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RESEARCH ARTICLE

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Exploring self-organization and self-adaption for smart manufacturing complex networks

Abstract Trends toward the globalization of the manufacturing industry and the increasing demands for small-batch, short-cycle, and highly customized products result in complexities and fluctuations in both external and internal manufacturing environments, which poses great challenges to manufacturing enterprises. Fortunately, recent advances in the Industrial Internet of Things (IIoT) and the widespread use of embedded processors and sensors in factories enable collecting real-time manufacturing status data and building cyber–physical systems for smart, flexible, and resilient manufacturing systems. In this context, this paper investigates the mechanisms and methodology of self-organization and self-adaption to tackle exceptions and disturbances in discrete manufacturing processes. Specifically, a general model of smart manufacturing complex networks is constructed using scale-free networks to interconnect heterogeneous manufacturing resources represented by network vertices at multiple levels. Moreover, the capabilities of physical manufacturing resources are encapsulated into virtual manufacturing services using cloud technology, which can be added to or removed from the networks in a plug-and-play manner. Materials, information, and financial assets are passed through interactive links across the networks. Subsequently, analytical target cascading is used to formulate the processes of self-organizing optimal configuration and self-adaptive collaborative control for multilevel key manufacturing resources while particle swarm optimization is used to solve local problems on network vertices. Consequently, an industrial case based on a Chinese engine factory demonstrates the feasibility and efficiency of the proposed model and method in handling typical exceptions. The simulation results show that the proposed mechanism and method outperform the event-triggered rescheduling method, reducing manufacturing cost, manufacturing time, waiting time, and energy consumption, with reasonable computational time. This work potentially enables managers and practitioners to implement active perception, active response, self-organization, and self-adaption solutions in discrete manufacturing enterprises.

Keywords cyber–physical systems, Industrial Internet of Things, smart manufacturing complex networks, self-organization and self-adaption, analytical target cascading, collaborative optimization

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1 Introduction

The manufacturing industry is the physical basis of the national economy, the main body of industry, and the main indicator of economic developments. According to the gross domestic product (GDP) data from the National Bureau of Statistics of China, GDP from manufacturing made up around 32.5% of the total in 2021, ranking only after the service sector. However, the accelerating globalization and the increasing demands for small-batch, short-cycle, and highly customized products result in complexities and fluctuations in both external and internal manufacturing environments, which causes exceptions and disturbances in the manufacturing processes, such as new job arrivals, order changes, and equipment failures. Discrete manufacturing enterprises are especially facing great challenges of control and management processes such as variable process routes, flexible equipment utilization, various types of materials, long manufacturing processes, and complex part supporting relations. Nevertheless, challenges and opportunities coexist. Advanced technologies such as Industrial Internet of Things (IIoT) (Franco et al., 2021), edge-cloud computing (Hastbacka et al., 2022), cyber–physical systems (CPSs) (Guo et al., 2021b), 5G (Nguyen et al., 2021), big data analytics (Cui et al., 2020), and artificial intelligence (Liu et al., 2022) have driven technological innovations and the evolutions of manufacturing paradigms from lean, agile manufacturing (Qamar et al., 2018), cloud manufacturing (Wang et al., 2018), and service-oriented manufacturing (Atmojo et al., 2020; Wang et al., 2021b; Jiang et al., 2022) to smart manufacturing (Zheng et al., 2018; Zhang et al., 2020) and green manufacturing (Lazarou Tarraco et al., 2021), which provides promising opportunities to solve these challenges. Many countries and global manufacturers have also proposed next-generation manufacturing strategies such as Industry 4.0 (MacDougall, 2014) and Industrial Internet (Evans and Annunziata, 2012) to facilitate the research and development of innovative manufacturing techniques.

