Driving Intelligent Manufacturing: An Application Study on Digital Twin in Factory Digitalization

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ABSTRACT

With the rapid development of digital transformation, digital twin has got rising attention from both academia and industry. Based on new generation of information technology, digital twin has built an integration of virtual and real world with the ability of interconnection and intelligent inter-operation, which has narrowed the gap between physical and digital world, becoming an important enabler for intelligent manufacturing. The paper mainly discusses the application of digital twin in manufacturing scenarios, and its role in enterprises' digital transformation through intelligent operation and maintenance, virtual debugging, anomaly diagnosis, risk prediction, decision-making assistance, intelligent production scheduling and system optimization, so as to help improve production efficiency and promote digital economy. The paper aims to provide reference for the industry in planning and building a digital twin world, and help with the world's technological evolution and industrial development.

CCS CONCEPTS

• **Computing methodologies** → Modeling methodologies.

KEYWORDS

digital twin, intelligent manufacturing, industrial internet, visualization, interconnection, production scheduling

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1 INTRODUCTION

With the rise of new generation information technologies such as cloud computing, IoT, AI, big data and 5G, all industries are developing towards digitalization and intelligence [1]. In recent years, digital twin, combining with these advanced technologies, has helped and acted as an important driving force of manufacturing towards digital transformation, contributing to a new digital economy which is pervasive and driven by digitalization of all value chains in various aspects including economic, social, political, and natural ecosystems [2-7]. Under this background and with 4IR, intelligent manufacturing coming as a main trend and new direction, nations around the global are joining in promoting the digital transformation and upgrading of the manufacturing industry [8, 9]. Digital transformation includes the digitalization of all essential components such as digital equipment, digital parts, digital services and intelligent manufacturing solutions [10, 11]. The goal is to further optimize industrial structure as a whole, and promote industrial development towards modernization with better quality, higher efficiency and greater added value [12]. To achieve this, deep integration of digital technology and industry becomes a necessity, digital twin, with data as a new factor of production and important source of value to connect the industrial chain, value chain and supply chain, is playing a more and more important role.

1.1 Development trend towards intelligent manufacturing

Intelligence is a promising and key driver in manufacturing, application of intelligence in R&D, design, production and service help solve common problems in manufacturing including rising cost, low efficiency and limited economic benefits, so as to improve overall production level and market competitiveness [12, 13]. The goal of manufacturing intelligence is to build seamless connection between internal equipment, equipment & personnel, and various enterprises to build a networked intelligent production, so as to realize real-time automatic optimization of resource allocation. Intelligent manufacturing, as a development trend, comes with new features [14, 15].

● Advanced technologies as a solid foundation for intelligent manufacturing

Cutting edge technologies such as 5G have helped manufacturing with its revolutionary breakthrough. With 5G, a new networked infrastructure for inter-connection and interworking is possible among factories, enterprises, regions and even nations. Besides, machine learning and human-computer interaction have further optimized production process [16-18].

● Cross-border integration and international cooperation

As economic globalization is accelerating, a global production network promoted by transnational corporations has gradually formed, global industry chain and value chain are developing towards a closer transnational cooperation [2, 12, 19].

● On-demand production opens up new markets

On-demand production allows consumers to send their requirement directly to the manufacturer through the Internet. The manufacturer then design and produce customized products accordingly that better meet users' needs [11, 20].

● Countries are competing in formulating related policies

In recent years, major developed countries have made strategic plans for the development of manufacturing such as the Germany's Industrial Strategy 2030, and Manufacturing USA Strategic Plan, and help enterprises to become world-leading industrial manufacturers or solution providers [1, 5, 6].

1.2 Digital twin as a new driver of intelligent manufacturing

Intelligent manufacturing emerges from deep integration of digital technology and real economy. Digital twin is to create a virtual model of physical entities in a digital way, simulate the behavior of physical entities in the real environment, and add or expand new capabilities for physical entities through virtual reality interactive feedback, data analysis, and decision iteration, etc. As a technology that makes full use of models, data, and intelligence, digital twin featured with interdiscipline can act as a bridge between physical and digital world, serve for product's whole life cycle management, and provides real-time, efficient and intelligent services featuring flexibility, reliability, transparency and risk & error pre-warning.

