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Digital Twin Based Real-time Production Logistics Synchronization System in a Multi-level Computing Architecture

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ABSTRACT

The increasing demands for customized products have brought a lot of inevitable operational dynamics to the production logistics system. How to systematically monitor and evaluate its overall real-time operation status, and to invoke the most appropriate decision-making level, use the most economical computational resource, and conduct a synchronized decision-making and control to the most accurate operation scope to address a randomly occurred dynamics has remained a long-term challenge for researchers. This paper proposes a multi-level cloud computing enabled digital twin system for the real-time monitor, decision and control of a synchronized production logistics system. In the IoT-driven production logistics synchronization (PLS) system with complete real-time information, the dynamics that occurred in the physical layer could be accurately and real-timely captured and its negative effects on the system's overall operation state could be effectively evaluated in the digital layer. For slight, moderate and severe dynamics, edge computing, fog computing and cloud computing and their dynamically formed multi-level distributed decision-making system will be used to deal with the dynamics in the most effective and economical mode. Finally, the PLS optimization model of production and storage is presented with an industrial case, and the effectiveness is also demonstrated and analyzed.

Introduction

The increasing demands for customized products have brought a lot of inevitable operational dynamics to the production logistics (PL) system [1]. These dynamics cause some uncertainties in the overall PL system, such as the raw materials uncertainty, production equipment uncertainty, production process uncertainty, and so on [2]. In response, enterprises have to deal with all kinds of dynamics in a more flexible way of production.

The PL system is a large-scale complex system with multiple operation stages (e.g., production stage, transportation stage, and storage stage) and multiple management levels (e.g. workshop level, department level, and enterprise level) [3]. Therefore, the existing long-term challenges when a random dynamic occurs in such a complex environment for researchers and practitioners are shown as follows: (1) how to systematically monitor and evaluate the overall real-time operation status of the PL system; (2) how to accurately invoke the most appropriate decision-making level, and; (3) how to properly use the most economical computational resource, and conduct a synchronized decision-making and control to the most accurate operation scope.

In terms of system state monitoring, the Internet of Things (IoT) technology can obtain some real-time data of the PL system to help managers realize certain dynamic planning. However, this dynamic planning has limitations because of IoT technology is unable to obtain the multi-dimensional, multi-scale heterogeneous data of the PL system, and thus cannot carry out the overall and systematic planning of the PL system [4]. In terms of computing resources, although cloud computing can provide powerful computing power, it has poor real-time performance because it is far away from the site. Fog computing technology overcomes the distance problem, which is close to the site, it however has limited computing power, and cannot support the calculation of complex systems [5]. Therefore, a novel flexible computing technology with timeliness and economical efficiency should be developed. In terms of dynamic response, some of the current advanced production

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management methods (e.g., just-in-time (JIT) production, lean production, etc.) have advantages on optimizing statically certain subsystems of the PL system, and have deficiencies on how to optimize the PL system to deal with the dynamics systematically, holistically and dynamically. In terms of system optimization, the traditional optimization methods of the PL system which objects are centralized in one model for optimization or optimized independently in serial cannot reach the optimum of the system. From the perspective of the system theory, the reason is the integration optimization makes the optimization object lose independence and the serial optimization reduces the scope of optimization.

In response, a three-level (unit-level, subsystem-level and system-level) digital twin framework is constructed by edge computing, fog computing and cloud computing technologies to realize the real-time monitoring of the system and meet the requirements of different levels for computing power and response time, and provide information and computing power for later decision-making. Then, the dynamics can be divided into three levels according to the influence range of dynamics, and take different countermeasures according to the level of dynamics. Finally, the whole PL system is optimized in the light of countermeasures and Multidisciplinary Design Optimization (MDO) methods. The solution uses the MDO methods to schedule and configure resources of the PL system to obtain systematic optimization based on advanced information technology and synchronization mechanism.

In order to verify the validity of the method proposed under the premise of general significance, this paper aims at the synchronization of production and storage subsystems, only considers the dynamics of equipment failure, with limited production capacity and unlimited storage resources as the assumption. The model of production scheduling and storage optimization is established, respectively. According to the double-layer structure of the system goal and stage target, the Collaborative Optimization (CO) theory is selected and the mathematical model of the PL system is established. and the impact of dynamics of different degrees on the PL system is studied by an example, and uses the MATLAB software to simulation, comparative analysis of the feasibility of using synchronization and un-synchronization methods. Finally, find out the law of different time of different levels dynamic impact on the PL system and obtain the significance of management.

The remainder of this paper is organized as follows: Section 2: Literature review, Section 3: Elaborates the problems studied in this paper and analyses challenges of PL system; Section 4: Proposes a solution based on advanced information technology and synchronization mechanism for the problems and challenges described in Section 3; Section 5: Verifies the effectiveness of the proposed method through simulation and analysis of an example. Conclusions and future research are drawn in Section 6.

Literature Review

Related research is reviewed under four categories: (1) synchronic optimization of production logistics in dynamic situation, (2) Digital twin and its application, (3) collaborative architecture of edge computing and cloud computing, and (4) application of MOD methods in PL system.

Production logistics synchronization under dynamics

The PL system is a large-scale complex system, it starts from the purchase of raw material and ends with the warehousing of finished products [6]. Usually, scholars think that the PL system includes production, transportation and storage stage [2]. At present, scholars have made extensive research on production scheduling, vehicle scheduling and warehousing management in the PL system. Yang and Peters [7] propose a flexible mechanical layout method for different machines with different time windows in the dynamic environment. For the three kinds of uncertainties (of the service market, service execution and the user side respectively), based on the Analytic Hierarchy Process and big data, Yang et al. [8] proposed to evaluate whether the intended cloud manufacturing services should be reserved to make sure that eligible services are ready to use without compromising cost or time. Witczak et al. [9] investigated the fault diagnosis and fault-tolerant control and proposed a fault-tolerant control framework, which is based on a fusion of the predictive control and interval max-plus algebra. Alimian et al. [10] proposed a new integration method for cell formation, group scheduling, production, and preventive maintenance (PM) planning problems in a dynamic cellular manufacturing system (CMS). Based on cloud-based disassembly, Jiang et al. [11] proposed the cloud-based disassembly system, and built a mathematical model that considers the uncertainty nature of the disassembly process and precedence relationships of disassembly tasks, according to the user dynamic requirement. Noroozi et al. [12] proposed a novel viewpoint of coordinating decisions in an Integrated Supply Chain scheduling, coordinating Batch Delivery, and Order Acceptance, and formulated a coordinated order acceptance and supply chain scheduling with batch direct delivery and using the 3 PL provider and proposed two mixed integer programming.

Digital Twin and Its Application

Digital twin (DT) is used to create virtual models of physical entities in a digital way, to simulate the behavior of physical entities in the real environment by data, and add or expand new capabilities for physical entities through virtual-real interactive feedback, data fusion analysis, decision-making iterative optimization, etc. [13]. The concept of the DT was first proposed by Professor Grieves of the University of Michigan in the course of Product Life Cycle Management [14]. Subsequently, related researches were carried out in the fields of the DT modeling [15,16], interaction and collaboration [17,18], and service application [19,20]. At present, scholars have carried out a lot of researches around digital workshop/factory and put forward many valuable theories and technologies. Qi et al. [5] propose a three-level DT architecture based on cloud computing, fog computing, and edge computing. Zhou et al. [21] breaks traditional procedures and presents a DT-based optimization strategy on the consideration of both machining efficiency and aerodynamic performance, as well as builds a reified 5-dimensional DT model. Negri et al. [22] proposed a way to integrate a Digital Shadows (DS) simulation model with the Manufacturing Execution System (MES) in this way creating a DT, which can feedback actions on the control system of the equipment. DT is applied to product production process control to guide the change of production mode from mass production to personalized production [20]. Brenner and Hummel [23] combine knowledge learning with the DT, and propose a method of extracting and reasoning knowledge from large-scale production line data, and improved manufacturing process management by reasoning ability. Tao et al. [24,25] summary the progress of the application and theoretical research of the DT in enterprises, propose a five-dimensional structure model of the DT and six application criteria of the DT drive, explore the key problems and technologies needed to a breakthrough in 14 kinds of application conception and implementation process of the DT drive, and provide theories and methods for further application of the DT in the future.