Generally, discrete manufacturing systems integrated with heterogeneous manufacturing resources including machines, vehicles, and materials can be regarded as a complex system with a collection of components. Self-organization is frequently observed in active collectives such as ant rafts and flocks of birds, in which a large group of separate particles act in an organized manner (Chvykov et al., 2021). To explore the self-organization of discrete manufacturing systems, advanced technologies can offer potential solutions. For example, with the help of IIoT, edge-cloud computing, and communication networks, real-time data can be sensed and captured to model multilevel key manufacturing resources. Thus, they can connect and interact with one another. By leveraging big data analytics and artificial intelligence for decision making and optimization, the whole system can operate stably and efficiently to generate and transport high-quality products. To explore the flexibility and adaptability of discrete manufacturing systems, scheduling/rescheduling has been studied by academics and experts, and widely used as a conventional solution to deal with unpredictive dynamic uncertainties, such as flexible job shop scheduling problem (FJSP) (Lv et al., 2022), flexible job shop rescheduling problem (FJRP) (An et al., 2022), and distributed job shop scheduling problem (DJSP) (Şahman, 2021). However, scheduling and rescheduling are complex and time consuming for large-scale problems. Rescheduling is triggered by typical events passively or periodically and causes system nervousness. To improve the intelligence, flexibility, and resilience of discrete manufacturing systems, the topic of dynamic collaboration and networked control has attracted increasing attention from academic and industry communities (Si et al., 2020; Guo et al., 2021b; Wu and Li, 2021). Predecessors have studied flexible manufacturing systems (Chen et al., 2017), production logistics synchronization (Qu et al., 2016), and smart manufacturing paradigms (Kusiak, 2017) for solving system dynamics. To achieve networked control, scholars have focused on network modeling and synchronization (Wu et al., 2018), supply–demand matching hypernetwork (Cheng et al., 2020), and network reliability (Wang et al., 2019). As a few works have explored self-organization and self-adaption for discrete manufacturing systems, existing methods are insufficient to address the emerging challenges and problems in future IIoT-based networked discrete manufacturing environments. These challenges are summarized as follows.

(1) Advances in technologies including CPSs and IIoT and their industrial applications bring new changes to contemporary manufacturing environments. Networked control requires the high integration and collaboration of heterogeneous manufacturing resources, such as machines, vehicles, and materials. Passive response is replaced by active response while the control of manufacturing processes is more collaborative and accurate. In terms of decision making, assignment is replaced by consultation. To deal with these new changes, the self-organization and self-adaption mechanisms of discrete manufacturing systems need to be investigated further and precisely comprehended.

(2) To implement self-organization and self-adaption in discrete manufacturing systems, new demands arise in the modeling of smart manufacturing services on the shop floor. To ensure real-time bidirectional interaction and interoperability between top-level manufacturing systems and lower-level key manufacturing resources, new demands also arise in the perception of real-time manufacturing service status. Thus, a deeper integration of manufacturing resources in the physical world and manufacturing services in cyber space is needed. Based on the above, smart manufacturing services, with a higher level of intelligence in communication, decision making, and perceptible service status, can be flexibly connected to discrete manufacturing systems.

(3) The self-organization and self-adaption of discrete manufacturing systems require good performances of manufacturing services including agile response, dynamic collaboration, and self-adaptive elimination of exceptions in operational processes. In the context of advanced manufacturing paradigms, the demand for efficient manufacturing processes also needs the real-time interaction and collaboration of heterogeneous manufacturing resources. Therefore, the mechanisms and methodology of self-organizing optimal configuration and self-adaptive

collaborative control for multilevel key manufacturing resources are needed to tackle typical exceptions and disturbances in discrete manufacturing processes.

