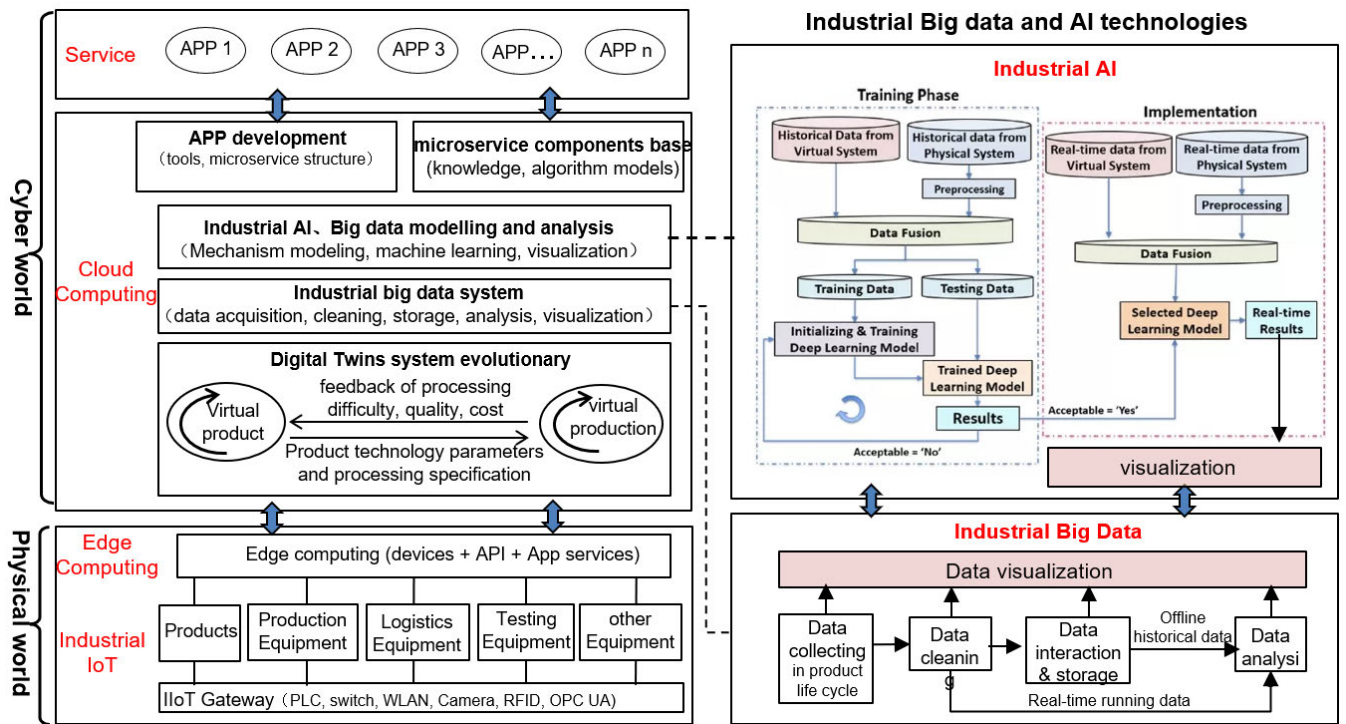


FIGURE 4. New IT driven DT product development technology architecture.

thereby causing wastes. Thus, it is necessary to simulate and optimize the virtual model of the production system in the cyber space, and then integrate the virtual product model into the virtual production system to adjust, optimize and iterate the entire system, and finally achieve a balance between investment and output before the production system is set up (see Quadrant VII).

## V. TECHNOLOGIES OF DIGITAL TWIN BIONICS FOR PRODUCT RAPID DEVELOPMENT

### A. SUPPORTING TECHNOLOGIES OF DIGITAL TWIN BIONICS FOR DRODUCT RAPID DEVELOPMENT

The rapid integration and development of New IT (IoT, cloud edge computing, big data, AI) and industrial applications provide technical support for the rapid development of digital twin product [49]. New IT is the supporting technologies of DTB and the digital twin product development technology architecture driven by new IT is shown in FIGURE 4.