2 RESEARCH BACKGROUND

2.1 General introduction of digital twin

Digital twin is a dynamic, virtual representation of a part, machine, or even an entire production process [15]. It consists of the physical entity itself, the virtual representation, and the connective functionality that allows data to pass back and forth between the physical and virtual entity [9-11, 21]. In Digital Twins: A Guide for Manufacturers written by Patrick Lemay, digital twin empowers physical object with the ability to respond under varying circumstances while leveraging real-time data from the physical world, but in a virtual environment [2]. The concept of digital twins was first introduced in the 1991 book Mirror Worlds by David Gelernter [22]. In this book, he describes "Mirror Worlds" as high-tech voodoo dolls, digital representations of large-scale physical environments that can be manipulated and interacted with using a desktop computer. Michael Grieves raised the first model of "Mirror Worlds" in his Product Lifecycle Management (PLM) course in 2003, and applied the concept to manufacturing [22]. NASA first embraced the concept to create digital simulations of space capsules and craft for testing, and gave the concept its name. This technology was widely spread since 2017 and got to broader applications in various industries and areas [7].

2.2 Structure of Digital Twin

Digital twin is developed and applied based on innovation and fusion of digital technologies including IoT, modeling, data, mapping and simulation, 5G, cloud computing, AI, GIS (Geographic Information System) and BIM (Building Information Modeling). Depending on different scenarios, other technologies may also be included [16]. A digital twin team from Beihang University (BUAA) proposed a digital twin model in Five-dimension digital twin model and its ten applications, typically, the digital twin is composed of several parts [8].

- Physical entities

Physical entities are the very starting point of digital twin, from which different functions are developed and data are collected for further analysis. Physical entities are the premise of building a digital twin model.

- Visual entities

Visual entities or visual model are mapping of physical entities, with authenticity and interactivity further enhanced by technologies like VR and AR.

- Data

Data includes information data and physical data, which provides accurate and comprehensive full element / full process / full business support to each digital twin function.

- Connection

Physical entities and virtual entities are connected for interaction, consistency and synchronization during operation. Data generated by physical entities and from interaction with virtual entities are stored in real time to drive the operation.

- Services

With digital twin, various services related to data, models, algorithms and simulations required by different fields are provided in software or mobile app, etc., making it possible for users to have a convenient and on-demand use of services.

2.3 The role of digital twin in manufacturing

The virtual model not only demonstrate physical entities in multiple dimensions, but also create a coexistence of virtual and reality, and provide monitoring, simulation, prediction and optimization with a broad application and development prospect.

Digital twin can be applied throughout product life cycle, including product design, manufacturing, service, operation and maintenance, etc. In the future, it is expected that all things would have their digital twins, interconnected to create more value.

Data is the key factor in digital twin as more needs are raised such as connecting more equipment and platforms to better meet of users' needs. In a digital twin system, data could be collected from manufacturing equipment, sensors, cameras and industrial software systems. They would be gathered for virtual data enhancement, virtual reality collaboration and model training, as well as analyzed to provide predictions, enabling the system to provide data services including data development, data synchronism, data-as-asset, data/data value visualization, and inter-discipline connection & construction.

Table 1: Structure of iDTS

Layer	Definition
Physical layer	physical objects participating in the process such as personnel, devices, material and manufacturing environment, etc.
Perception layer	collect and transmit real time data gathered from the physical layer, and gain data perception according to actual needs.
Twin layer	virtual objects of whole factors and process in manufacturing, including twin data, twin model and twin environment.
Application layer	provide application services for the whole life cycle of product design, processing, manufacturing, operation and maintenance, etc.
Control layer	online and real-time control of the physical objects by decision-maker, control program, control equipment, control mode and control system.

3 DIGITAL TWIN IN INDUSTRIAL APPLICATIONS

3.1 Industrial Digital Twin System (iDTS)

Digital twin is first applied in the industry of manufacturing. By connecting manufacturing equipment, materials, personnel, energy, etc, an industrial digital twin system is built to offer services including design, intelligent manufacturing, product fault diagnosis and operation maintenance, etc. With multi-modal data collected from manufacturing process, many more functions can be provided according to different use. With digital twin technology to establish a system combining all elements, processes and businesses, and through bidirectional mapping and real-time interaction between physical objects and digital twins, Digital Twin System for Industrial applications is developed. Industrial Digital Twin System (iDTS) acts as an interactive human-machine-environment integration, and oriented to the whole life cycle of industrial products, such as demand analysis, scheme design, manufacturing and operation maintenance [18]. With key technologies such as digital twin modeling and evaluation, multi physics field simulation fusion and product life cycle management, various modes could be developed facing different applications. The system is divided into five different layers, which can be interacted by function interface.

Besides, iDTs also integrate capabilities with cloud computing and edge computing to make full use of the intelligent heterogeneous resources of cloud, edge and end in real time multimedia processing and maximize data value. For example in AI scenario, useful data are collected on the edge, and reprocess in the cloud by communication and connection. Data will be collected from the edge and get trained in the center, and then the trained model will be sent back to the edge [23].