To address the above challenges, the mechanisms and methodology of self-organization and self-adaption are investigated for networked discrete manufacturing systems. In the context of IIoT-based complex manufacturing environments, real-time manufacturing status data are collected and processed to build CPSs for smart, flexible, and resilient manufacturing systems. In the physical world, discrete manufacturing systems generally consist of heterogeneous manufacturing resources such as machines, vehicles, and materials. In cyber space, a general model of smart manufacturing complex networks (SMCNs) is developed using scale-free networks to interconnect heterogeneous manufacturing resources represented by network vertices at multiple levels. Moreover, the capabilities of physical manufacturing resources are encapsulated into virtual manufacturing services using cloud technology, which can be added to or removed from the networks in a plug-and-play manner. Materials, information, and financial assets are passed through interactive links across the networks. Subsequently, analytical target cascading (ATC) is used to formulate the processes of self-organizing optimal configuration and self-adaptive collaborative control for multilevel key manufacturing resources while particle swarm optimization (PSO) is used to solve local problems on network vertices. Consequently, an industrial case based on a Chinese engine factory demonstrates the feasibility and efficiency of the proposed model and method in handling typical exceptions considering four key performance indicators (KPIs), namely, manufacturing cost, manufacturing time, waiting time, and energy consumption. This work potentially enables managers and practitioners to implement active perception, active response, self-organization, and self-adaption solutions in discrete manufacturing enterprises.

The remainder of this paper is organized as follows. In Section 2, a literature review of the related works and the motivation are introduced. In Section 3, an overall architecture of SMCNs is constructed to integrate heterogeneous manufacturing resources. In Section 4, the mechanisms and methodology of self-organization and self-adaption are proposed for SMCNs. In Section 5, an industrial case based on a Chinese engine factory is presented to validate the feasibility and efficiency of the proposed model and method. In Section 6, the conclusions and future research are discussed.

2 Related work and motivation

Three categories of literature are related to this paper: 1) enabling technologies including IIoT, edge-cloud computing, and CPSs; 2) existing scheduling and rescheduling methods for exception handling; and 3) self-organization and self-adaption in the manufacturing industry. The contributions of these works are highlighted, and the motivation of this paper is presented.

2.1 IIoT, edge-cloud computing, and CPSs

The Internet of Things (IoT) technology has been widely used for the interconnection of smart devices and management platforms. IIoT is a natural evolution of IoT, which provides many promising opportunities to develop smart manufacturing systems and industrial applications (Liao et al., 2018). Using radio-frequency identification (RFID) technology, automatic identification systems are capable of sensing, identifying, tracking, and tracing (Ding et al., 2017). In real-life scenarios, IoT and cloud computing are deployed together more pervasively. Botta et al. (2016) investigated and surveyed the integration of IoT and cloud. Cloud computing enables ubiquitous network access to storage and computing resources, supporting information technology services and applications in an on-demand manner (Saikrishna et al., 2017). Especially in the case of online services and applications, cloud computing can provide fast, cost-effective resource allocation solutions (Díaz et al., 2017; Guo et al., 2021a). As the recent exponential growth of IoT services becomes a burden to the traditional cloud platform, edge computing is an emerging solution moving computing resources close to data sources to satisfy real-time demands (Pham et al., 2022). For example, edge-cloud computing can host the emerging CPSs integrating physical processes and digital computing systems. Many research efforts have been made toward the implementation of CPSs for smart manufacturing (Wang and Haghighi, 2016). Self-manageable, adaptive industrial CPSs are realized using self-manageable agents, which can rapidly respond to changes in production environments (Dai et al., 2017). To integrate heterogeneous CPSs, Jirkovsky et al. (2017) proposed a semantic heterogeneity reduction method for data integration. CPSs and digital twins (DTs) share the same essential concepts of an intensive cyber–physical connection, real-time interaction, organization integration, and in-depth collaboration; thus, DTs are considered necessary foundations and paths to realize CPSs (Tao et al., 2019).

