Strengthening Digital Twin Applications based on Machine Learning for Complex Equipment

1st Zijie Ren
School of Mechanical and Automotive Engineering
South China University of Technology
Guangzhou, China
me_zijieren@mail.scut.edu.cn

2nd Jiafu Wan
School of Mechanical and Automotive Engineering
South China University of Technology
Guangzhou, China
mejwan@scut.edu.cn

***Abstract*—Digital twin technology and machine learning are emerging technologies in recent years. Through digital twin technology, it is virtually possible to virtualize a product, process or service and the information interaction and co-evolution between physical and information world. Machine Learning (ML) can improve the cognitive, reasoning and decision-making abilities of the digital twin through knowledge extraction. The full life cycle management of complex equipment is considered the key to the intelligent transformation and upgrading of the modern manufacturing industry. The application of the above two technologies in the full life cycle management of complex equipment is going to make each stage of the life cycle more responsive, predictable and adaptable. In this study, we have proposed a full life cycle digital twin architecture for complex equipment. We have described four specific scenarios in which two typical machine learning algorithms based on deep reinforcement learning are applied which are further used to enhance digital twin in various stages of complex equipment. At the end of this study, we have summarized the application advantages of the combination of digital twin and machine learning while addressing future research direction in this domain.**

***Index Terms*—complex equipment, digital twin, deep reinforcement learning, full life cycle management**

I. Introduction

The manufacturing industry is an important part of the national economy and plays an important role in promoting economic development and social employment stability. With the integration and development of Big-Data, Internet of Things, Cloud Computing, Artificial Intelligence and other advanced technologies with manufacturing industry [1], [2]-[3], the modern manufacturing industry is in the stage of rapid development. China has introduced policies, such as '*Made in China 2025*' and '*Internet Plus*' to promote the transformation and upgrading of the manufacturing industry. The digital economy is booming, and intelligent manufacturing with core cyber-physical integration has become the weathervane of future manufacturing development [4].

The essence of intelligent manufacturing is to perceive, collect and analyze various data in the production process through the combination of advanced manufacturing technology and information communication technology. This is to actualize information depth perception, adaptive control and self-optimization decision-making. It runs through the whole life cycle of manufacturing activities such as design, production, operation and maintenance management, recovery and scrap. The emergence of digital twin technology provides a solution to connect the physical world with the information world while realizing data interaction and integration. As an important artificial intelligence algorithm, machine learning can mine useful knowledge in data and provide decision support for users to solve problems through deep learning and processing of fusion information. In the recent development of Intelligent Manufacturing '*Industry 4.0*', the theories of digital twin and machine learning have been enriched and widely utilized [5]-[6].

Complex equipment, such as aerospace vehicles, complex electromechanical equipment and large-scale weapon equipment is considered the backbone in the manufacturing industry chain. It consists of characteristics, such as complex customer requirements, complex component composition, complex product technology, complex manufacturing process, complex test and maintenance, complex working environment and complex project management [7]. There are cross and fusion of multi-disciplinary knowledge and experience in complex equipment design, manufacturing, use and maintenance. Product life cycle management and service for complex equipment is an important direction for the transformation and upgrading of the global manufacturing industry. It is considered the key to the development of traditional manufacturing to '*Manufacturing Plus Service*' and the understanding of '*Made in China 2025*'. At present, due to the lack of a management system covering the whole life cycle of complex equipment, there are problems such as information disconnection in complex equipment design, processing, manufacturing, operation and maintenance, low knowledge reusability, difficulties in real-time maintenance of equipment operation state and closed-loop iterative optimization.

In this study, we propose and develop a new digital twin architecture for the full life cycle management of complex equipment while discussing the combination and application scenarios of ML and digital twin. The rest of the article is organised as follows; Section II introduces the digital twin architecture for complex equipment. Section III discusses the

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combination of deep reinforcement learning and digital twins at various stages and answers the question that how to perform relevant functions. Section IV summarizes this study and discusses future aspects of this work.