Cloud Computing, Fog Computing, and Edge Computing

Cloud computing is a kind of distributed computing, which refers to decomposing huge data computing processing programs into countless small programs through the network cloud and then processing and analyzing these small programs through a system composed of multiple servers to get results and return them to users [26]. Fog computing is an extension of cloud computing, which shifts the capability of computing and storage of cloud to the edge network [27]. Edge computing refers to an open platform that integrates the network, computing, storage and application core capabilities close to the object or data source to provide

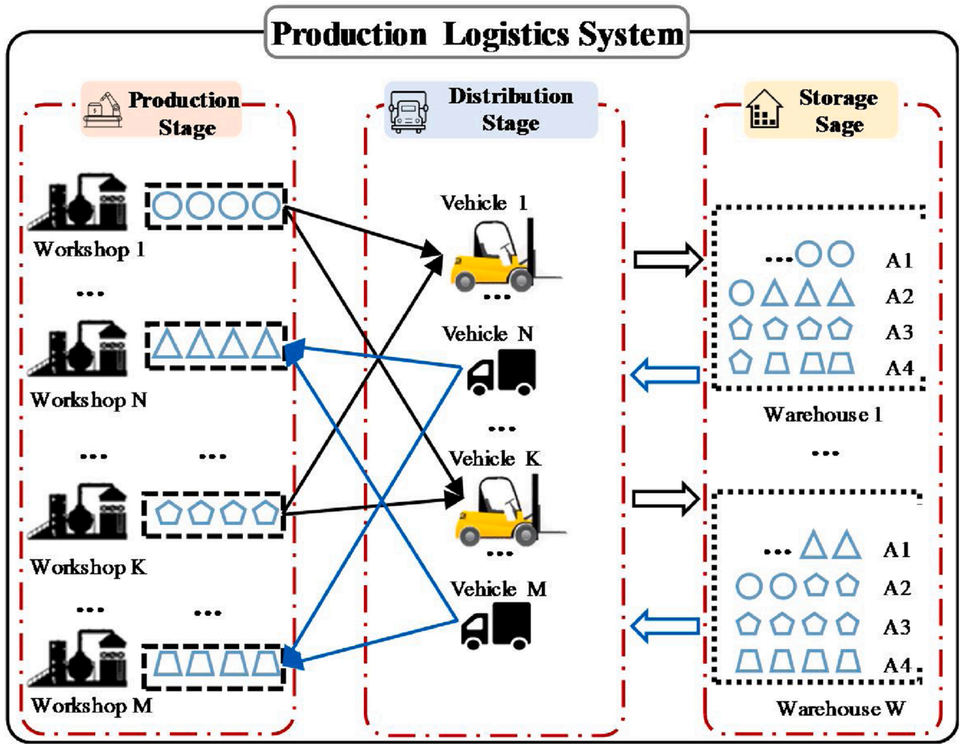

Fig. 1. The operation process of the production logistics system.

the nearest service [28]. Dolui and Datta [29] discuss the differences between edge computing, fog computing, cloud computing in detail and compare their features, and then define a set of parameters, through a use-case present a decision tree for the selection of the optimal implementation. Wu et al. [30] evaluated the performance of solving a large-scale engineering problem using finite element analysis on several public high performance computing (HPC) clouds as well as introduce a new workflow for Cloud-Based Design and Manufacturing (CBDM). Liu et al. [31] introduced a new paradigm of Cyber-Physical Manufacturing Cloud (CPMC) to bridge gaps among cloud computing, cyber-physical systems, and manufacturing. Hong [32] proposes a Fog computing ecosystem and implements a real testbed. Meanwhile, the author evaluates the ecosystem with diverse usage scenarios and optimizes the fog computing platform. Singh et al. [33] explain the appearance reasons for fog computing and discuss the taxonomy of fog computing and the difference of cloud computing and edge computing technologies, its applications, emerging key technologies.

MDO methods and its application in the PL system

Multidisciplinary Design Optimization (MDO) is an effective method to solve complex design problems in aerospace engineering at the end of the last century. At present, it has been widely used in many fields with complex engineering systems, such as aviation, aerospace, automobile manufacturing, and so on. MDO methods mainly include CO, Analytical Target Cascading (ATC), and Augmented Lagrangian Coordination (ALC), etc. Braun et al. [34,35] use the CO method to decompose and optimize the design and manufacture of the launch vehicle. Sobieski and Kroo [36] use the CO method to decompose and optimize aircraft manufacturing. Qu et al. [37] use the CO method to solve the problem of coordination between production and storage in cloud manufacturing. Zhang et al. [38] propose a decentralized decision mechanism and an analytical target cascading model based on the analytical target cascading method to solve the cloud manufacturing service configuration problem. In order to allow participants to keep autonomous decision rights in cloud manufacturing, Zhang, et al. [39] propose a distributed optimization mechanism base on the Augmented Lagrangian Coordination.

Literature summary

At present, production scheduling and warehousing management are still in the stage of independent research. Few studies are conducted from the perspective of product flow as a whole system. Even if there are studies on a subsystem of the PL system or static research. There is no consideration of the overall operation of the production system and no dynamic optimization research of the whole system. The DT technology provides an effective management model and technical framework for digital modeling and interactive control of physical objects, but its application scope is mostly limited to independent objects. This technology is very few for the research of the whole correlation twin and on-line cooperative control for the complex operation system composed of multi-stages. Therefore, how to extend the DT model to the large-scale complex production system and realize the whole process timely, adaptive, multi-level, system synchronized control and CO under high-frequency dynamics has become an urgent problem to be solved. The MDO methods have been widely used in industrial production, all the methods however focus on the supply chain, nevertheless, they have not been applied to dynamic optimization and on-line distributed dynamic optimization coordination of large-scale production systems at present. However, due to its support for independent decision/control and low computational complexity, the MDO has fast response speed and great potential application value in dynamic on-line control of the production system.

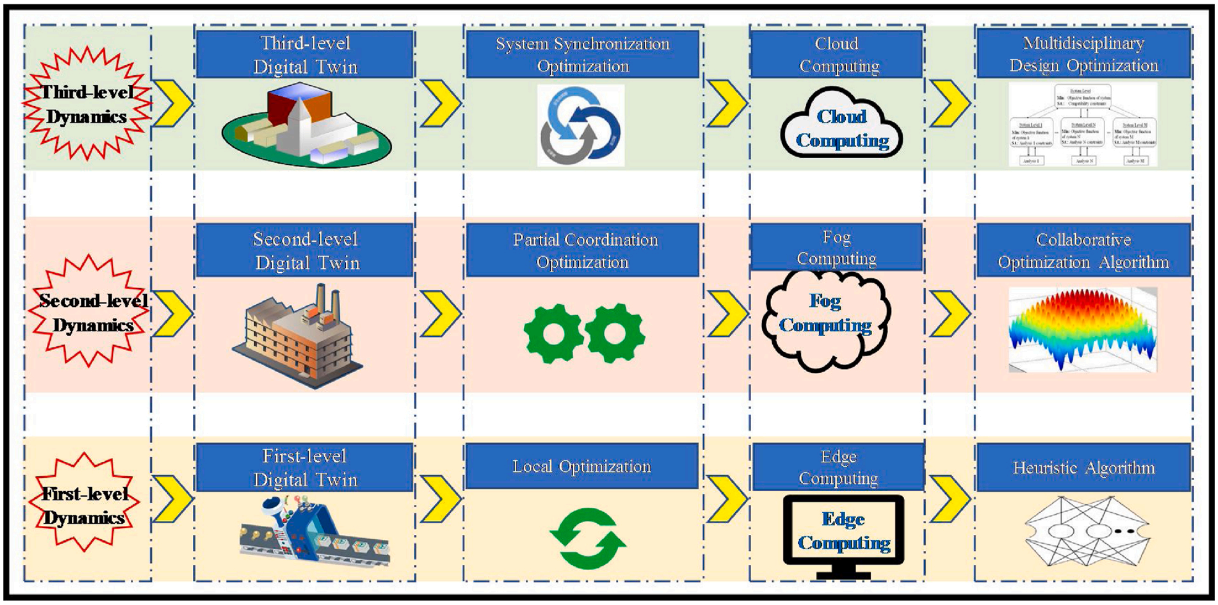

Fig. 2. Overall solution diagram.

Problems Description

In this section, this paper firstly describes the operation process of the PL system, and then introduces the difficulties faced by the PL system.

Introduction to Production Logistics Operation

The process of the PL system operation is divided into three stages: production stage, transportation stage and storage stage. The production stage is the process of product processing according to customer order, the transportation stage is the transport process to realize the cargo movement from the workshop to the warehouse, and the storage stage is the storage behavior to meet the on-time delivery of the finished product. The production process is generally composed of one or more production workshops, each order needs to go through one or more of the production workshops, when the production is completed, the fleet according to the finished product off-line time to collect and transport, and then according to the storage arrangements to move the finished product to the warehouse for storage. The PL operation process is shown in Fig. 1.

Problems Analysis in Production Logistics

Under the diversification and personalization of customer demand, because of the randomness of order, the dynamic of production demand, the service of external resources and the low repeatability of the production process, the operation process of the PL system is inevitably disturbed by various dynamics. However, due to the limited plant area, fixed production resources, difficult adjustment of production lines, and backward management methods, the dynamic of any stage will cause the production logistics system to jam and stop, resulting in overtime work of workers, delay of completion time, increased cost of enterprises, and poor market competitiveness.