2.2 Existing scheduling/rescheduling methods for exception handling

Flexibility is the ability to respond and adapt to environmental changes. Academics and experts have studied flexible job shop scheduling/rescheduling problems such as FJSP, FJRP, and DJSP. Türkyılmaz et al. (2020) reviewed various heuristic methods for solving multi-objective FJSP. To minimize makespan, energy consumption, and instability, Caldeira et al. (2020) proposed a backtracking search algorithm for multiobjective FJSP considering new job arrivals. In the case of dual resource-constrained FJSP, Wu et al. (2021) proposed a similarity-based scheduling algorithm to reduce setup time. In addition, adaptability has been studied for manufacturing systems in a dynamic, non-deterministic environment. As rescheduling serves for the adaption of initial schedules to dynamic events, Lv et al. (2022) proposed rescheduling decision mechanisms for new job arrivals and machine breakdowns in energy efficient FJSP. To reach a trade-off between rescheduling frequency and the accumulation of delays, Li et al. (2020) proposed a rescheduling method combing machine learning techniques and optimization algorithms. Wang et al. (2021a) proposed a dual Q-learning method to enhance adaptability to environmental changes in assembly job shops. During feature selection, Zhang et al. (2021) proposed individual adaptation strategies to utilize the information of features and individuals for dynamic FJSP. Different from traditional scheduling with a single decision maker in a centralized manner, Bukchin and Hanany (2020) studied decentralized job shop scheduling problems using non-cooperative game theory to minimize flow time. In economic globalization, manufacturing enterprises require multiple-factory networks to adapt to changing market demands and dynamic events. In this context, Şahman (2021) proposed a discrete spotted hyena optimizer for solving DJSP. By integrating reconfigurable machines with the rescheduling module, Mahmoodjanloo et al. (2022) proposed a self-adaptive hybrid equilibrium optimizer for DJSP. However, scheduling and rescheduling are complex and time consuming for large-scale problems. Rescheduling is triggered by typical events passively or periodically and causes system nervousness.

2.3 Self-organization and self-adaption in the manufacturing industry

Discrete manufacturing systems integrated with heterogeneous manufacturing resources are regarded as complex systems with a collection of components. In the context of large-scale systems, complex networks have attracted much attention from the academia and industry in recent years (Tang et al., 2014). Random networks (Aljadeff et al., 2015), scale-free networks (Kleineberg, 2017), small-world networks (Malkov and Yashunin, 2020), clustered random networks (Hackett et al., 2011), and core–periphery networks (Verma et al., 2016) have been used to formulate the topological structures of complex networks. For instance, the concept of global production networks (GPNs) and a framework for designing and operating GPNs have been proposed recently (Lanza et al., 2019). In this work, uncertainty, complexity, sustainability, and disruptive innovation are considered as challenges for GPNs. In discrete manufacturing systems, self-organization is a process where heterogeneous manufacturing resources form stable structures with many interactive links that pass materials and information by vertices of networks (Chertow and Ehrenfeld, 2012). For example, Zhang et al. (2018) proposed self-organizing configuration mechanisms to strengthen integration between production and logistics in job shops. Focused on highly dynamic environments, Dias-Ferreira et al. (2018) proposed a bio-inspired self-organizing architecture for manufacturing systems to ensure performance levels and simplify deployment and reconfiguration procedures. As the cross-linking of embedded systems creates adaptive, self-organizing cyber–physical production systems (CPPSs), Berger et al. (2021) classified CPPS entities and illustrated their relations. To address unpredictive dynamic uncertainties including external and internal exceptions, self-adaption has been studied by academics and experts. For instance, Guo et al. (2017) studied self-adaptive collaboration for IoT-enabled production–logistics systems using timed colored Petri nets. In the case of anomaly detection with unknown patterns and dependencies, Singer and Cohen (2021) proposed a framework for self-adaptive smart control using adaptive machine learning models. To adapt to changes dynamically, Hsieh and Lin (2016) proposed a viable self-adaption scheme to reconfigure agents and services based on an architecture of holonic multiagent systems. Moreover, a self-adaptive collaborative control mode has been proposed for smart production–logistics systems to enhance the capability of intelligence, flexibility, and resilience (Guo et al., 2021b). However, great challenges still exist in specific complex manufacturing situations such as dynamic collaboration and networked control. Therefore, the mechanisms and methodology of self-organization and self-adaption is worthy of study for discrete manufacturing processes to handle dynamic events such as new job arrivals, order changes, and equipment failures.