II. Digital Twin Architecture for Complex Equipment

One of the primary features of digital twin is to integrate the cyberspace and physical space. [8]. Apply digital twin to the life cycle management of complex equipment and understand, analyze, monitor and optimize the state or behaviour of physical equipment. This can be implemented through virtual interactivity and feedback, data mining and analysis and multi-source data association and fusion [9] and it can fulfil the requirements of complex equipment modern manufacturing. A product digital twin for complex equipment is constructed to perform different functions, such as geometric perception, behaviour simulation and process recovery of physical equipment and its architecture (Fig. 1). Establishing a full life cycle data centre for complex equipment, use a single data source to realize the bidirectional connection between physical space and information space and the communication of information at all stages of the full life cycle. The digital twin sub-models in design, manufacturing, maintenance, recycling and scrapping are integrated into the digital twin of complex equipment. They provide model support for the life cycle management of complex equipment. These four sub-models complement each other and evolve together to use Analytic Hierarchy Process (AHP), Bayesian Estimation, Expert System, D-S Reasoning Method, Artificial Intelligence and other related methods to analyze and utilize data sources. This also explores the high potential added value brought by the virtual data and services behind physical products and realize dynamic fusion for updating and monitoring. This is essential to drive the whole life cycle process to real-time and intelligent development.

A. Digital Twin in Design (DTD)

Product design is based on the target function of the design object and the requirement from the user. After completing the discussion, analysis and design processes, the requirements are transformed into specific text or graphic expression to provide reasonable planning for the production stage [10]. Driven by the product digital twin data, *DTD* provides a two-way interactive connection for data sharing between physical products and virtual products. It also strengthens the synergy between the two and continuously explore innovative, unique and valuable product optimization design schemes. Thus, it can achieve active innovation that meets the customized requirements ahead of the time.

The concept of a digital twin is not only a digital product display model, but it can improve the accuracy of the design and it can assign the behaviour of the actual product to the virtual product. It can also verify the performance of the product in the real environment through simulation. Design originates from practice and serves practice. *DTD* emphasizes the virtual-physical integration of the complete life cycle. It establishes links between products, production tools, environments, processes and integrates information at different stages of the product life cycle into the design phase while providing a coherent overview of the development cycle. This is going to promote decision-making and improve design quality and efficiency in every way through its various functions to improve and optimize products and their corresponding manufacturing systems.

B. Digital Twin in Manufacturing (DTMF)

It is evident to complete the construction of *DTMF* before delivering the actual production tasks. It is also necessary to extract manufacturing-related process information from *DTD* along with associated manufacturing resources information,

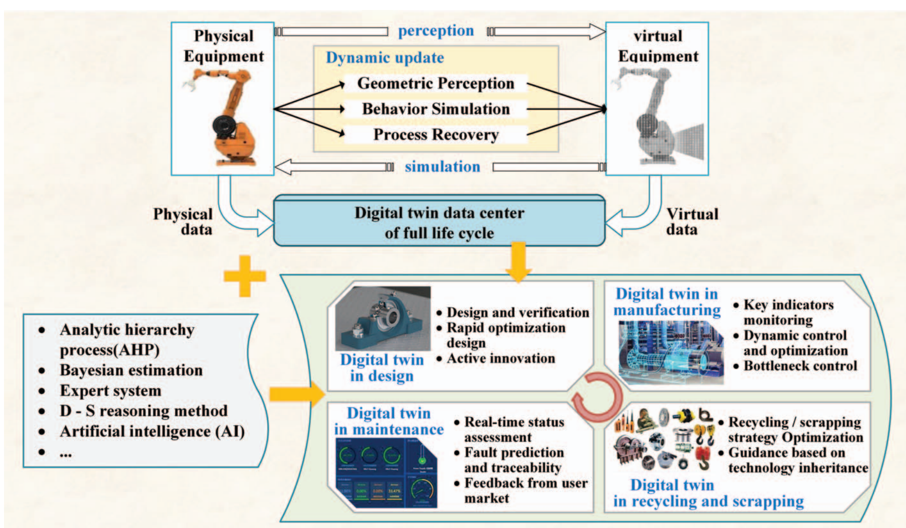

Fig. 1. Digital Twin Architecture for Complex Equipment

such as processing equipment, process parameters, tooling and moulds. To use *DTMF*, it is important to simulate the production process of complex equipment under agreed conditions through virtual production in advance. This process can predict bottleneck resources, bottleneck workpieces or bottleneck stages. Thus, we can achieve bottleneck control and improve the speed and accuracy of a new product during the production process through redistribution of bottleneck resources, optimization of component combination and operation sequence before production.