(1) **Industrial big data** is the source and driving force of product rapid innovative development. First, massive industrial big data are generated and processed in the product evolutionary process to obtain the value behind the data through data mining and analysis [56]. Then the industry knowledge in related fields will be extracted continuously to obtain the insight into the complex innovative development of product-twins and production-twins. Second, the running mechanism of DTs is described through the association relationship of data, to predict and regulate the co-evolution process of product-twins and production-twins. Industrial big data enables DTs to possess the capabilities of self-learning,

self-optimization, self-regulation, and self-evolution. Finally, the big data and the algorithm model are encapsulated in the data service APPs in accordance with specific application scenarios. The APPs provide customers with visual and transparent analysis results in the form of micro-service.

(2) **Industrial IoT** is the application of IoT in the industrial field. Providing a data acquisition platform for product rapid development to obtain multi-source, reliable, and accurate data, it also helps to realize the interaction between heterogeneous data. The Industrial IoT system enables the interconnection between cyber-physical networks of devices (i.e., manufacturing resources, facilities, equipment, materials, products, and even people) by using industrial communication technology (ICT) to link intelligent sensing devices, actuators, and embedded devices [50]. It also performs sensing, collecting, sending, and receiving of data and becomes a bridge between the cyber networks and physical objects [51].

(3) **Cloud computing** provides a platform for product rapid design and manufacturing through multiple services, it enables DTs to use huge cloud computing resources and data centers through a dynamically scalable computing resource sharing pool service [52], to dynamically meet the different requirements of DTs [53], such as scalability and flexibility. Cloud computing adopts virtualization technology to perform configurable modeling and simulation of manufacturing resources, manufacturing processes, and multi-source data [54]. Cloud computing is featured as high performance and lower cost, virtualization, dynamic scalability, high flexibility, and reliability.