2.4 Motivation

To deal with unpredictive dynamic uncertainties including external and internal exceptions in manufacturing environments, scheduling/rescheduling has been widely used as a conventional solution. However, existing scheduling/rescheduling methods are complex and time consuming for large-scale problems. Rescheduling is triggered by typical events passively or periodically and causes system nervousness. Fortunately, emerging advanced technologies such as IIoT, edge-cloud computing, CPSs, and DTs can be implemented in factories to collect and process the real-time manufacturing status data of key manufacturing resources for decision making and optimization. Nevertheless, the existing literature is insufficient to study the collaboration of dynamic complex networks in discrete manufacturing systems. Thus, this paper investigates the mechanisms and methodology of self-organization and self-adaption for networked discrete manufacturing systems. The main contributions of this paper include three aspects: 1) A general model of SMCNs is developed using scale-free networks to interconnect heterogeneous manufacturing resources represented by network vertices at multiple levels. Materials, information, and financial assets are passed through interactive links across the networks. 2) The capabilities of physical manufacturing resources are encapsulated into virtual manufacturing services using cloud technology, which can be added to or removed from the networks in a plug-and-play manner. 3) Subsequently, ATC is used to formulate the processes of self-organizing optimal configuration and self-adaptive collaborative control for multilevel key manufacturing resources while PSO is used to solve local problems on network vertices.

3 Overall architecture of smart manufacturing complex networks

Within the context of Industry 4.0, discrete manufacturing enterprises seek to generate high-quality products with low cost, less time, high efficiency, and long-term sustainability. Recent advances in technologies such as IIoT, edge-cloud computing, CPSs, and DTs have provided promising opportunities to collect and process real-time status data for modeling, monitoring, evaluation, decision making, and optimization. By leveraging these technologies, a three-layer system architecture of SMCNs is proposed to connect and interact with heterogeneous physical manufacturing resources and virtual computational resources. SMCNs represent a high level of organization and control in discrete manufacturing systems, offering tremendous potential for the improvement of intelligence, flexibility, and resilience. In Fig. 1, the overall architecture of SMCNs includes three layers, namely, physical world, cyber space, and complex networks.

In the physical world of job shops, raw materials are processed by a sequence of machines and then transported by vehicles between production cells. Moreover, a decentralized control and management system connects these physical entities and represents their relationships. IIoT technologies such as RFID and sensors are widely used to capture the real-time status data of heterogeneous manufacturing infrastructures including machines, vehicles, raw materials, and work in process (WIP). Embedded processors and communication modules on key manufacturing resources such as machines and vehicles are used to preprocess, aggregate, and transmit the collected data to cyber space. Consequently, active perception is realized by collecting and transmitting the real-time status data of physical entities through sensors and wireless communication networks such as 5G, Wi-Fi, Bluetooth, ZigBee, LoRa, and Sigfox.

In cyber space, the multisource, multidimensional, and real-time manufacturing status information of heterogeneous physical manufacturing resources such as WIPs, machines, and vehicles are stored as data cubes in the data warehouse. As a way to realize CPSs, the DT technology is used to establish the mapping relationships of physical entities and virtual representations. The capabilities of physical entities are encapsulated into virtual manufacturing services using cloud technology. DT models synchronize the real-time status and dynamic behaviors of physical entities with virtual models including virtual WIPs, machines, and vehicles. Big data analytics