The increasingly customized and sophisticated manufacturing process of complex equipment requires effective process planning and key indicator monitoring [11]. In the manufacturing stage, the connection is established between the manufacturing entity and the virtual product by *DTMF*. Mapping of the measured data related to product production, processing and quality control processes, such as geometric measurement, vibration measurement, force measurement and progress data, to the virtual product and display them in real-time. This process ensures a comprehensive collection of production factors, manufacturing information and achieves online process control as well as monitoring based on actual production data.

There are dynamics and uncertainties in the manufacturing process, such as tool wear, ageing of processing equipment and changes in material properties which are caused by environmental conditions. Despite careful planning, these situations are going to result in a gap between the actual production results and expected results. *DTMF* helps to integrate process planning data with production measured data while monitoring key manufacturing parameters. When an abnormal situation occurs, such as violation of plans, or discovering a better production plan through learning, the intelligent decision-making module is going to make in-time related treatment and adjustment scheme. The new adjustment scheme is going to fed back to the manufacturing entity to improve the manufacturing quality and realize the dynamic control and self-optimization. Which in the end is going to achieve the purpose of the virtual control.

C. Digital Twin in Maintenance (DTMT)

Complex equipment usually has the characteristics of cost which is related to high maintenance. Users and enterprises expect to achieve the maximum value of the equipment at the lowest cost. In the product use and service phase, *DTMT* is used to track and monitor the product status in real-time. It also acquires real-time data that characterize the quality and functional status of the equipment during operation (such as engine rotor speed, vibration value, lubricating oil temperature, exhaust pressure, etc.) through smart sensors. It also helps in building a remote monitoring system with quantitative indicators and establishes a hierarchical health management system for complex equipment parts, subsystems, systems based on equipment historical use and maintenance data. It analyzes and predicts equipment operating conditions, remaining life, potential failures and asset failure time in advance. It also achieves beforehand maintenance to improve the efficiency of spare parts management, reduce or avoid customer losses and troubles caused by unexpected equipment shutdown. Virtual product adjusts itself to constantly adapt to changes related to physical space conditions. It reflects and evaluates the health status of physical service products through virtual products. Through this method, the risk of manual evaluation using one-way physical information flow is reduced. The insights gained in the application of *DTMT* can also be used to improve product design and manufacturing processes.

For physical equipment with fault or quality problem, it is better to use a virtual product to quickly locate the fault. This can also be combined with the historical operation data before failure, realize the simulation traceability in the virtual product and analyze the causes of the quality problem from the root cause. It is also evident to develop discovery methods and solutions of the same type of problem and verify the feasibility of solutions. It also feeds the final results back to the physical space to guide the early warning and troubleshooting.

The use of complex equipment has a strong driving force for enterprise production and social progress. The rationality of complex equipment design parameters and operating parameters settings and the adaptability under different working conditions determine the functional level, quality advantages and customer satisfaction of the in-use equipment. Equipment providers collect real-time data during product service through *DTMT*. They construct an empirical model for parameter optimization for different application scenarios and provide customers with guidance on its configuration. It can improve the usage quality of customer products, enhance the user experience and maximize the functionality of in-use equipment. At the same time, customers can connect with the product through *DTMT* and provide positive feedback for manufacturers. Through the use of customer preferences, manufacturers can gain insight into real-time customers and potential needs for products while meeting them in advance. Thus, it can avoid research and development decisions from offsetting market demand, shorten the design and introduction cycle of new products and enhance market competitiveness.

D. Digital Twin in Recycling and Scrapping (DTRS)

The application of *DTRS* meets the requirements of green ecology and sustainable development. The *out-of-service* equipment records data and information related to scrapping and recycling through digital twin, such as reasons for scrapping and recycling, expected product life and actual life. *DTRS* provides a reference for product scrapping or recycling operations through relative data analysis. The related data includes material data of parts (such as scarce resources, recyclable materials or toxic materials) in *DTD*, information related to the working environment of components and equipment (working conditions such as exposure to uranium and other radioactive elements) in *DTMT*.