However, the current optimization of the PL system (large-scale complex system) is either the integration optimization of multiple objects into a single model or the independent serial optimization of multiple objects. From the perspective of system theory, no matter how, the optimization of the whole system cannot be achieved. Even if the system can be optimized, in the process of system execution is full of various dynamics, how to judge the impact of these dynamics on the system and how to deal with these dynamics are very difficult problems. Besides, if we can deal with different dynamics, how to take accurate calculation methods and economic computing capacity to making a fast and accurate decision is also a real problem.

Therefore, solving the above problems faces the following challenges:

- Lack of dynamics discrimination and coping mechanisms: Because the PL system is a large-scale complex system with multiple operation stages, each stage is full of uncertainty, there will be a variety of dynamics. Also, the dynamics of different dimensions (time, quantity, object, etc.) have different influences on the system. Due to the lack of effective response mechanisms, enterprises can only increase resources, extend working hours and other measures of mechanical relative dynamic.
- Lack of real-time comprehensive state perception methods for complex systems: Each stage of the PL system involves mass dynamics data, such as time dimension information, quantity dimension information, etc. The acquisition of real-time information can support to realize the discrimination of dynamics, optimal scheduling decisions.
- Lack of a quantitative real-time optimization method and economic computing capacity for the multi-level and multi-stage complex systems: The decision-making of each stage in a complex system is independent of each other. Because of the lack of control methods to achieve real-time and dynamic coordination of complex systems, it is impossible to realize the overall and systematic optimization of the system. Besides, at all levels of the system, we need more appropriate computing technologies to achieve real-time, accurate and economic computing, and to avoid the decision failures caused by the delay of computing and the waste of resources caused by the excess computing power.

According to the analysis of the above problems, to realize the systematic optimization of PL system through multiple stages synchronized

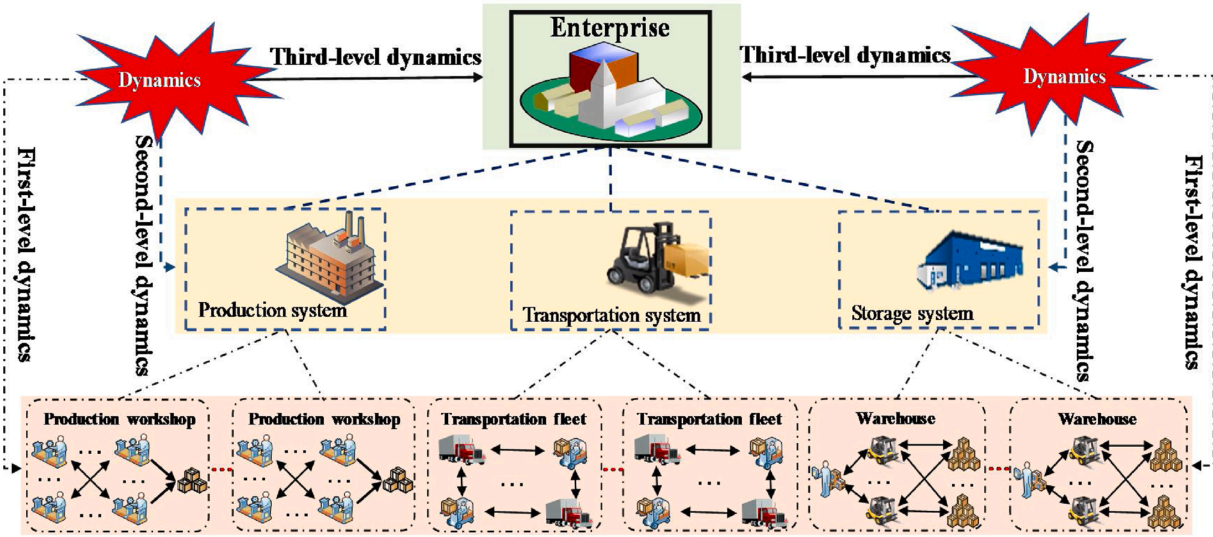

Fig. 3. Three levels of dynamic classification.

decision, not only need build a real-time state perception of the physical system and information fusion framework of the virtual system but also a synchronization decision-making mechanism to deal with the dynamics is needed. Also, the optimization method of complex large-scale systems and the flexible and economic computing capacity is also needed to support optimal decision-making.

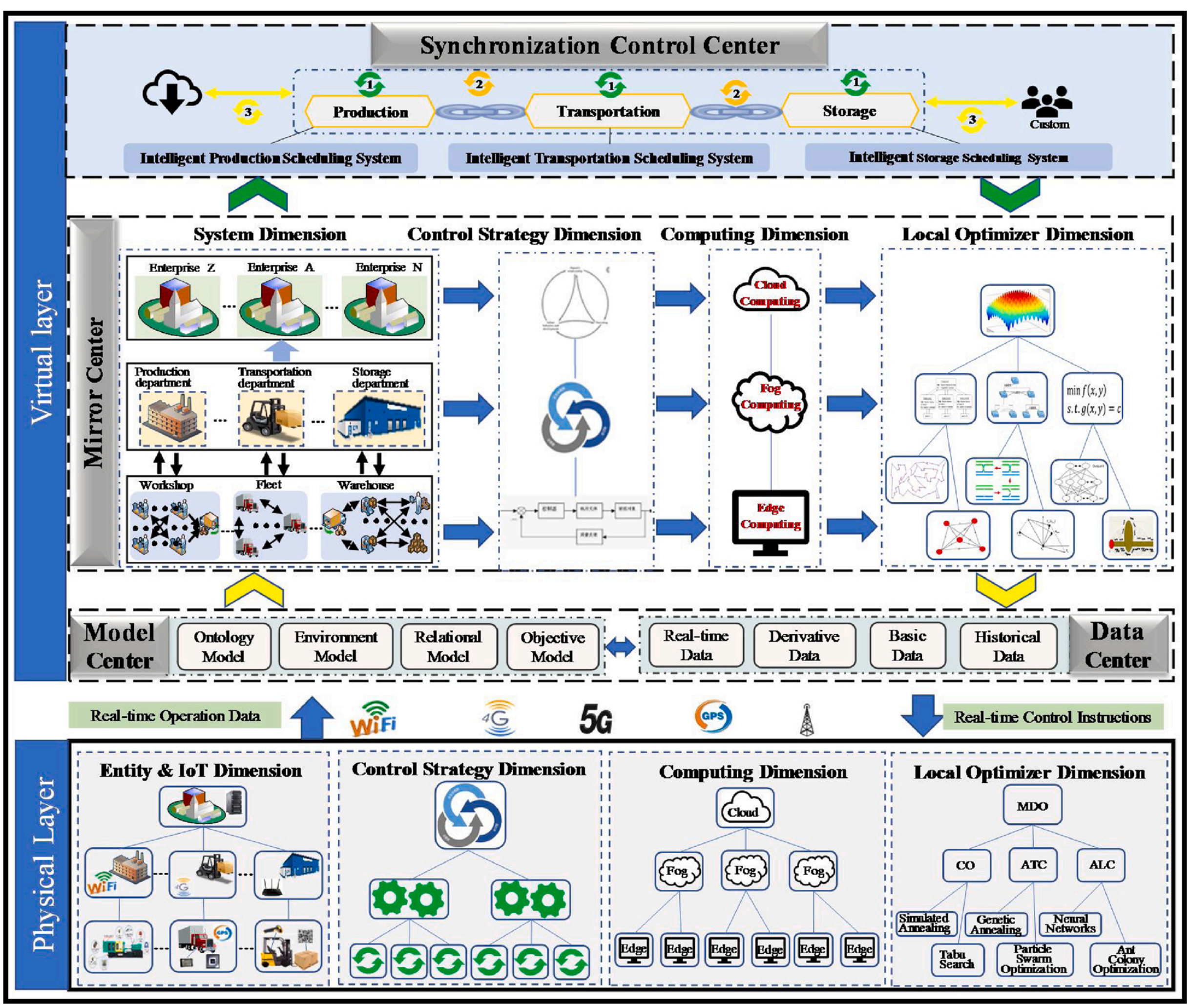

Fig. 4. The cloud-fog-edge-based digital twin control framework.

Solutions

In view of the above difficulties, this paper firstly divides the dynamics into three levels according to the influence scope of the dynamics. When the dynamics occur, according to the dynamics of different levels, the DT, control strategy, computing power and optimization algorithm of different levels are adopted to restore the system to the optimal state. Details are shown in Fig. 2.

When the dynamic property belongs to the first level, its influence scope is limited to the unit (workshop). It only needs to obtain the real-time state through first-level DT, and then the optimal solution is obtained by running the heuristic optimization algorithm based on edge computing. In this way, it can deal with dynamics quickly and avoid the waste of computing resources.

When the dynamic property belongs to the second level, its influence scope goes beyond the unit and affects the subsystem. At this time, we can obtain the real-time state of the subsystem through second-level DT, and then run the coordinated optimization algorithm and heuristic optimization algorithm to obtain the optimal solution by relying on the fog computing and edge computing. Such a two-level collocation operation form cannot only respond quickly but also realize the economy of computing resources.