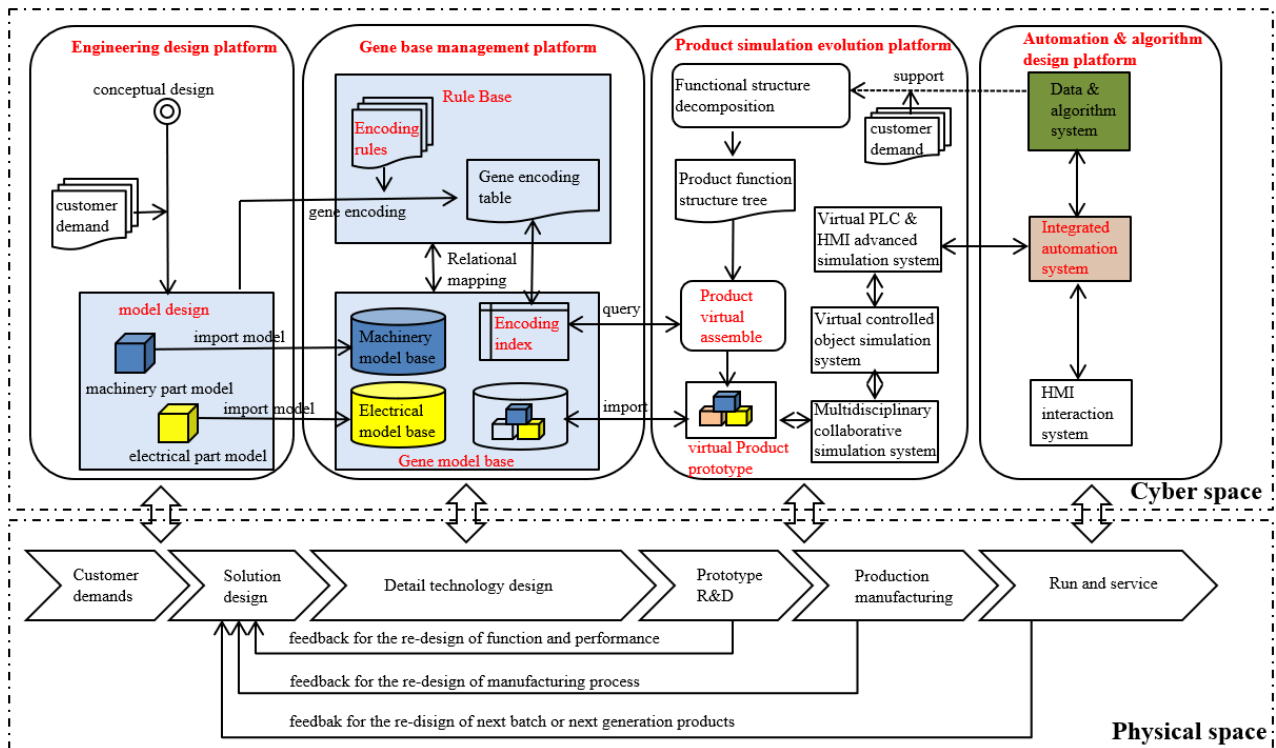


FIGURE 5. Technical architecture of DT co-evolution for product rapid development.

(4) **Edge computing** is deployed on edge side of DT system close to physical entities or data sources [55]. It is an open platform that focuses on scheduling, optimization, and routing on basis of data analysis. Without having to send all the data to the cloud, edge computing helps to process and analyze the data acquired on the edge in real time for local user immediate decision-making, rapid response, and timely execution, reducing cloud data load and accelerate DTs evolution, iteration, and update [53]. **Cloud-edge cooperative computing** is a good choice to utilize cloud resources. Cloud-edge cooperative computing helps to set up a closed-loop cloud-edge ecosystem to realize the data-driven evolution of DTs.

(5) **Industrial Artificial Intelligence**, for example, machine learning and deep learning, can automatically perform data preparation, analysis, and fusion without the participation of experts, conduct in-depth knowledge mining on DT data, and provide rapid data analysis, prediction, and verification services for digital twin product development [53]. Massive amounts of industrial data from DTs can be preprocessed through unsupervised learning with special rules to obtain lots of labeled data automatically, and then the labeled data will be processed and trained to get an AI model. Industrial AI has become a key technology to drive product development and production optimization.

### B. KEY TECHNOLOGIES OF DIGITAL TWIN BIONICS FOR PRODUCT RAPID DEVELOPMENT

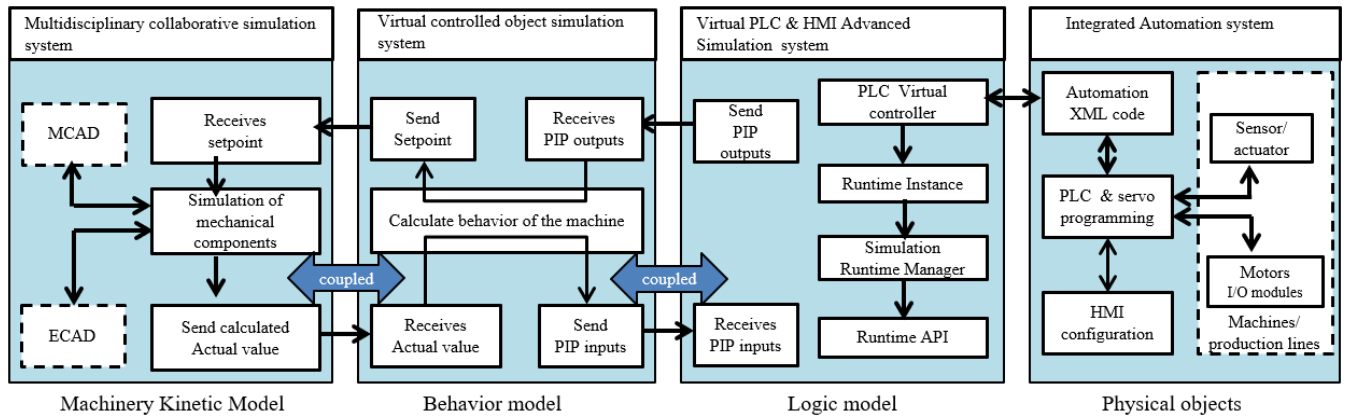
The evolution of product DT is determined by product genes. The product genes are carried in the information of

product functional components and are stored in the product DT models, the evolution of product DT models is the key to control product evolution laws and promote product innovative development.