When the physical product is scrapped or recycled, the corresponding virtual product is kept and archived in digital form. Based on the concept of technological inheritance, the production and application data from the previous generation are passed to the next generation. Information is integrated from different stages of the product life cycle into the design stage and finally, form closed-loop management of product life cycle data. Based on specific product requirements, it guides the design improvement and functional innovation of the next generation and improves the efficiency of new product development and production. The historical normal operation and failure data of scrapping and recycling equipment also provide data to support the quality analysis and health management of the same or similar product groups.

III. Applications of Machine Learning in the Digital Twin for Complex Equipment

Digital twin embeds data integration, analysis, management and insight into business processes, and completes the detection or verification of physical products in a virtual space. It can provide guidance, recommend services or support decision-making based on operational results. It contributes real value to all stages of the life cycle of complex equipment and promotes the transformation and upgrading of customized and precise services in the complex equipment manufacturing industry. Therefore, the development and utilization of data resources are essential for the establishment, association, expansion and evolution of digital twins for complex equipment.

Machine learning is an important tool for mining potential rules and knowledge [12]. Proper selection and rational use of machine learning algorithms and establishment of an inference model can enhance and expand the functions of digital twin function for complex equipment and enhance its characteristics, such as data-driven and intelligent [13]. In the following sections, we have discussed the combined applications of two typical learning algorithms: deep learning and intensive learning, with digital twin technology.

A. Generative Design

In the current time, customer requirements are diverse, the work and service environment of complex equipment is complex and changeable with its degree of personalization is increasing. The design process of complex equipment is highly dependable on technology and intellectual elements. Its development cycle and manufacturing costs are much higher than in other industries and it is difficult for enterprises to cope with the rapidly changing market demand under the new situation. As an automatic design method oriented to user needs and constraints, generative design is used as a helping tool to inspire designers in various fields, such as architecture, product manufacturing, automotive and aerospace, making it possible to shorten the design time.

The generative design is based on the non-deterministic design of digital interaction [14]. The application of digital twin technology can enhance the interactive perception of the designer with the generative model in the process of generative design. It provides a hybrid model that combines virtual environment with real operation and enhance the freedom and control of the design. The generative design method is

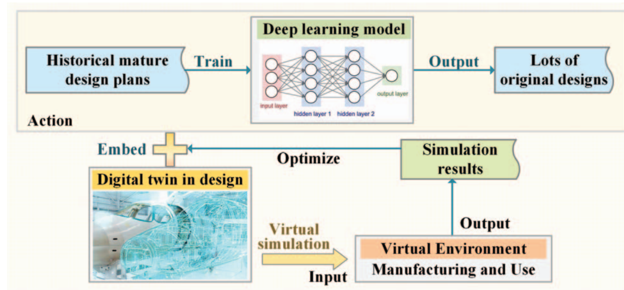

Fig. 2. Generative Design Model Based on Deep Reinforcement Learning and Digital Twin

integrated into *DTD*, and the integration method is shown in Fig. 2. The design method or idea is abstracted as a set of rules or algorithms which is embedded in the digital twin generation program and the corresponding *DTD* is generated for user needs and constraints.

At the same time, deep reinforcement learning is embedded in the digital twin of generative design. Use of historical and typical or mature design schemes is to pre-train the deep neural network and reveal the correlation between reduced-order model topology and large-scale practical application model topology. Based on the correlation, deep learning automatically proposes a large number of original and innovative designs for selection and depends on its randomness to fully realize the diversity of designs and assist and improve human designs. Through *DTD*, the manufacturing and use environments are verified beforehand in the virtual space and the mapping from the *design environment state* to the *topology change action* is completed. With the strong decision-making ability of reinforcement learning, model generation method is optimized and accuracy of the design iteration and incrementation is improved. On the one hand, design schemes are easily selected through the intuitive presentation. On the other hand, it uses *DTD* to cope with the subsequent complex, dynamic external environment in simulation mode and realizes the reverse intervention optimization of the virtual environment on the model generation method. It also enhances the rationality and reliability of design schemes under the corresponding optimization rules or algorithms.