When the dynamic property belongs to the third level, its influence scope is the whole system. In this case, we can obtain the real-time state of the system through third-level DT, and then run the MDO algorithm, coordination optimization algorithm and heuristic optimization algorithm respectively by cloud computing, fog computing and edge computing to obtain the globally optimal solutions. This kind of three-level collocation avoids the resource waste and time delay caused by the over-dependence on cloud computing.

Dynamics Classification

The different dynamics of the PL system have different influences on the PL system. In order to take an effective method to deal with the dynamics of the PL system, we need to classify the dynamics firstly. This section will analyze the dynamics of the PL system from the range of impact. From the range of dynamic influence of the PL system, the dynamics can be differentiated into three levels, as shown in Fig. 3.

First-level dynamics

When the dynamics just interfere with the unit (workshop, fleet, warehouse) of the system (production, transportation, storage), and it can be solved by the workshop through the task and resource scheduling, which is defined as the first level dynamics. For instance, forklift failures.

Second-level dynamics

When the dynamics just interfere with the system of production or transportation or storage, and it can be solved by the system through the cooperation of the workshops and fleets, or fleets and warehouses, which is defined as the second level dynamics. For instance, the change in transportation planning.

Third-level dynamics

When the dynamics interfere with the enterprise, and it can be solved through the cooperation of the three systems, which is defined as the third level dynamic. For instance, the change of orders.

Cloud-Fog-Edge-based Digital Twin Control Framework

At present, there are more researches on DT for simple systems, and less researches on DT for complex systems. In many existing DT architectures, any decision is made in a single decision center, and every decision requires relevant information to be transmitted to the decision level, the decision is then made by the decision level, which makes large computation scale, low computation efficiency and high information delay. To solve these problems, a DT control framework based on Cloud-Fog-Edge computing is proposed in this paper. As shown in the Fig. 4.

Table 1
The difference of the DT of three levels.

	Edge computing-base DT	Fog computing-base DT	Cloud computing-base DT
Location	Nearer	Near	Far
Number of physical entities	Less	Many	More
Number of Virtual models	Less	Many	More
Model complexity	Low	High	Highest
Computing capacity	Weak	Strong	Strongest
Amount of information	Less	Much	More
Information complexity	Low	High	Highest
Timeliness	Faster	Fast	Slow

This framework is mainly divided into two layers, i.e., the physical layer and the virtual layer.

The physical layer is the physical system, which mainly includes the capability resources, such as the processing capability, the information collection capability, the calculation capability, the control logic capability and the algorithm optimization capability. Thus, any manufacturing system in practice is a collection of these capabilities, whether at the unit (workshop) level, the subsystem (department) level, or the system (enterprise) level.

The virtual layer consists of four parts: model center, data center, mirror center and synchronization control center.

- The model center is a model library to construct DT, which is composed of various models, including ontology model, environment model, relational model and objective model. The ontology model is mainly a model that reflects various geometric characteristics and physical characteristics of the entity, the environment model is a model that reflects the environment of the system, such as temperature, humidity, brightness, etc. As the core of the whole model center, the relational model includes the elements model, the process model, the business model, the data fusion model, the coupling model among the models and other models that reflect the relationship of the production logistics system. The objective model is a kind of optimization target model pursued by all levels and stages of the PL system.
- The data center mainly contains real-time data, basic data, derivative data and historical data. Real-time data reveals the real-time state of the system operates within a short period close to the current moment. Derivative data is some fused, processed and computed data produced by the system at runtime. The historical data is the collection of the operating data before the system, which not only contains the data but also contains the knowledge generated based on the data, which can provide the decision-making basis for the synchronization control center. The basic data mainly reflects some system characteristics, such as geometric information, physical element information, operation information, standard information and feature information.
- The mirror center realizes the real mapping of the physical layer through the coupling of the model and the fusion of the data,

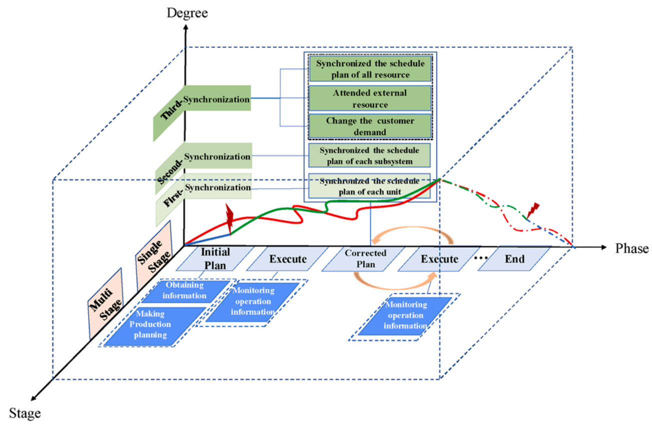

Fig. 5. Synchronization mechanism description.

ensuring the agility, precision and consistency between the physical layer and the virtual layer. According to the level of the system, it can be divided into the unit-level mirror, subsystem-level mirror and system-level mirror. In each level, the corresponding capabilities of this level are reflected. Through the interrelationship of these capabilities, the system can operate organically and highlight its capabilities.

- The synchronization control center is the core and brain of the whole DT system, which contains various functional modules needed for the operation of the system and is used to support the decision making and optimal control of the whole system. In production logistics system, different levels of the synchronization control center are located in a different position, the unit (workshop) control center is located at the devices of the edge computing, the subsystem (departmental) control center is located in the fog computing devices, and the system (enterprise) control center is located in the cloud computing device. The function of the three levels control center has the characteristics from simple to complex, from small to large, from weak to strong.

The differences between the edge computing-based DT, fog computing-based DT, and cloud computing-based DT are shown in Table 1.

Production logistics Synchronization Mechanism

The DT control architecture proposed in the previous section provides accurate real-time status information for the efficient execution of the PL system. But, when, where, and how can we use this real-time data information to support the efficient operation of the "production-logistics" system? Qu et al. [3] put forward a set of effective synchronization mechanism to deal with the dynamic factors that will appear in the actual system execution process based on the TPS synchronization mechanism. The synchronization mechanism will be explained in detail from the dimension of the phase and degree in this paper. As shown in Fig. 5.

Phase Dimension

The synchronization mechanism includes two processes: Initial plan and Corrected plan.

- Initial plan: When the PL system receives an input (order), the synchronization control center obtains real-time data of production elements (personnel, machine tool, vehicles and cargo) from the data center. The synchronization control center then analyzes, evaluates and predicts the status of the elements, determines resource configuration, task allocation and processing technology based on the model center according to the requirements and constraints of the task, and formulates production plans. After that, the production plans are transmitted to the mirror center, and make some simulations based on the elements, behavior and rule model. According to simulation data and knowledge, the synchronization control center modifies and optimizes the production plans and transmits it to the mirror center again. This iteration is repeated until the optimal production plan (Initial plan) is obtained.
- Corrected plan: After receiving an initial plan, the physical object layer organizes the activities of production, transportation, and warehousing according to the instructions. In the actual execution process, the physical object layer transmits real-time data to the synchronization control layer, which compares the actual operation data of the physical object layer with the initial plan simulation data of the virtual model layer. If the difference between the two data is greater than a predetermined degree, the synchronization control layer is triggered to identify the dynamics of the physical object layer, and triggers the corresponding synchronization according to the level of dynamic, to work out the correction planning scheme through the virtual model layer which similar to the making of the initial plan. Finally, the corrected plan is obtained and the instruction is reached to the physical object layer execution. Repeat the iteration until the end of the implementation task.

Degree Dimensions

In actual implementation, countermeasures are divided into three levels according to the dynamics, and corresponding synchronization methods are proposed for each level.