The technical architecture of product DT evolution is shown in Figure 5, in which product-twins co-evolve and interact in real-time in the physical and cyber spaces. In the physical space, the product undergoes multiple evolutionary iterations in its life cycle. In the cyber space, there are four areas: (a) engineering design platform, (b) gene base management platform, (c) product simulation evolution platform, and (d) automation and algorithm design platform. Next, the potential key technologies for product rapid development driven by DTB are introduced below.

(1) Gene modeling and gene base management technologies in Figure 5 include: (a) gene expression and gene coding rule design for product DT model; (b) Design, coding, and storage of gene model; (c) Definition and description of gene model relationship based on semantics; (d) Gene base management technologies, such as optimization algorithm for gene base search engine, gene model intelligence push algorithm, fast matching between search results and demands as well as the verification technology.

First, on the engineering design platform in Figure 5, product gene models are designed and assembled. The product genes and genome are composed of mechanical (M), electrical (E), automation (A), and data and algorithm (D), etc. And the gene models of product parts are obtained through the mechanical design in MCAD (Computer aided mechanical design), electrical design in ECAD



**FIGURE 6.** Multidisciplinary collaborative simulation and virtual commissioning process of DTs.

(Computer aided electrical design) and other multidisciplinary design. Second, on gene base management platform in Figure 5, the product gene models are extracted, defined, described, classified, coded, and stored in product gene base, and they will also be searched, matched, and evaluated when they are chosen for assembly.

(2) Cyber-physical co-evolution technologies are illustrated on the product simulation evolution platform and automation & algorithm design platform in Figure 5. The key technologies include: (a) multidisciplinary design and simulation modeling [16]; (b) virtual commissioning, virtual testing, and verification [16]; (c) cyber-physical real-time interaction, such as cyber-physical interface and data interaction standards; cyber-physical data with time stamp synchronization technology based on event changes.

On the product simulation evolution platform in Figure 5, the following work is finished: product prototype virtual assembly, simulation, virtual commissioning, virtual testing, and virtual verification. First, according to the functional structure tree of product, the gene models of product modules will be queried from the gene model base to assemble an original product virtual prototype. Sometimes the prototype should be also stored in the product gene base. The product simulation evolution platform consists of a multidisciplinary collaborative simulation system, a virtual controlled object simulation system, and a virtual PLC & HMI (Human-Machine Interfaces) advanced simulation system and so on. The product virtual prototype is simulated, commissioned, tested, optimized, and verified in the multidisciplinary collaborative simulation system, virtual controlled object simulation system, virtual PLC & HMI advanced simulation system, as well as Integrated automation system on the automation & algorithm design platform in Figure 5.

To show the data flow and system interaction process in detail among the four systems above, a multidisciplinary collaborative simulation and virtual commissioning process of DTs is illustrated in Figure 6 [16]. (a) In the multidisciplinary collaborative simulation system, the assembled product