B. Design optimization assistance for complex equipment

Complex equipment has a huge and complex structure and heavy work tasks. In its process of manufacturing, assembly and engineering practice, there are many different sources, causes and types of uncertain factors. Such as processing tolerance disturbances, cyclic loads and physical coefficient variations which are going to have an unavoidable impact on equipment performance. Therefore, after considering these factors during the design stage and the optimization of the key structures of complex equipment, it is possible to obtain equipment with real high performance and meet actual requirements. During the stage of equipment design, *DTD* is created based on feedback data from the manufacturing and operation stages. The use of *DTD*, combined with reinforcement learning, can

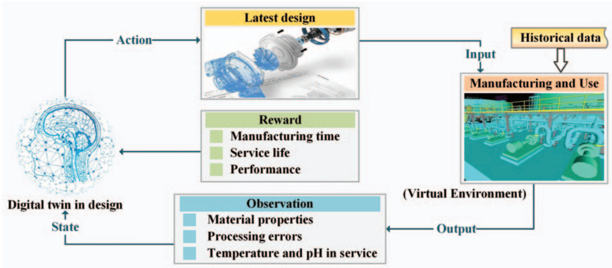

Fig. 3. Aided Optimization Design Model Based on Reinforcement Learning and Digital Twin

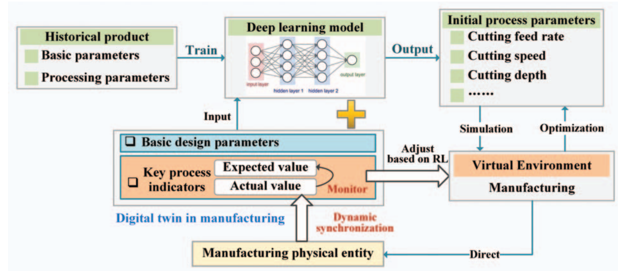

Fig. 4. Optimization Model of Manufacturing Process Based on Deep Reinforcement Learning and Digital Twin

enhance the adaptability of the design to subsequent stages to reduce the gap between expectations and reality.

The method of establishing a design optimization model based on digital twin and reinforcement learning is shown in Fig. 3. In the method, the important design variables, in the complex equipment design twin, are used as model monitoring variables. The inputs are material properties, processing errors, service temperature, acidity and other environmental uncertainties. With the support of historical manufacturing and usage data, the constructed *DTD* is simulated for production and operation. Consider the three practical value goals of manufacturing: time, service life and performance. These goals are considered as rewards for the design optimization model. Digital twin learns by interacting with the environment in a virtual space by changing design variables to maximize the accumulation of target returns. As a result, the final physical design plan anticipates the performance requirements.

C. Optimization of Manufacturing Process

There are numerous components and complex processes in complex equipment manufacturing. The selection of process parameters is going to have a critical impact on processing quality and energy loss. Uncertain factors in the process are going to cause fluctuations in the quality of finished products. Therefore, the quality control of the manufacturing process is a difficult problem faced by modern manufacturing enterprises for a long time. For safety assurance, the optimization of the manufacturing process is to make use of *DTMF* to select proper process elements and parameters before scheduling. It adjusts the plans according to the feedback from the actual manufacturing situation. In the end, it achieves the purpose of quality control and improvement, energy-saving and consumption reduction.

The following Fig. 4 shows the application of deep learning algorithms in *DTMF* and mining the implicit relationship between basic parameters, such as geometric characteristics of historically mature products and their processing parameters, such as cutting feed, cutting speed and cutting depth. Deep learning automatically learns these relationships for training and generates the corresponding initial process parameters by identifying the target *DTMF*. It stimulates the manufacturing process through *DTMF* with complete process parameters. It modifies and optimizes process parameters continuously based on the feedback obtained from the simulation results and include them into actual production. Based on deep reinforcement learning, to establish decision-making correspondence between key process indicators and comprehensive production indicators (cost indicators, energy consumption indicators, product quality indicators). Using *DTMF* to perform monitor during the production process. When a key manufacturing parameter or a comprehensive production index is abnormal, an adjustment scheme is automatically obtained in the twin by pushing back the expected value of the index and interacting with the system. Construct a closed-loop optimization system based on feedback compensation of deep reinforcement learning and guide the production of manufacturing entities. At the end of the process, it realizes product quality optimization and adaptive control.