- First-synchronization: When the dynamic is First-dynamics, the manager can get accurate information about the unit operation through the unit-level DT. On the premise of guaranteeing its interest, the unit can eliminate the dynamics by rescheduling resources capacity and tasks based on edge computing, which cannot affect the operation of other decision-making units.
- Second-synchronization: When the dynamic is Second-dynamics, the manager can get accurate information about the subsystem operation through the subsystem-level DT. On the premise of guaranteeing its interest, the subsystem can eliminate the dynamics by rescheduling resources capacity and tasks based on fog computing, which cannot affect the operation of other decision-making subsystems.
- Third-synchronization: When the dynamic is Third-dynamics, the manager can get accurate information about the system operation through the system-level DT. On the premise of guaranteeing its own interest, the system can eliminate the dynamics by rescheduling its resources, adding new resources, and changing customer demand based on cloud computing.
- *Third-synchronization(A): If the dynamics can be solved by all units through capacity scheduling through cloud computing, it is defined as the Third-A level synchronization.*
- *Third-synchronization(B): If the dynamics cannot be solved by the Third-synchronization(A), and it can be solved by adding the new resource through the cloud, it is defined as the Third-B level synchronization.*
- *Third-synchronization(C): If the above methods cannot solve the dynamics, it can be solved by changing the demand of the customer, it is defined as the Third-C level synchronization.*

Collaborative Optimization

The PL system is a multiple subsystems coordination optimization problem, due to the process of synchronization has emphasized the dynamics, the independence of the decision-making model and the agility which comes from the decision-making. CO is a kind of stratified two-layer MDO method, which has a system-level optimization function. For the subsystem, the analysis and optimization design are within the space of each subsystem. It's suitable for the subsystem variable much more than the subject (subsystem) variable, which applies to solve the

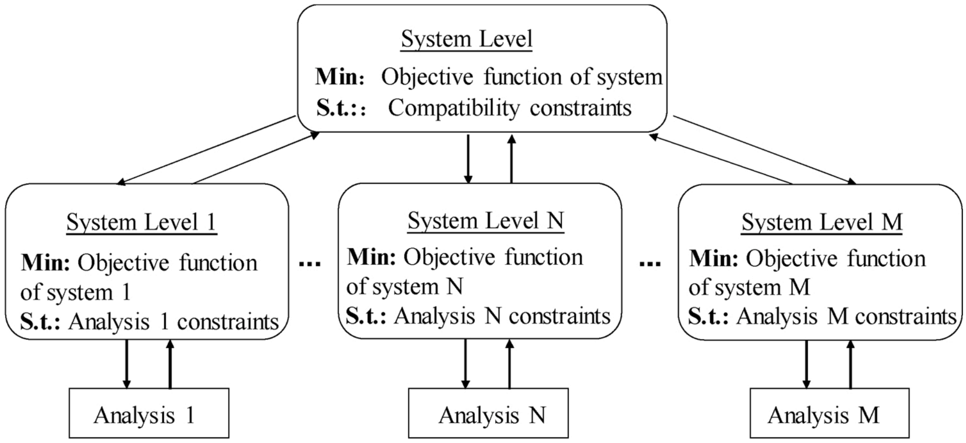

Fig. 6. CO framework.

Table 2
Order data

Index of order	Demand in tray	Delivery date (mins)	Index of order	Demand in tray	Delivery date (mins)
1	20	65	6	60	120
2	30	60	7	30	50
3	25	80	8	56	135
4	40	115	9	60	140
5	50	130	10	40	95

multidisciplinary design optimization problem that has the goal of system-level design. Therefore, CO is used to solve the PLS optimization problem in this paper.

The mathematical model of the PL system is established by using the CO optimization method as follows.

System-level optimization model.

$$\mathrm{Min}F = t_1 + t_2 \tag{1}$$

$$\text{Subject to}J_1 = (t_{11} - t_1)^2 \leq \varepsilon \tag{2}$$

$$J_2 = (t_{22} - t_2)^2 \leq \varepsilon \tag{3}$$

The objective function (1) is the minimum customer waiting time. Constraint (2) and (3) are system consistency constraints, t_{11} is the system-level design variable for the production subsystem, t_{22} is the system-level design variable for the storage sub-system, 1 and 2 are system-level design variables.

$$\min J_1(x_i) = \sum_{j=1}^{t_1}(x_{ij} - z_j^*)2 = 0 \tag{4}$$

$$\text{Subject to } c_i(\chi_i \leq 0), \mathrm{i} = 1, 2, 3 \tag{5}$$

The variable χi is design vector of the subsystem *i*, χij is the design variable *j* of subsystem *i*, *zj** is the expected value of the design variable *j* for the system assigned to the subsystem *i*, and (χi) is a system-level constraint.

The optimization structure of the above the mentioned mathematical model is shown in Fig. 6.

The collaboration optimization method for the consistency constraint of the system-level optimization problem is the equality constraint. But the consistency of equality constraint is too strict for the subsystem. Therefore, the system-level equality constraints are changed to inequality constraints, so that the system level has a feasible solution domain.

Table 3
Parallel machine quantity of operation

Index of process	Process	Parallel machine numbers
1	Dispersion	3
2	Grinding	4
3	Mixing	4
4	Filtration	2
5	Packaging	2

Table 4
The machining time for unit pallet

Process	Index of machine	Processing time per unit(mins)
1	1	0.3
	2	0.3
	3	0.2
2	4	0.4
	5	0.3
	6	0.4
	7	0.3
3	8	0.4
	9	0.3
	10	0.5
	11	0.3
4	12	0.1
	13	0.2
5	14	0.1
	15	0.1

Table 5
Warehouse goods aisle data

Goods aisle categories	Goods aisle numbers	Capacity per goods aisle
Internal goods aisle	12	30

Table 6
The element of PL cost

Cost categories	Cost (100)
Production fixed cost	40
Production cost in each process	1.2
Warehouse fixed cost	50
Single internal goods aisle cost	10
Single hired goods aisle cost	15
Delay penalty cost per unit time	3.5

Case study

This section verifies the feasibility of the proposed method. We applied an industrial case of paint manufacturers whose key stage includes production and logistics stage. By comparing the four indicators under the synchronization and un-synchronization method, the advantages of the proposed method are highlighted.

Case description

The case company is a large-scale paint production enterprise. At present, the application process of the PL system optimization method is mainly explained the production stage and storage stage. After receiving the order, the production stage phase needs to make a production plan, and the storage stage phase needs to arrange the storage location. However, the dynamics are often occurred in production processes and storage processes, such as product out the line early or delay, equipment failure, worker absenteeism, and unavailable storage location, etc., resulting in poor scheduling and storage location planning results, high production operating costs, etc.

Suppose that 10 production orders need to be produced through the two latex paint shops, and stored in two warehouses. This paper assumes that the processing time of the unit pallets for any operation is fixed. The product is transported to the warehouse for storage and waiting for shipment out of the warehouse. After the equipment failure, to cope with dynamics. Used the PL system method of this paper proposed to minimize the PL system costs. The goal of the production subsystem is the maximum order completion time is the shortest, the storage subsystem is the minimum use of the cargo aisle and the shortest order time in the library. The base data for this example is shown in Tables 2–6.

Collaborative Optimization Model

This case is based on the synchronization between production and storage (i.e., production scheduling and storage planning) and the CO model is established.

System Model

The task of the system model is to coordinate the difference between production and warehousing, to make the execution process of production and warehousing as smooth as possible, and the goal of the system model is to minimize the cost of the PL system operation.

$$\min f(z) = z_p + z_w \tag{6}$$

S.T.

$$J_p^* = \left(z_1 - z_p\right) \leq \varepsilon \tag{7}$$

$$J_w^* = \left(z_2 - z_w\right)^2 \leq \varepsilon \tag{8}$$

In the formulation, objective (6) is to minimize the total cost of the PL system, where z_p is the design variables of production subsystem and, z_w is the design variables of the storage subsystem and z_1 and z_2 are the initial value of the objective function. Constraint (7) and (8) are compatibility constraints.

Subsystem model

(1) Production-subsystem model

$$\min z_p = p_1 + p_2 \tag{9}$$

S.T.

$$J_{p1}^* = \left(q_1 - p_1\right)^2 \leq \varepsilon \tag{10}$$

$$J_{p2}^* = \left(q_2 - p_2\right)^2 \leq \varepsilon \tag{11}$$

$$p = pc_{\text{cost}} + f_p \times pt_{\text{cost}} + \sum_i n + a\max\left(C_{i,m} - D_i, 0\right) d_{i\ \text{cost}} \tag{12}$$

In the formulation, objective (9) is to minimize the total costs of the production subsystem, where p_1 and p_2 are the design variables of the production subsystem and, q_1 and q_2 are the initial value of the objective function. Constraint (10) and (11) are compatibility constraints. Constraint (12) means the design variable at the production stage is equals to production cost, which contains fixed production costs, operation costs, and order delay penalty costs.

(2) Storage-subsystem model

$$\min z_w = w_1 + w_2 \tag{13}$$

S.T.

$$J_{w1}^* = \left(\chi_1 - w_1\right)^2 \leq \varepsilon \tag{14}$$

$$J_{w2}^* = \left(\chi_2 - w_2\right)^2 \leq \varepsilon \tag{15}$$

$$w = wc_{\text{cost}} + pi_{\text{cost}} \times \sum_{l=1}^{w_{in}} u_{l,t} + po_{\text{cost}} \times \sum_{l=w_{in}}^{w_{out}} u_{l,t} \tag{16}$$

In the formulation, objective (9) is to minimize the total costs of the production subsystem, where w_1 and w_2 are the design variables of the storage subsystem and, χ_1 and χ_2 are the initial value of the objective function. Constraint (10) and (11) are compatibility constraints. Constraint (16) is the design variable at the warehouse stage, namely warehouse cost including fixed warehouse cost, the total cost of using its own goods aisles and the cost of hired goods aisles.