The cloud is featured with high-performance computing and storage capabilities, which can realize centralized management of model and data of the digital twin system, and provide services like system analysis, calculation, control and storage. Cloud computing is capable of resource coordination and optimization in heterogeneous environment. In processing or storage, resources can be integrated to avoid repeat calculation and redundant storage. Running in a centralized manner, components of cloud computing can be updated in a centralized way without shutting down operations.

Edge computing is introduced for computing, network, storage and security at the edge location. Cloud, edge computing and the Internet of things (IoT) are connected and coordinated to improve computing capability. In edge computing, resources are scattered, and the load varies greatly depending on time and space, reasonable resource scheduling can bring the best effect of resource, make the system more efficient and stable.

3.2 A Proposed Model of Digital Twin

Based on the above, and with IoT, 3Rs (AR, VR and MR), edge computing, cloud computing, 5G, big data, blockchain and AI, we propose an industrial digital twin model for factories. The system could be divided into four layers: data source, data asset, scenarios building and applications (Figure 1).

To better meet requirements of different applications, modular design is used here for various and changing demands, with main modules listed below (Table 2).

The model is capable of connecting components, equipment, production line and the entire factory, providing services including logistics simulation, predictive maintenance, smart storage, intelligent manufacturing, real time mapping, simulation calculation, decision analysis, data collection and aggregation, data governance and data application, etc. which applies for equipment whole life cycle management. With highly modular and highly intelligent design, it can bring users with more functions, low cost, low delay and high safety.

3.3 Application & Case Study of Digital Twin

To meet with the requirement of intelligent and digital manufacturing, further integrate digital twin and manufacturing, and fasten the way towards digital economy, we developed a new digital system with data as a key concern called D3OS, which is capable of data processing, avoid data silos and explore for further data value.

3.3.1 D^3OS Digital Twin System. D3OS as it names, consists of three key "D" modules, namely Data Engine, Digital Twin Studio, and Data Thread, with IoT Plat used for data acquisition and control (Figure 2).

- IoT Plat, connecting equipment to provide data

In D3OS, there is an IoT platform to connect assets and devices called IoT Plat. IoT Plat is able to build enterprise IoT system in a

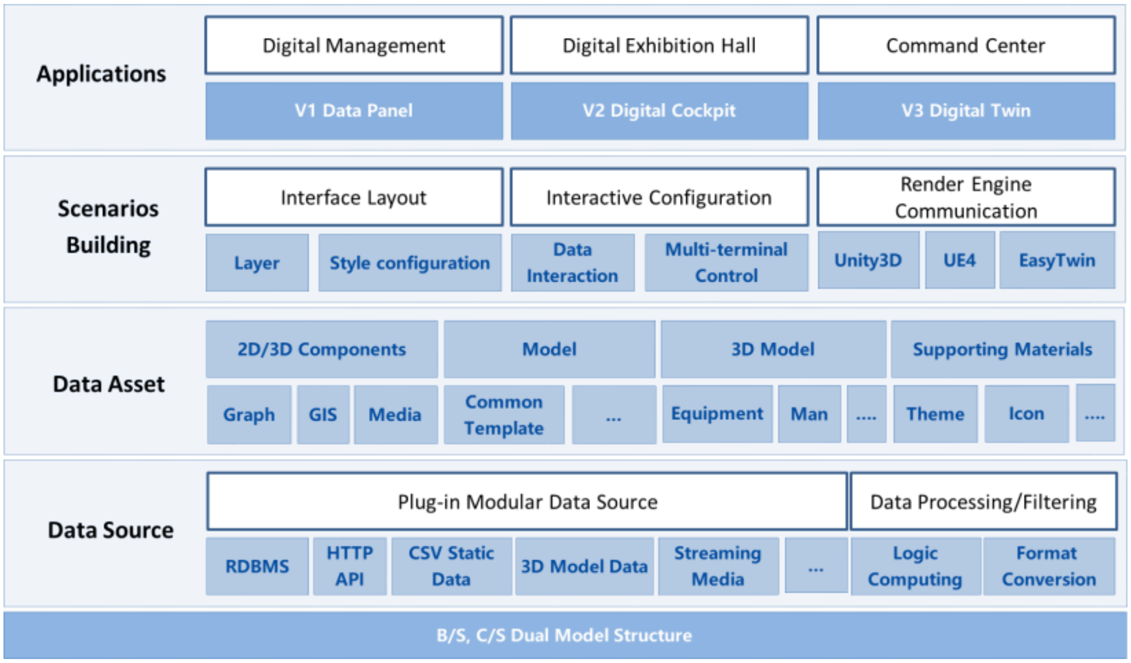

Figure 1: Structure of a digital twin model

Table 2: Main modules

Module	Definition
Data collection	real time data collection and value creating
Modeling and simulation	digital twin modeling and simulation
Visualization	remote monitoring and real time exhibition
Intellectualization	autonomous machine learning, fast decision-making
PLM	production lifecycle management
Cloud and edge computing	distributed computing based on cloud-edge-end