D. Operation and Maintenance Health-management

Complex equipment is important equipment support for modern national economic industries. Unexpected shutdowns caused by failures are going to have a direct and dispensable impact on the economy and society. Therefore, the health management of complex equipment during service is particularly important. Through the combination of *DTMT* and deep learning technology, real-time monitoring and predictive evaluation of equipment status are conducted to improve the stability and reliability of equipment operation [15].

As shown in Fig. 5, mapping of the physical operating status data of the equipment entity to *DTMT* is performed with the synchronous simulation operation in the virtual space. It enables real-time monitoring of equipment status, simulation of future operation and avoids interference of redundant monitoring data on equipment operation status. Data is the basic and core driving force in using *DTMT* for health monitoring and fault prediction of real equipment. The multi-layer nonlinear network structure of deep learning has advantages in discovering useful information and essential characteristics of data and has higher accuracy and completion in tasks like fault identification and prediction.

To extract high-dimensional association features between monitoring data under normal and abnormal conditions in historical data, the use of the hierarchical abstraction capabilities of data features of deep learning algorithms is useful. It establishes association rule models between data and

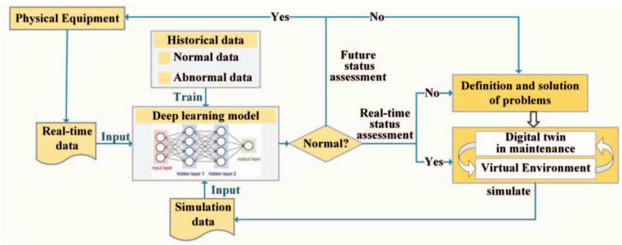

Fig. 5. Operation and Maintenance Health-management Model Based on Deep Learning and Digital Twin

failures to monitor and predict the behaviour and status of equipment. When discovering an abnormality in equipment operation through real-time data analysis, that is, when the fault already exists, it automatically identifies and classifies fault based on the correlation model. It analyzes the type and cause of fault in time, formulates a maintenance plan quickly and restores or guarantees the normal operation of the equipment. In case of simulation data anomalies at the time of any potential fault in *DTMT*, it inputs the corresponding solution into *DTMT* for simulation validation. If the monitoring data returns a normal value according to simulation results, it means that the potential fault has been eliminated. It feeds the corresponding decision-making plan back to the physical entity to guide maintenance and realizes prior repair. It can reduce the cost of equipment maintenance and uncertainty in the operation process, and achieve self-perception, self-prediction and self-decision of equipment.

IV. Conclusion

Digital twin technology is an emerging key technology of digitalization, capable of transforming physical entities or processes into quasi-real-time digital mirrors that operate synchronously. It realizes monitoring and simulation analysis relying on virtual space. Digital twin provides a new solution for the cyber-physical integration with complex dynamic systems, and also brings new opportunities and challenges for the complete lifecycle management and optimization of complex equipment. The combination of machine learning algorithms, especially deep learning and reinforcement learning, with digital twin technology helps to mine the rules and internal relationships of data and discover the nature of problems. Through the integration and feedback of data and knowledge at each stage, the collaboration and optimization of the whole life cycle can be achieved. The application of digital twin technology and machine learning in the field of smart manufacturing can help break the embarrassing situation where there are more data but less information, the disconnection between processing, manufacturing, operation and maintenance. This has broadened the prospects for future industrial development. In this study, we have built a full-lifecycle digital twin for complex equipment based on the data dimension and describe the digital twin sub-models in each phase of design, manufacturing, maintenance, scrapping and recycling. We have discussed four application examples of deep reinforcement learning algorithm embedded with digital twin models at each stage improving the cognitive, inferential and decision-making abilities of digital twins.

Our research has attempted to explore and discuss the possibility and ways of combining machine learning with digital twin technology. At present, the research and application of digital twin technology are still in the stage of development and perfection, and still requires a lot of work. Future research on this topic needs to be undertaken as follows: 1) to further refine the digital twin models at each stage and accumulate, integrate and utilize life cycle knowledge; 2) to create a synchronous and efficient mapping mechanism between physical data and virtual data to meet the requirements of real-time analysis and dynamic decision-making; 3) to establish a deep learning model suitable for time series data in manufacturing and maintenance.

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