Unit-model

(1) Production unit-model

The production sub-model in this paper will take intermittent production as an example to model. The objective function is to minimize the makespan.

$$f_p = \min(\max\chi C_{i,m} \,|\, i = 1, 2, \ldots, n + \alpha_T) \tag{17}$$

S.T.

$$\sum_{k_j=1}^{M_j} x_{i,j,k_j} = 1, i \in \{1, 2, \ldots, n + \alpha_T\}, j \in \{1, 2, \ldots, 5\} \tag{18}$$

$$\sum_{i=1}^{n} y_{i,p} = 1, p \in \{1, 2, \ldots, n + \alpha_T\} \tag{19}$$

$$pt_{i,j} = \sum_{k=1}^{M_j} x_{i,j,k} \times t_{i,j,k} \times Q_i, i \in \{1, 2, \ldots, n + \alpha_T\}, j \in \{1, 2, \ldots, 5\} \tag{20}$$

$$C_{i,j} = st_{i,j} + pt_{i,j} \tag{21}$$

$$C_{i,j-1} \leq st_{i,j}, i \in \{1, 2, \ldots, n + \alpha_T\}, j \in \{1, 2, \ldots, 5\} \tag{22}$$

$$C_{i,m} \leq D_i, i \in \{1, 2, \ldots, n + \alpha_T\} \tag{23}$$

In the formulation, constraint (17) presents order i only can choose one machine M_j in process j. Constraint (18) is the processing sequence of orders. Constraint (19) is processing time constraints. Constrain (20) reflects the completion time of order i in process j. Constraint (21) presents before starting with process j of order i, process j-1 must be done. Constraint (22) and (23) presents the completion time of order i cannot be greater than the delivery date.

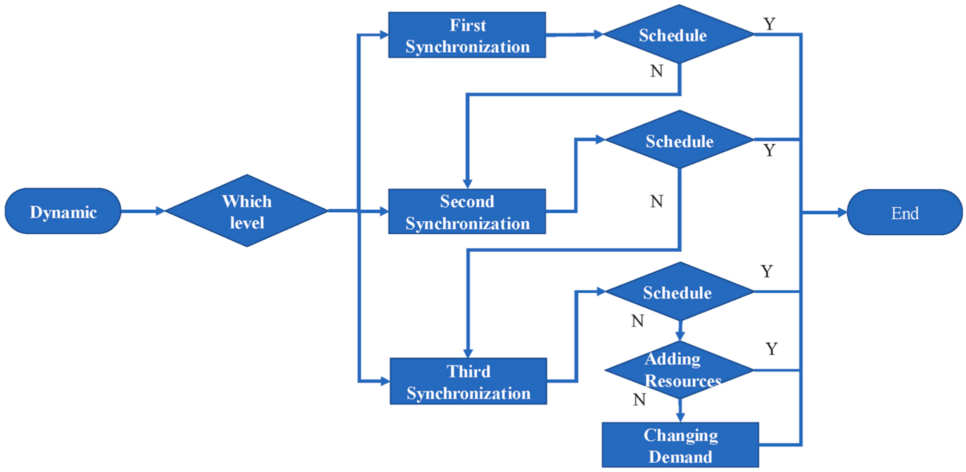

Fig. 7. Synchronization rules.

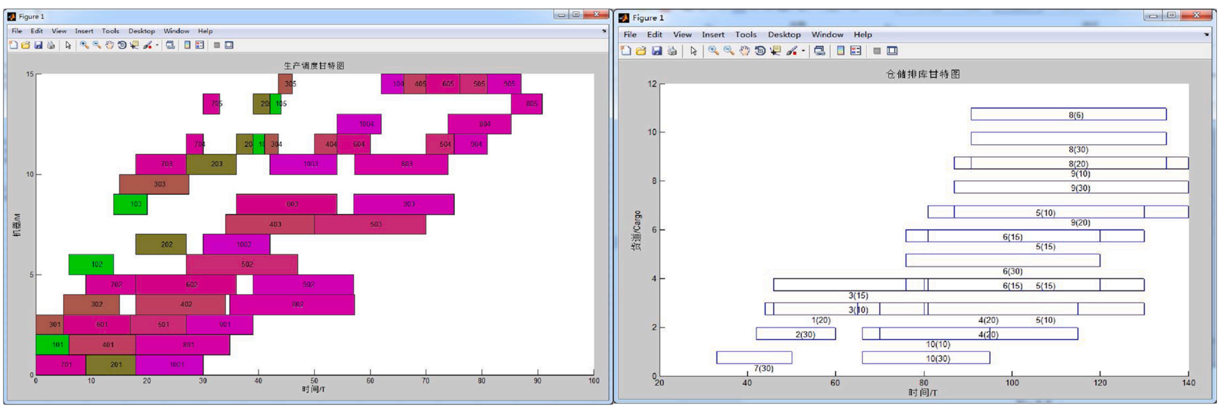

Fig. 8. The Gantt chart of detailed production plan and storage plan.

(2) Storage unit-model

In this paper, the warehouse sub-model is modeled with a plane warehouse as an example.

$$\min f_{w1} = \sum_{l=1}^{w_{in}} u_{l,t} + \sum_{l=1}^{w_{out}} u_{l,t} \tag{24}$$

$$\min f_{w2} = \frac{\sum_{i=1}^{n+\alpha_T} (Ot_i - C_{i,m})}{n + \alpha_T} \tag{25}$$

S.T.

$$\sum_{i=1}^{n+\alpha_T} put_{t,i,l} \le 2, l = 1, 2, \ldots, w_{in} + w_{out} \tag{26}$$

$$\sum_{a,b=1}^{n+\alpha_T} \left(put_{t,a,l} p_{t,a,l} + put_{t,b,l} p_{t,b,l} \right) \le cp_l, l = 1, 2, \ldots, w_{in} + w_{out}; a \ne b \tag{27}$$

$$\sum_{l=1}^{w_{in}+w_{out}} put_{t,i,l} p_{t,i,l} = Q_i, i = 1, 2, \ldots, n + \alpha_T \tag{28}$$

$$Ot_i - C_{i,m} > 0, i = 1, 2, \ldots, n + \alpha_T \tag{29}$$

$$\sum_{l=1}^{w_{in}+w_{out}} u_{l,t} \le w_{in} + w_{out} \tag{30}$$

$$\sum_{l=1}^{w_{in}+w_{out}} out_{t,i,l} p_{t,i,l} = Q_i, i = 1, 2, \ldots, n + \alpha_T \tag{31}$$

Table 7
The results of the PLS

Dynamic occurrence time	Parameter	Repair time 1 h	Repair time 2 h	Repair-time 3 h	Repair-time 4h	Repair-time 5h	Repair-time 6h	Repair-time 7 h
T = 0	Production cost	144.40	149.21	153.60	159.12	165.52	171.13	177.31
	Warehouse cost	161.12	163.27	165.21	168.04	171.23	174.82	177.63
T = 10	Production cost	144.40	150.36	155.80	160.36	167.61	173.11	179.23
	Warehouse cost	161.47	163.28	166.62	170.02	174.12	178.67	183.47
T = 20	Production cost	144.40	151.03	156.17	163.60	172.40	179.75	187.78
	Warehouse cost	162.51	164.71	168.97	172.49	177.53	184.07	189.40
T = 30	Production cost	144.40	151.55	156.2	164.9	172.2	180.55	187.8
	Warehouse cost	163.4	167.06	171.1	175.6	180.0	185.20	189.40

Table 8
The results of the N-PLS

Dynamic occurrence time	Parameter	Repair time 1 h	Repair time 2 h	Repair-time 3 h	Repair-time 4h	Repair-time 5h	Repair-time 6h	Repair-time 7 h
T = 0 T = 10	Production cost	144.40	151.63	158.86	166.09	173.32	180.55	187.78
T = 20 T = 30	Warehouse cost	164.20	168.40	172.60	176.80	181.00	185.20	189.40

$$Ot_i \le D_i, i = 1, 2, \ldots, n + \alpha_T \tag{32}$$

In the formulation, objective (18) and (19) are to minimize the total number of used goods aisles, which include internal and hired from cloud goods aisles, and average time in the warehouse. Constraint (20) presents there are no more than two orders in any goods aisle at any moment. Constraint (21) is storage capacity, which is larger than occupied volume. Constraint (22) means the total number of products of order i existing in the warehouse is equals to the demand of order i. Constraint (23) means warehousing time is less than delivery time. Constraint (24) presents the number of used goods aisles is less than the total number of goods aisles including internal and cloud goods aisles at any moment. Constraint (25) presents the number of delivered products must be equals to the number of order demands. Constraint (26) reflects actual delivery time is earlier than the delivery date.

Synchronization rules and applications

As shown in Fig. 7, when dynamics occur, first of all, it is necessary to determine whether dynamics belong to the overall dynamics or local dynamics, if it is overall dynamics, directly start the secondary synchronization; if it is local dynamics, then from the first level of synchronization calculation, and then to calculate whether to address the dynamics, if it can be addressed, then end. If it cannot be handled, jump to the next level of synchronization until the end.