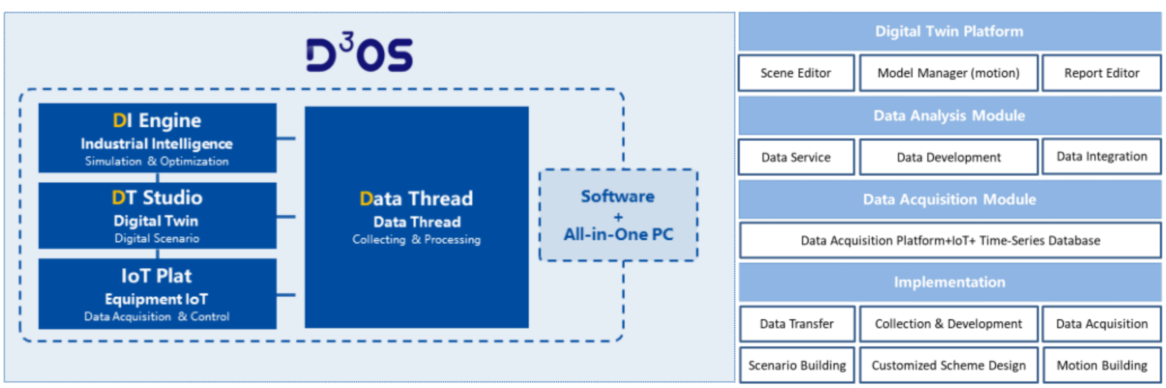

Figure 2: Structure of D^{3}OS and its data modules

fast speed, offering services like device access, asset management, regulation engine and visualization. Equipment access and data acquisition in industrial environment is done through encrypted transmission of protocols including MQTT, HTTP and CoAP. In this way, equipment in traditional enterprises can be connected and

Figure 3: D^{3}OS digital twin factory

put onto the cloud, access of mass data and real time data transmission in industrial environment are made possible, authenticity and dynamic uniformity of physical model and digital model are then realized. IoT plat breaks down the barriers between equipment manufacturers and end users, and realizes full life cycle management including remote monitoring, online operation and maintenance, data analysis and predictive maintenance.

- Data Thread to further explore data value

Cross system data aggregation, processing and value mining help enterprises gather IoT and system data in a quick and efficient way. Data thread supports multi-source heterogeneous structured and unstructured data, build data ETL processing flow through movable modular components. Besides, a low code data processing engine is built to flexibly process and manage various enterprise data, and provide analysis of equipment, production, process, quality and energy consumption, which greatly improve efficiency, accuracy and convenience of data collection and cleaning. Users can handle complicated scheduling by simply adjusting configurations on the panel, and provide basis for decision-making. Data thread brings enterprises with data assets and help with scientific decision-making of data BI.

- DT Studio scene editor for immersive scene

DT studio integrates data to build virtual scenes. With scene editor, a data-driven twin factory could be created in only ten minutes, which allows enterprises to monitor and manage equipment, production lines and factories conveniently. DT studio supports digitization, visualization and virtual manufacturing simulation of various scenes.

- DI Engine for manufacturing process re-construction

To meet the need of dynamic scheduling and complex supply chain management, DI Engine proposed a new intelligent scheduling mode based on AI. By AI and machine learning, and simulating production line, production process and production plan, D3OS is able to predict production process and results, optimize and adjust production scheduling and techniques, pre-warn potential interruption and impact, solve supply chain problems, and improve operation status [13, 17, 24]. DI Engine helps enterprises with efficient, accurate, rapid and scientific production scheduling. By breaking data silos between each system, production process is rebuilt to save cost and improve efficiency.

By data acquisition, data management and intelligent application, a virtual factory is built, devices and data between equipment and systems are connected, and the operating process is made visible (full scene 3D/real scene visualization, full element data visualization), manageable (data management, equipment management and tracking, production process control), and predictable (production plan scheduling optimization, equipment predictive maintenance) (Figure 3).

3.3.2 D^{3}OS for interconnection and data sharing. With the four modules, D3OS has built an intelligent production system and creates an industrial Meta universe featured with large scene, high fidelity and real-time action mapping between virtual world and physical world.