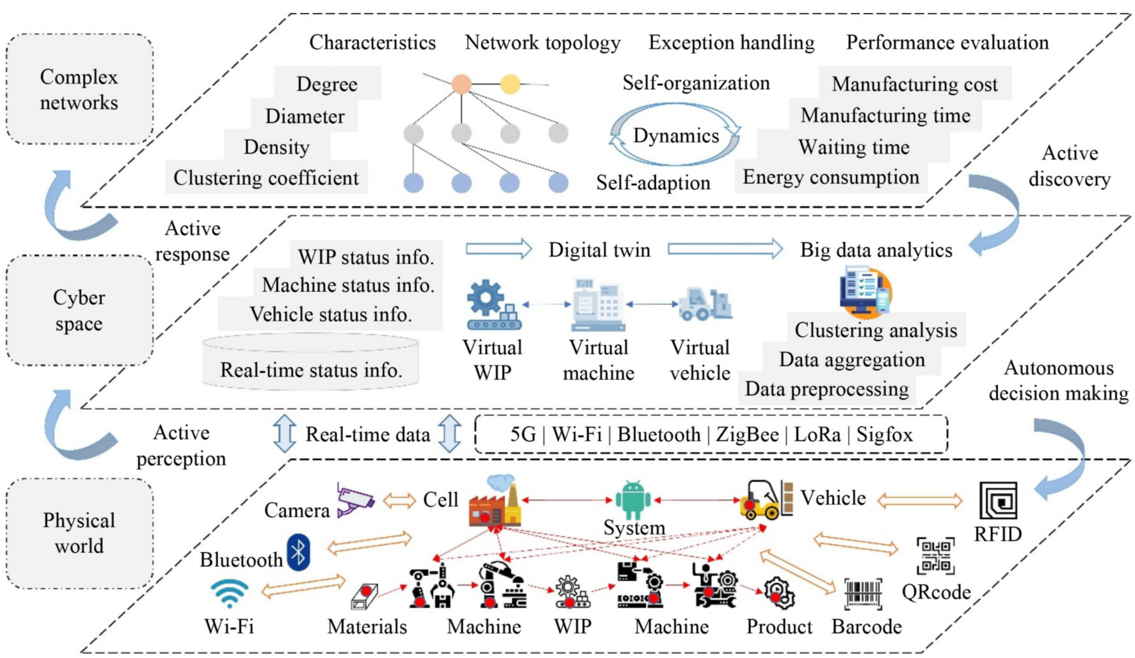


Fig. 1 Overall architecture of smart manufacturing complex networks.

is used to process and analyze large-scale real-time data for data preprocessing, aggregation, and clustering analysis. As a result, autonomous decision making on key manufacturing resources is achieved by integrating DT models and the extracted knowledge. The active response of manufacturing services is formed when exceptions and disturbances occur in discrete manufacturing processes.

In complex networks, network characteristics including degree, diameter, density, and clustering coefficient are analyzed. SMCNs consist of hubs with higher degrees and vertices with lower degrees. For example, a job shop system is a hub connected to production cells and vehicles, and a production cell is also a hub connected to machines. Thus, system and cell hubs have higher degrees, but the machine and vehicle vertices at the bottom have lower degrees. These hubs and vertices can pass materials, information, and financial assets through interactive links across the networks. Based on the power flow of degree distribution, a general model of SMCNs is constructed using scale-free networks to interconnect heterogeneous manufacturing resources represented by network vertices at multiple levels. To handle typical exceptions and dynamics, ATC is used to formulate the processes of self-organizing optimal configuration and self-adaptive collaborative control for multilevel key manufacturing resources while PSO is used to solve local problems on network vertices. The performance of SMCNs is evaluated using four KPIs, namely, manufacturing cost, manufacturing time, waiting time, and energy consumption. Active discovery is realized by adding or removing virtual manufacturing services in SMCNs in a plug-and-play manner.

Figure 2 illustrates the mechanisms of self-organization and self-adaption in SMCNs. At the initial stage, a new or change order arrives in the job shop, and then the order is decomposed into a series of manufacturing tasks including production tasks and logistics tasks. During the manufacturing execution stage, a process flow is first formed according to the requirements, and then SMCNs configures a set of optimal manufacturing services to finish these tasks in a self-organizing manner. When an exception occurs, the self-organizing optimal configuration for manufacturing services is executed again until all tasks are finished. At the same time, the whole discrete manufacturing system is divided into a three-layer ATC hierarchy, namely, the system, cell, and equipment levels. Then, the optimization targets are first input into the system-level ATC element while the local problem at the system level is solved using PSO. Subsequently, targets are propagated to lower-level ATC elements until reaching the bottom ATC elements. When the optimization results of the local problem at a lower level cannot meet the cascaded targets, responses are sent to the upper-level ATC element for the redivision and propagation of targets. Self-adaptive collaborative control is realized using multiple-granularity solutions including the nodal, local, and global networks to handle the corresponding scale of exceptions. Moreover, self-adaptive collaboration