Results Display

The application example of the above-mentioned PL system method is programmed to simulate using the software of the MATLAB 2013a. The instance simulation operating environment configuration parameters are 8GB of memory, Intel (R) Core (TM) i5-2450 M, and Windows 7 64-bit operating system.

Initial plan result

In the initial plan stage, according to the requirements of the case, obtains the actual state of the system through the digital twin architecture, and then uses the cloud server and CO method to obtain the initial plan. The Gantt chart of detailed production plan and storage plan in the initial plan is shown in Fig. 8, on the left is the Gantt chart of the production plan and on the right is the Gantt chart of the storage plan. In the result of the initial plan is shown, of which the production cost is 144.4, the storage cost is 160, and the order tardiness cost is 0.

Corrected plan results

It is assumed that when the PL system performs the initial plan results, equipment failure occurs at the time of T = 0 h, T = 1 h, T = 2 h, and T = 3 h, respectively. At each timestamp, the repair time of the faulty equipment is increasing from 1 h to 7 h. Then we adopt the method proposed in this paper (PLS) and the non-synchronization method (N-PLS), that is, wait for the machine to be repaired before continuing production, and will not assign the tasks on this machine to other equipment, to deal with the dynamic.

The results of the PLS and the N-PLS are shown in Tables 7 and 8.

According to the above results, the later the dynamic occurs, the worse the result will be. In general, the PLS method is better than the N-PLS method. Also, some interesting findings are shown below.

- No matter when the dynamic occurs, under the same dynamic strength, the production cost and storage cost under the non-synchronization mode remains unchanged. That is because, in the non-synchronization mode, the task of the faulty equipment can only be carried out after the equipment is repaired. According to the formula in Section 5.2, when the dynamic occurs, the production cost and storage cost are only affected by the maximum completion time, while the maximum completion time is only affected by the repair time of the equipment. Therefore, the occurrence time of the dynamic will not have any impact on the production cost and storage cost. So, the same dynamic will have the same impact on the system no matter when it occurs.
- When the repair time of the equipment is 1 hour, the production cost remains unchanged regardless of the synchronization method or non-synchronization method, and no matter when the dynamic occurs. This is because, in the initial plan, the end time of the faulty equipment is 1 hour less than the maximum completion time. Therefore, when the repair time is 1 hour, the maximum completion time of the N-PLS and PLS is less than or equal to the initial planning

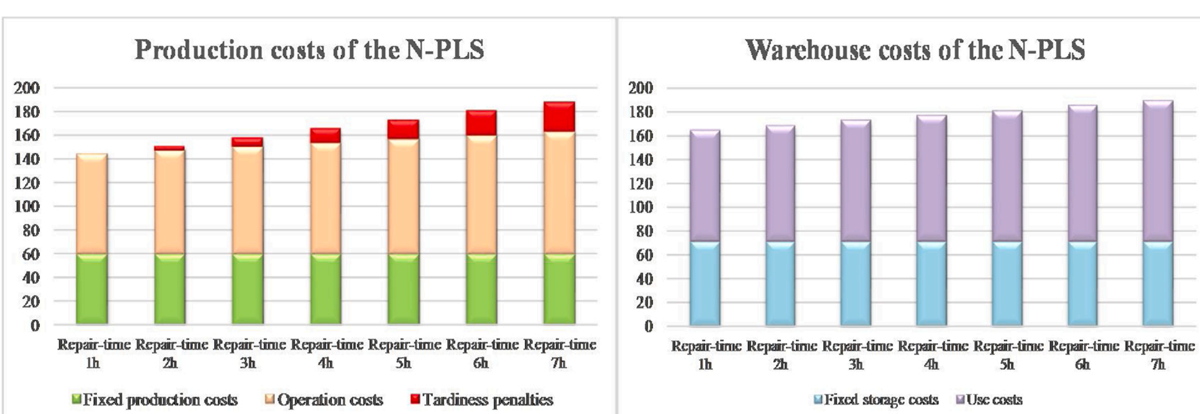

Fig. 9. The production and warehouse cost components of the N-PLS.

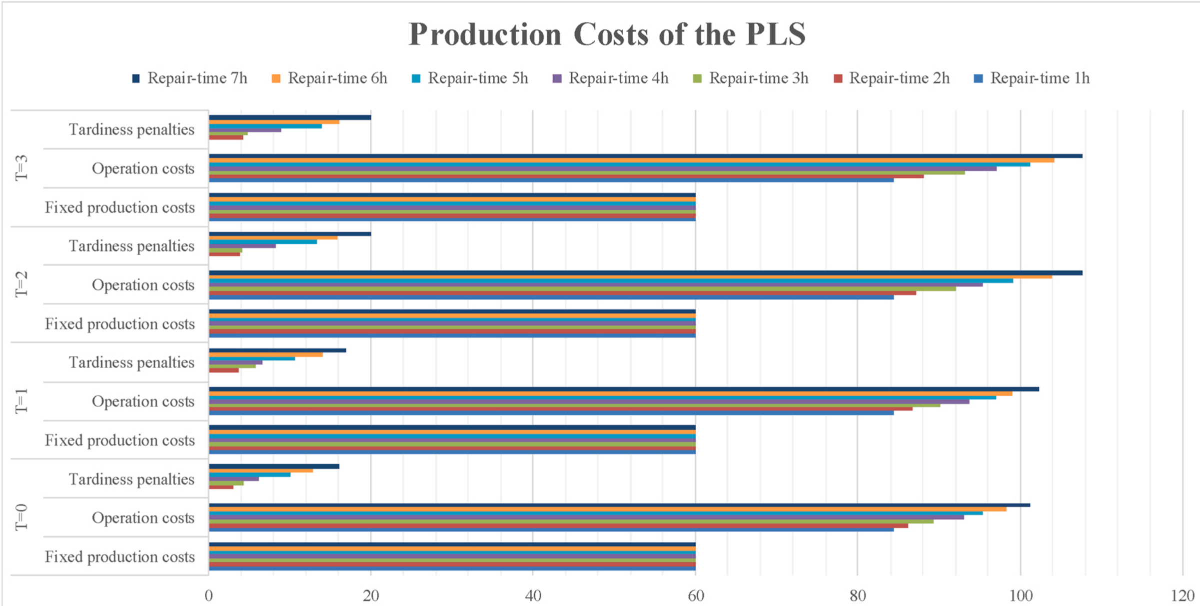

Fig. 10. The production cost components of the PLS.

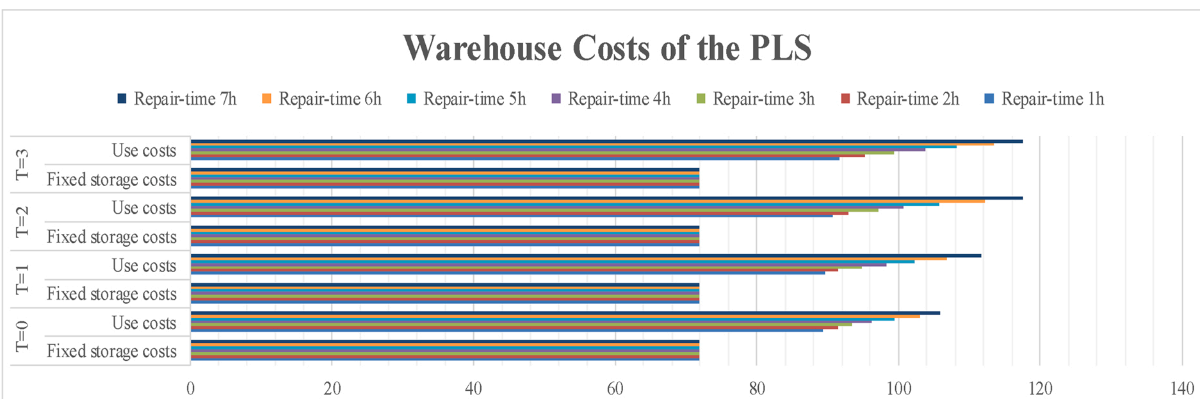

Fig. 11. The warehouse cost components of the PLS.

maximum completion time. Therefore, when the repair time is 1 hour, the production cost will not change whether it is synchronization or not.