In factory applications, there are some common problems and challenges:

- Weak data base

Manufacturing scene is various with massive multi-source heterogeneous industrial data, which makes it easy to cause data silo and low data utilization, data has not shown its full value.

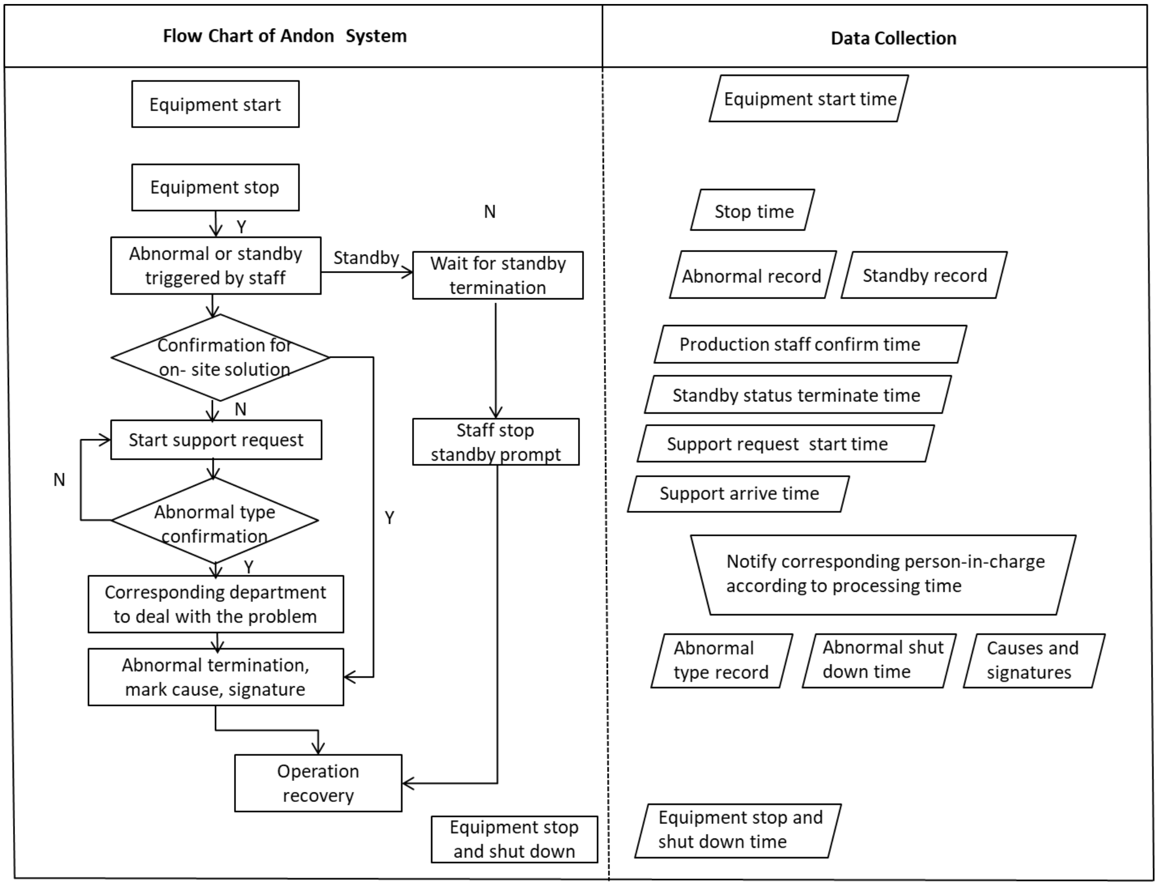

Figure 4: Working flow in Andon system

- Weak equipment monitoring

As each equipment in the factory is kept in high-intensity operation state at all times, it's hard to timely and effectively monitor the voltage, current and environmental state, etc., making it nearly impossible to pre-estimate energy consumption and equipment status, safety hazards may happen and affect the service life of the equipment.

- Uncoordinated capacity

In traditional manufacturing enterprises, there's no interconnection and production capacity is not coordinated. By building a twin factory completely consistent with the physical entity, model and production data are displayed in 3D for users to see real time production process and virtual & reality synchronization is realized.

To promote production visualization and a quick data transmission, an Andon system is developed (Figure 4). It contributes a communication channel that the operator can seek help without leaving his working seat, and help the operator to deliver high-quality products safely and on time. Besides timely information transmission and quick problem-solving, by collecting and analyzing data, it can identify the location where the problems occur most, and make adjustments for continuous improvement.