3D geometric model is imported to simulate the product function and motion process, to verify the performance of kinetics and dynamics as well as behaviors, and to find some potential problems (e.g., collision and interference) before it is put to manufacturing. (b) In the virtual controlled object simulation system, the controlled objects (e.g., sensor, actuator, remote I/O modules, valves, meters, motors) are virtualized and encapsulated into program blocks. The controlled objects 3D geometric model and the variables of virtual PLC CPU PIP (process image partition) are connected through the program blocks, and then the virtual PLC will drive the product 3D model to simulate the logical process and behaviors of products. This process is the same as they are in the real environment. (c) In the virtual PLC and HMI advanced simulation system, the virtual control system is applied to replace the physical entities (e.g., PLC CPU, servo driver and HMI) to run the PLC programs and drives the product 3D geometric model to simulate the behavior, motion, and dynamics performance. This is a type of software-in-loop virtual commissioning. (d) The programs in virtual PLC CPU and HMI will be imported to the physical PLC CPU for further verification and optimization after the virtual product prototype is tested and turns out to be in outstanding performance. Then the integrated automation system will replace the virtual advance simulation system to connect the virtual controlled object simulation system through a switch unit to drive the product 3D geometric model to go on a precise simulation. This is a type of hardware-in-loop virtual commissioning.

After all the simulation is finished, the physical automation system will be integrated in the physical equipment to control the equipment, acquire data, as well as to connect the virtual product 3D geometric model.

(3) Product evolutionary design optimization algorithms, including optimization algorithm for product gene module division, product gene module combination, and algorithms for product function evolution, structure evolution, and shape evolution.

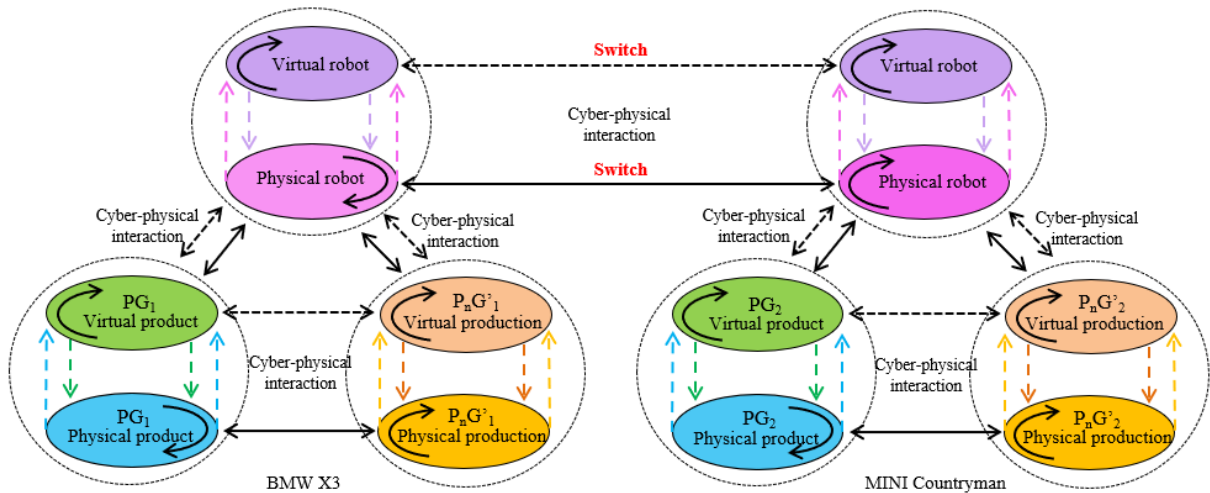


FIGURE 7. Parallel hybrid production technical framework of welding production line based on DTB.

VI. CASE STUDY

A. CASE OF DTB-DRIVEN AUTOMOTIVE RAPID MANUFACTURING IN A WELDING LINE

In this paper, taking an OEM manufacturing plant for BMW automotive as an example, a case of product rapid development based on the co-evolution framework of products and production line driven by DT is introduced. As it is shown in Figure 7, the OEM plant needs upgrading the old BMW X3 production line to establish a prototype production line of MINI Countryman, and to produce the MINI Countryman and BMW X3 in the same production line, while the existing resources of the BMW X3 production line must be fully utilized. Thus, quickly designing, transforming, and upgrading the old welding production line and controlling the risks and costs in the project are the key issues OEM plant was facing.