- Both production costs and storage costs will increase with the increase of repair time. According to the formula in Section 5.2, with the increase of repair time, the maximum completion time will increase, so the delay time will increase, so the processing cost and delay cost will also increase, so the production cost will increase; besides, the storage time will also increase with the delay time, so the storage cost will also increase.
- With the increase of repair time, the production cost and storage cost under the PLS gradually approach the result of the N-PLS, and finally,

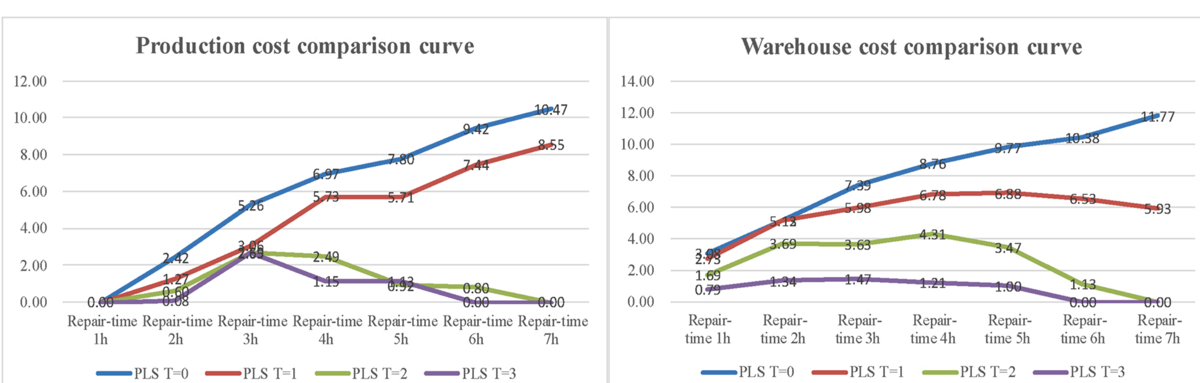

Fig. 12. The cost comparison chart of the PLS and n-pls results.

they reach the same. The reason is that with the increase of dynamic occurrence time and maintenance repair time, the available resources will be less and less, so the space for optimization will be smaller and smaller, and the effect of the synchronization method will be worse and worse until the effect is the same as the un-synchronization.

Sensitivity Analysis

In this section, we will analyze the cost components in detail to find out the reasons why the results differ between the PLS and N-PLS.

As shown in Fig. 9, for the N-PLS, with the increase of dynamic strength, fixed production costs and fixed storage costs did not increase, but operation costs, use costs and tardiness penalties increased. On the surface, the increase of the operation costs, use costs and tardiness penalties are due to the increase of dynamic strength. In fact, the use costs and tardiness penalties are caused by the delay caused by the dynamic, while the increase in operating costs is caused by the increase in maximum completion time caused by the dynamic. This is also the reason for the interesting finding (1).

The composition of the production cost using the PLS method is shown in Fig. 10. In the figure, the fixed production costs are the same regardless of the conditions. This is because the number of devices has not changed. But the operation costs and tardiness penalties are increasing with the dynamic strength and occurrence time. This is because the original production plan (initial production plan) has been disrupted after the occurrence of dynamism, and the production system had to be re-planned. However, due to the constraints of equipment resources, the new plan (corrected production plan) cannot reach the level of the initial production plan. Therefore, the maximum completion time of the corrected production plan will be greater than the maximum completion time of the initial production plan, which will cause the delay.

The composition of the warehouse cost using the PLS method is shown in Fig. 11. As it shows, the fixed storage costs remain unchanged regardless of the conditions, because the number of the aisle has not changed. However, the use costs are increasing with the dynamic strength and occurrence time. The reason is that the initial storage plan was disrupted by the production plan, and the storage system needs to re-plan. The corrected storage plan needs to modify the initial storage plan without interfering with other order storage plans, which will inevitably receive various resource constraints, so the corrected storage plan is not better than the initial storage plan, which will increase the use cost.

In Fig. 12, the curve represents the cost difference between the PLS and NPLS. As shown in Fig. 12, with the increase of dynamic strength and occurrence time, the difference between the PLS and N-PLS is getting smaller and smaller until the end is the same. That means the effect of the PLS will be worse and worse, and it will be the same as the N-PLS in the end. When the equipment failure occurs at T = 0 h and the repair time is 7 h, the production costs and warehouse cost difference between the PLS and N-PLS is the biggest. This means that the earlier the dynamic occurs, the greater the dynamic strength, and the better the effect of the PLS method When the equipment failure occurs at T = 3 h and the repair time is 7 h, the production costs and warehouse cost difference between the PLS and N-PLS is zero. This means the later the dynamic occurs, the greater the dynamic strength, and the worse the effect of the PLS method. Besides, it can be seen from the figure that when the dynamics occur in 2 h and 3 h, and the repair time is 4 hours, the effect of the PLS begins to decline. Therefore, relative to the dynamic strength, the time of dynamic occurrence is the key factor affecting the PLS.

According to the above analysis, in dealing with the problem of dynamic failures of equipment, the advantages of the synchronization method can be obtained. (1) The earlier equipment failure occurs, the higher the benefit of using the synchronization method. (2) The maintenance time of faulty equipment within a reasonable range, the PLS method can bring better profits to the enterprise by making full use of other production equipment and the idle capability of the cargo aisle. (3) The later equipment failure occurs and the greater the dynamic strength, the worse the effect of the PLS.

Conclusions

The equipment failure leads to a series of management problems in the PL system operation process. In order to solve the problem, the dynamics are divided into three levels according to the influence range of dynamics in this paper. And then a Cloud-Fog-Edge based DT architecture for different levels of dynamics to meet the requirements of real-time synchronization control of the DT control system is proposed and extends the TMS synchronization mechanism from the qualitative perspective. As well as the CO algorithm is adopted, aiming at maximizing the benefit from the quantitative perspective. Finally, a case is simulated as an example to prove the feasibility and effectiveness of the synchronization mechanism, and some managerial significances are introduced.

The main contributions of this paper include the following aspects:

- To deal with different levels of dynamics, different levels of DT are proposed based on edge computing, fog computing, and cloud computing.
- Extends the TMS synchronization mechanism from a qualitative perspective.
- This paper discusses the influence of equipment faults of a different time and intensity on the PL system, and provides significant managerial implication to managers to better deal with dynamics.

The limitations of the proposed solution are shown as follows:

- The single cognition dimension of dynamics. Each dynamic has multiple attributes, the time, place, range of influence, etc. From different dimensions, there are different control mechanisms. But, in this paper, both the DT architecture and the synchronization control mechanism are proposed for the dynamic influence range. For the dynamic of different dimensions, by looking for its relationship with the range of impact, and then its influence is transformed into the range of impact, and then the method of this paper is used to control.
- Limitations of research objects. The PL system is a complex large system that contains many stages. In this paper, the two-stage synchronization between production and storage is only considered. If the research objects are larger than two stages, the model of the CO need to change with the number of research objects, also, other large system optimization methods can be used, such as ATC, ALC, etc.

The future works of this research could be summarized as follows. Firstly, two-stage synchronization will be extended to three-stage synchronization. Secondly, the superposition influence of different dynamics on the system will be studied.

Declaration of Competing Interest

The authors report no declarations of interest.

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Appendix A

Tables A1 and A2

Table A1
Parameter description

Notation	Description	Notation	Description
pc_{cost}	production fixed cost	pt_{cost}	production cost in each process
wc_{cost}	warehouse fixed cost	pi_{cost}	single internal goods aisle cost
po_{cost}	single hired goods aisle cost	d_{icost}	delay penalty cost of order i
n	the number of waiting for processing orders	T	time of customer demand change
α_T	number of a new order at T moment	i	index of order, $i = 1, 2, \ldots, n+\alpha_T$
m	total number of process	j	index of process
$S_{i,j}$	jth process of order i	M_j	total number of the parallel machine in process j
k_j	index of the machine in process j, $k = 1, 2, \ldots, M_j$	Q_i	demand quantity of order i which is related to warehouse sub-model
D_i	the delivery date of order i	$pt_{i,j}$	processing time of order i in process j
$y_{i,p}$	production decision variable, $= 1$ if order i is processed in position p	x_{i,j,k_j}	production decision variable, $= 1$ if process j of order i is processed in the machine k_j
$C_{i,m}$	completion time (time point/ moment) of order i in the last process which is related to the warehouse sub-model.	t_{i,j,k_j}	processing time per unit of process j of order i in machine k_j
$st_{i,j}$	the start time of order i in process j	$wt_{i,j}$	waiting time of order i in process j
$C_{i,j}$	completion time (period) of order i in process j	Ot_i	delivery time of order i
w_{in}	total number of internal goods aisle	w_{out}	the available number of cloud goods aisle hired from the cloud platform
l	index of goods aisle, $l = 1, 2, \ldots, w_{in} + w_{out}$	cp_l	the capacity of goods aisle l
$put_{t,i,l}$	warehouse decision variable, $= 1$ if order i is stored in goods aisle l at t moment		
$out_{t,i,l}$	delivery decision variable, $= 1$ if order i is out of goods aisle l at t moment		
$p_{t,i,l}$	when $put_{t,i,l} = 1$, the number of the tray of order i in goods aisle l at t moment, when $put_{t,i,l} = 0$, $p_{t,i,l} = 0$		
$u_{l,t}$	goods aisle decision variable, $= 1$ if goods aisle l is available		

Table A2
Abbreviations

Word	Abbreviations
Production Logistics	PL
Digital Twin	DT
Production Logistics Synchronization	PLS
Multidisciplinary Design Optimization	MDO
Collaborative Optimization	CO
Work in Progress	WIP
Just in Time	JIT
Internet of Things	IoT

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