As an auxiliary tool for the whole production process, Andon system is capable of quick information transmission, call application, real-time display, statistical analysis and report generation, etc., covering various on-site abnormal processes such as equipment failure, material shortage, quality problems, process problems and safety conditions, etc., so as to support the whole production process. The working flow is as follows:

When abnormal occurs, the on-site operator presses the abnormal " button, the system notifies team leader through on-site panel (e.g. LED or TV panel) or warning light, etc. the leader comes to confirm the abnormal type and confirm on mobile. The system then notifies relevant responsible person by SMS, internal email, etc. to deal with the problems.

The Andon system monitors the process in real time, in case the problem is not responded or solved within a certain period, it would be reported to higher level management team automatically. After getting resolved, a record with relevant data would be generated, with which multi-dimensional statistical analysis can be done to guide further operations.

3.3.3 D^3OS for production scheduling. Mass customization production featured with "multiple varieties and small batches", production line needs to be re-arranged each time when produce different products, and the preparation of necessary tools, fixtures, measuring

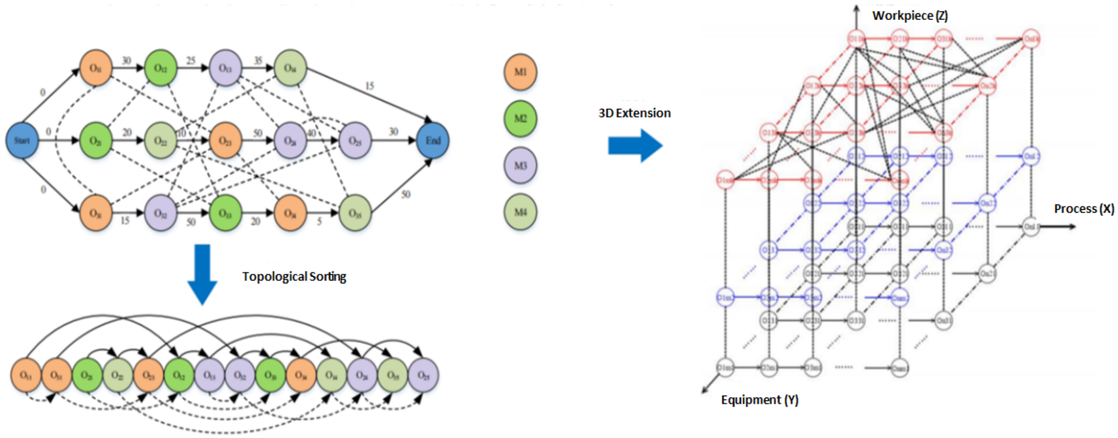

Figure 5: 3D disjunctive graph model in DI Engine

tools, drawings, etc., would take a lot of time. To cut time and save cost, intelligent production scheduling becomes a main concern.

It's very common for large enterprise to have two or more factories, usually each factory would have its own production plan and organizes production independently. Nowadays, production has changed from "sales based on production" to "production based on sales", which also leads to frequent change in production scheduling, mold and color, bringing difficulties in scheduling. Besides, material purchase based on experience makes it difficult to adapt to emergency changes. Sales plan change, equipment failure and shortage of raw materials all lead to production change and re-scheduling.

On the basis of the traditional 2D disjunctive graph model, DI engine adds process correlation constraints, process logistics turnover time, process preparation time, machine tool preference and resource calendar, gives mathematical description of each constraint, and builds a 3D disjunctive graph model (Figure 5).

For production scheduling of those with uncertain working hours, DI engine develops a scheduling selection framework, in this framework, a new expression, action setting, network structure, exploration and utilization strategy is adopted, and a new learning algorithm is used for flexible job shop scheduling with variable workpiece number, process number, machine tool number and man hour. The work flow is as follows:

1. Obtain data needed in scheduling: regularly collect required data from corresponding systems and put onto data layer.
2. Choose a suitable optimization algorithm based on targets and constraints, build customized model, calculate and deliver production plan in a reasonable period.
3. Monitor the scheduling with visual report and simulation software.

DI engine can support various scheduling scenarios and support multi-tenant calculations. With virtual production and APS technology, a simulation model is built for flexible production. With the APS, when actual operation deviates from the predefined scheduling, decision-maker will know in time and adaptively make adjustments, bring intelligent, predictive and autonomous scheduling for flexible production.

Automatic scheduling based on algorithm can respond to various unpredictable disturbances on site in a real-time manner, calculate and produce reactions as a respond, and generate a new production plan.