In Figure 7, a parallel hybrid production technical framework of body-in-white welding production line based on DTB is illustrated. This parallel hybrid production transformation undergoes the following stages: production system redesigns, layouts optimization, production process simulation and logistics optimization. The core of upgrading and transformation of the body-in-white welding production line lies in the reuse of welding robots on the original production line. Because most of the automotive body-in-white welding processes are realized by industrial welding robots. The welding robots are the core of the entire welding production line due to its complex motion, high precision, and strong collaboration ability.

In the redesign stage, the welding robots are designed to be reusable. They are highly cooperated with the body product-twins and welding line production-twins. It can switch the BMW X3 production status to MINI Countryman status easily and vice versa. There are approximately 180 robots, 280 welding torches, 100 grippers, and corresponding tool change systems on the plant's body welding line, with its automation degree exceeding 98%. In a limited space, it is

quite necessary to freely coordinate the interaction of up to six robots with multiple degree of freedom and arrange all solder joints on each manufacturing station within the required cycle time.

An application framework for the body-in-white and welding production system driven by DTB is proposed in Figure 8. First, the robot models, layout and usability were optimized, verified through the integrated virtual simulation of the production process (Seen in (1) and (2)). Before starting production, cycle time was analyzed, collisions were detected, and safety conditions were verified (Seen in (3) and (6)).

Second, after taking pictures of the workshop, the production planning engineer made use of point cloud technology and Siemens simulation software to build a virtual production system model for the old BMW X3 welding production line, as well as the 3D model of the entire automation system (including robots, tooling, and peripheral equipment). And then the robot virtual model and the automation system model were integrated into the virtual production system model.

Third, a new vehicle model of MINI Countryman, including all geometric data and solder joints, was simultaneously imported into the virtual production system model. Then the body shell planning engineer defined the welding sequence, evaluated the potential reusability of existing welding guns for all the solder joints on the production line in the simulation software (Seen in (3) and (4)). Finally, the solder joints are more reasonably defined and distributed through simulation (Seen in (2) and (3)). Besides, the simulation results of welding accessibility, cycle time analysis, and collision simulation would support the rapid turnover, and improve the quality of welding results (Seen in (3) and (6)).

Since the old products were still produced 24h/7day on the BMW X3 production line, the programs could not be tested on the actual line. Therefore, the robot control programs and operations were designed, simulated, optimized, and offline programmed in the simulation software before engineering simulation (Seen in (5), (6) and (7)). Next, the planner used