In the case of "large-scale, small batch" production and frequent temporary new orders jump in queue, factories need to schedule the orders into production plan with the least impact on the existing plan. In this case, the greater the new order's similarities with the scheduled plan, the better. The following table (Table 3) shows the change rate of the whole scheduling plan caused by adding / modifying orders in different one-off orders. It can be seen that more than 95% of the original scheduling plan does not need to be changed when individual orders change:

At technical level, real-time computing is developed for flexible scheduling, and different algorithms will be used for different scenarios, providing customers with on-site solutions. The system is trained under extreme conditions to handle special situations such as tight delivery time with long manufacturing period demand.

With DI Engine, scheduling time is shortened from the typical 30 minutes to less than 10 seconds. Production for small orders is done in batch to reduce mold change frequency. Besides, the order on-time delivery rate has increased from 70% - 80% (manual) to 95%.

4 CHALLENGES AND PROBLEMS

Digital twin, regarding its maturity on interaction with reality, is divided into six levels: imitating reality, reflecting reality, controlling reality, anticipating reality, optimizing reality, and symbiosis between virtual and reality. To realize those levels, digital twin develops with digital modeling, virtual & reality interaction, human-computer collaboration and intelligent prediction. At present, it is still on its way to virtual & reality symbiosis [4, 18, 25].

Currently, there are still challenges in digital twin, including data acquisition, data transmission and data management. For data acquisition, type, accuracy, reliability and working environment of sensors may be limited by the current technology; For data transmission, most of the network structure and transmission devices are still working to meet the high-level transmission rate and quality

Table 3: Scheduling plan created by D^{3}OS DI Engine

Scheduled Order	New/Modified Order	Similarity
100	1	97%
100	5	97%
100	10	95%
100	25	83%
100	50	75%
250	2	99%
250	12	90%
250	25	83%
250	62	75%
250	125	61%
500	5	94%
500	25	81%
500	50	72%
500	125	67%
500	250	62%
750	7	89%
750	37	78%
750	75	72%
750	187	61%
750	375	64%
1000	10	87%
1000	50	77%
1000	100	74%
1000	250	73%
1000	500	61%

requirements; For data management, life cycle data management needs distributed storage, storage and retrieval methods and real-time and reliable data reading become a demand [19, 26].

On the other hand, increasing public concern on data safety leads to higher demand on system security. The interaction between physical and visual entities is based on networked data transmission, as digital twin has turned original “closed system” into an “open development system”, and security problems follows [27]. For example, data transmission and storage may bring potential risks of data loss and data leakage. Security loophole in virtual & reality interaction may makes it vulnerable to external attacks and may cause system disorder, affecting interaction efficiency between digital twins and physical entities. However, more and more methods are introduced to ensure a safe and well-organized data transmission, and with the accumulation of experience and the increase of data amount, production simulation and prediction will become much more accurate [14, 28].

5 CONCLUSIONS

In digital transformation of manufacturing, innovation of key technologies is made to enhance core industry competitiveness and create new business models. During this process, digital twin plays an important role. In enterprise digital transformation, intelligent decision-making ability based on data analysis has become a demand. Digital twin can map the physical world, presents data, do real time analysis, respond with quick decisions and command, and instruct operations in real world. The paper discusses a digital twin system with its application in equipment interconnection and data sharing, and intelligent production scheduling, and its performance in making the production process visualized, controllable and predictable. The paper aims to provide a reference for a digital twin-driven intelligent manufacturing, helping to build a digital twin space in promoting technological evolution and industrial development.

REFERENCES

[1] B. Sniderman, M. Mahto, M.J. Cotteleer, Industry 4.0 and manufacturing ecosystems: Exploring the world of connected enterprises, Deloitte Consulting, 1 (2016) 3-14.

[2] G. Shao, M. Helu, Framework for a digital twin in manufacturing: Scope and requirements, Manufacturing Letters, 24 (2020) 105-107.

[3] Q. Qi, F. Tao, Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison, Ieee Access, 6 (2018) 3585-3593.

[4] M. Grieves, Digital twin: manufacturing excellence through virtual factory replication, White paper, 1 (2014) 1-7.

[5] C. Cimino, E. Negri, L. Fumagalli, Review of digital twin applications in manufacturing, Computers in Industry, 113 (2019) 103130.

[6] Y. Zheng, S. Yang, H. Cheng, An application framework of digital twin and its case study, Journal of Ambient Intelligence and Humanized Computing, 10 (2019) 1141-1153.

[7] E. Glaessgen, D. Stargel, The digital twin paradigm for future NASA and US Air Force vehicles, 53rd AIAA/ASME/ASCE/AHS/ASC structures, structural dynamics and materials conference 20th AIAA/ASME/AHS adaptive structures conference 14th AIAA, 2012, pp. 1818.