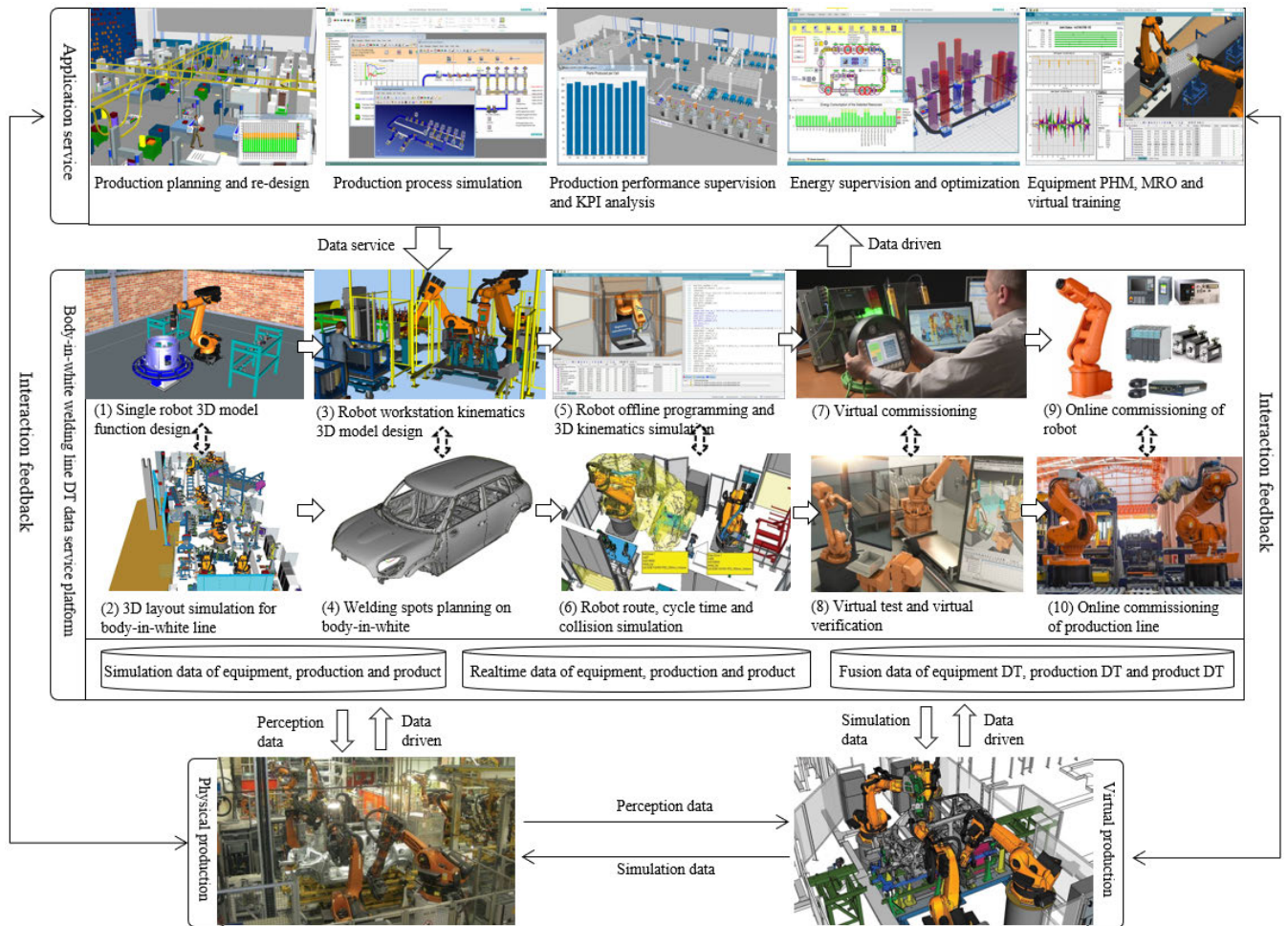


FIGURE 8. Application framework for a body-in-white and welding production system driven by DTB.

the simulation software to write and prepare all the programs, integrated the work of external service providers, and simulated the environment in detail to test and verify all the functions (Seen in (7) and (8)). All of these were done to ensure that BMW X3 and MINI Countryman can be produced on the old production line parallelly. Besides, the programs were defined as fine tuning, including aberration compensation, zero offset, and real-time testing. Therefore, a short intervention time, rapid implementation and flexibility, and continuous program adjustments were achieved in the actual online commissioning stage (Seen in (9) and (10)), which were in sharp contrast to conventional plans.

**B. DISCUSSION**

The final part deals with the conclusion of the research paper. As we can see from the previous research, a satisfying practical result was obtained from this technical innovation. Firstly, in the mixing phase, the shutdown of BMW X3 production line overlapped with MINI Countryman’s startup curve. Thus, no problems occurred. During this cycle, the BMW X3 production line could be run at full capacity in the OEM plant. Two batch of program blocks

in the control system were used to switch the production online between the two vehicles without any adjustments. Then, after a two-week shutdown holiday, the output of MINI Countryman was increased from 0 to 2/3 of the ridgeline of full capacity only in four weeks. Despite the temporary parallel manufacturing, the X3 continued to be produced without any quality loss. In addition, the start-up time of the new manufacturing process was shortened, and the production cost was reduced due to the cancellation of the prototype production line and the reuse of existing resources. Digital planning guarantees high process quality, thereby reducing the errors and material wastes.

In this project, a great success has been achieved based on the DTB framework and the related technologies such as virtual commissioning, verification and test. The key performance indicator (KPI) in the project is illustrated in Table 4.