[8] F. Tao, W. Liu, M. Zhang, T.-l. Hu, Q. Qi, H. Zhang, F. Sui, T. Wang, H. Xu, Z. Huang, Five-dimension digital twin model and its ten applications, Computer integrated manufacturing systems, 25 (2019) 1-18.

[9] F. Tao, B. Xiao, Q. Qi, J. Cheng, P. Ji, Digital twin modeling, J Manuf Syst, 64 (2022) 372-389.
[10] F. Tao, M. Zhang, A.Y.C. Nee, Digital twin driven smart manufacturing, Academic Press2019.
[11] F. Tao, Q. Qi, L. Wang, A. Nee, Digital twins and cyber–physical systems toward smart manufacturing and industry 4.0: Correlation and comparison, Engineering, 5 (2019) 653-661.
[12] F. Tao, J. Cheng, Q. Qi, M. Zhang, H. Zhang, F. Sui, Digital twin-driven product design, manufacturing and service with big data, The International Journal of Advanced Manufacturing Technology, 94 (2018) 3563-3576.
[13] J. Guo, N. Zhao, L. Sun, S. Zhang, Modular based flexible digital twin for factory design, Journal of Ambient Intelligence and Humanized Computing, 10 (2019) 1189-1200.
[14] M.G. Kapteyn, K.E. Willcox, Predictive digital twins: Where dynamic data-driven learning meets physics-based modeling, Dynamic Data Driven Applications Systems: Third International Conference, DDDAS 2020, Boston, MA, USA, October 2-4, 2020, Proceedings 3, Springer, 2020, pp. 3-7.
[15] Y. Xie, K. Lian, Q. Liu, C. Zhang, H. Liu, Digital twin for cutting tool: Modeling, application and service strategy, J Manuf Syst, 58 (2021) 305-312.
[16] Q. Qi, F. Tao, T. Hu, N. Anwer, A. Liu, Y. Wei, L. Wang, A. Nee, Enabling technologies and tools for digital twin, J Manuf Syst, 58 (2021) 3-21.
[17] Y. Cao, H. Xiong, C. Zhuang, J. Liu, W. Ning, Dynamic scheduling of complex product discrete assembly workshop based on digital twin, Computer Integrated Manufacturing Systems, 27 (2021) 557-568.
[18] B. Yao, Z. Zhou, L. Wang, W. Xu, J. Yan, Q. Liu, A function block based cyber-physical production system for physical human–robot interaction, J Manuf Syst, 48 (2018) 12-23.
[19] P. Zhi-Qiang, Y. Jian-Qiang, L. Zhen, Q. Teng-Hai, S. Jin-Lin, L. Fei-Mo, Knowledge-based and data-driven integrating methodologies for collective intelligence decision making: A survey, Acta Automatica Sinica, 48 (2022) 627-643.
[20] F. Tao, L. Zhang, Y. Liu, Y. Cheng, L. Wang, X. Xu, Manufacturing service management in cloud manufacturing: overview and future research directions, Journal of Manufacturing Science and Engineering, 137 (2015).
[21] Y. Cheng, Y. Zhang, P. Ji, W. Xu, Z. Zhou, F. Tao, Cyber-physical integration for moving digital factories forward towards smart manufacturing: a survey, The International Journal of Advanced Manufacturing Technology, 97 (2018) 1209-1221.
[22] D. Gelernter, Mirror worlds: Or the day software puts the universe in a shoebox... How it will happen and what it will mean, Oxford University Press1993.
[23] D. Wu, S. Liu, L. Zhang, J. Terpenny, R.X. Gao, T. Kurfess, J.A. Guzzo, A fog computing-based framework for process monitoring and prognosis in cyber-manufacturing, J Manuf Syst, 43 (2017) 25-34.
[24] R. Senington, F. Baumeister, A. Ng, J. Oscarsson, A linked data approach for the connection of manufacturing processes with production simulation models, Procedia CIRP, 70 (2018) 440-445.
[25] J. Wang, Y. Ma, L. Zhang, R.X. Gao, D. Wu, Deep learning for smart manufacturing: Methods and applications, J Manuf Syst, 48 (2018) 144-156.
[26] L. Rivest, A. Bouras, B. Louhichi, Product Lifecycle Management. Towards Knowledge-Rich Enterprises, Springer, 2012.
[27] Y. Lu, X. Huang, K. Zhang, S. Maharjan, Y. Zhang, Low-latency federated learning and blockchain for edge association in digital twin empowered 6G networks, IEEE Transactions on Industrial Informatics, 17 (2020) 5098-5107.
[28] P. Helo, M. Suorsa, Y. Hao, P. Anussornnitisarn, Toward a cloud-based manufacturing execution system for distributed manufacturing, Computers in Industry, 65 (2014) 646-656.