In the future, based on the established production DT system platform, the following functions can be added in the later stage: production performance monitoring and KPI data statistical analysis, energy supervision and comprehensive optimization utilization, and equipment Physical Health Management (PHM), MRO and virtual training, so as to

TABLE 4. Key performance indicator.

No.	KPI	Results
1	onsite commissioning time	reduced by 60%
2	overall project time	reduced by more than 30%
3	old production resources	reused by more than 98%
4	collisions during pilot production	reduced by more than 90%
5	product quality	no loss
6	overall project cost	reduced by 20%

provide decision support for continuous optimization and improvement of the production system.

Furthermore, the framework mentioned in this paper can be used as a reference for the digital transformation of discrete manufacturing enterprise. Besides, it can be also used to evaluate the design proposals and production investments when it is uncertain which technical route should be chosen in the plant.

## VII. CONCLUSION AND FUTURE WORKS

The combination of biological evolutionary theory and DT technology can help to realize rapid product development and cyber-physical co-evolution of product and production system in their life cycle.

In this paper, a biological evolution-based DT approach is proposed to achieve the rapid product development and the suitable production construction. It also provides insight for researchers into the exploration of product and production evolutionary rules, helps to control the product evolutionary process and to build a suitable production system for balancing the product development and production construction. It can be predicted that the combination of DT and bionics will become the focus of research on DT in the future.

The research can be extended in accordance with the following directions: (1) Gene modeling of DT. (2) Evaluation of DT. (3) Cyber security of DT.

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intelligent manufacturing, and digital twins.

**LINLI LI** was born in Luoyang, Henan, China, in 1982. He received the B.S. and M.S. degrees in mechanical engineering from Zhengzhou University of Light Industry, China, in 2004 and 2007, respectively. He is currently pursuing the Ph.D. degree with Zhejiang University, China. He is also a Senior Engineer with Siemens Ltd., China, and has many experiences of digital transforming in traditional manufacturing. His research interests include knowledge management, distributed



**FUGU** is currently an Associate Professor with the Department of Industrial Engineering, Zhejiang University, Hangzhou, China. He is also the Principal Investigator of a sub-project of the Chinese Key Research Plan Project, science and technology resource sharing model, and open sharing theory. His current research interests include knowledge management in product design, technology adoption and development, and life cycle management.



**HAO LI** was born in Nanyang, Henan, China, in 1981. He received the B.S. degree in mechanical engineering from Zhengzhou Institute of Aeronautical Industry Management, Zhengzhou, China, in 2003, the M.S. degree in mechanical design from Guizhou University, Guiyang, China, in 2006, and the Ph.D. degree in industrial engineering from Zhejiang University, Hangzhou, China, in 2013.

From 2015 to 2016, he served as a Research Assistant for the Department of Engineering, University of Cambridge, Cambridge, U.K. He is currently a Professor of intelligent manufacturing systems with the Department of Mechanical and Electrical Engineering, Zhengzhou University of Light Industry, Zhengzhou. His research interests include DTs, product design methodology, and product-service systems.



**JIANFENG GUO** received the Ph.D. degree in engineering from Zhejiang University, in 2007. He is currently a Professor with the Institutes of Science and Development, Chinese Academy of Sciences, Beijing, China. His work has appeared in journals, including *Applied Economics*, *Physica A: Statistical Mechanics and its Applications*, *Cluster Computing*, and *Applied Energy*. His research interests include innovation theory, decision support systems, and environmental and energy management.



**XINJIAN GU** received the Ph.D. degree in advanced manufacturing from Zhejiang University, China, in 1993. He is currently a Professor in advanced manufacturing with Zhejiang University. He is also the Deputy Director of the Research Center for Innovation Management and Sustained Competition Capability, Zhejiang University. His research interests include green manufacturing, manufacturing information engineering, advanced manufacturing technology, network manufacturing, mass customization, knowledge management, computer integrated manufacturing, group technology, mechanical manufacturing system and engineering, and industrial engineering.

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