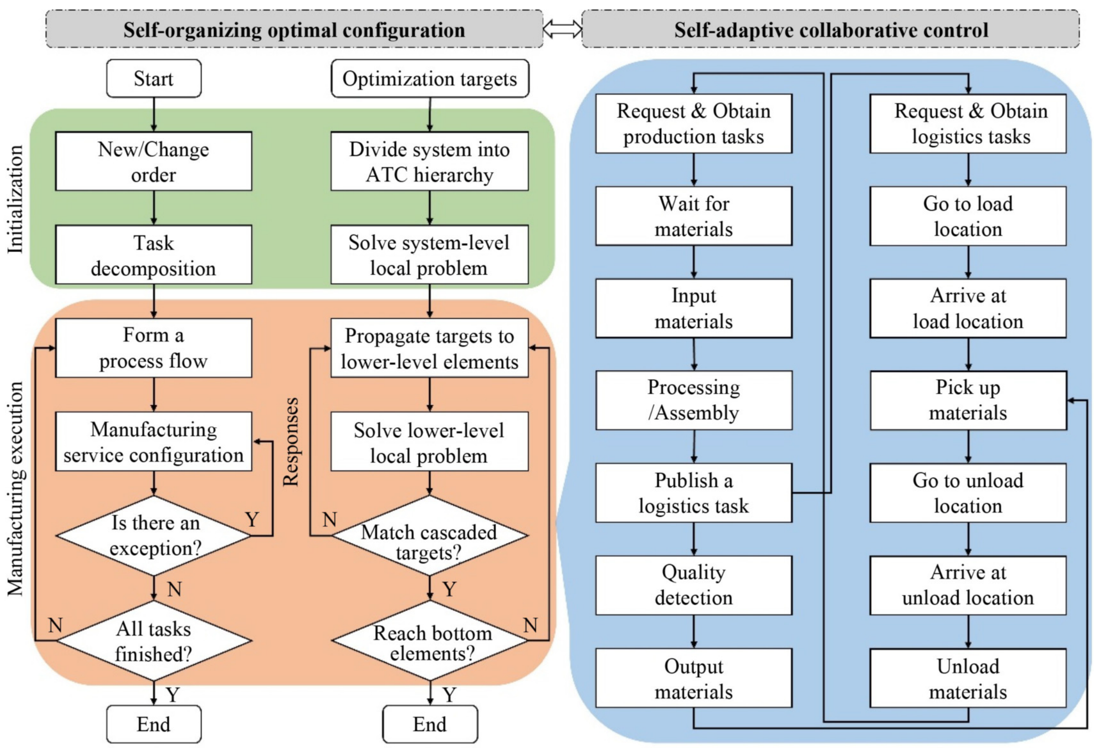


Fig. 2 Mechanisms of self-organization and self-adaption.

between production and logistics is achieved by machines and vehicles requesting tasks actively instead of being assigned tasks passively. For example, once a production task is published on the cloud platform, all machines actively request the production task. When a machine begins processing or assembly and publishes a logistics task, all vehicles actively request the logistics task and the nearest vehicle with enough space is selected as the optimal vehicle.

Overall, self-organization can form a stable network structure with vertices passing materials, information, and financial assets through interactive links across SMCNs. Self-adaption can deal with typical exceptions and dynamics such as new job arrivals, order changes, and equipment failures. When a failure occurs, the virtual representation in cyber space can perceive the real-time status of the corresponding equipment in the physical world, and the corresponding vertex is removed from SMCNs. If the equipment maintenance or procurement is completed, the virtual representation in cyber space can synchronize its real-time status and behaviors of the physical entity, and then the corresponding vertex is added in SMCNs. As a consequence, the network topology of SMCNs and the finite set of optional manufacturing services are updated in a timely manner.

4 General model of smart manufacturing complex networks

Mathematically, SMCNs can be formulated by scale-free networks, which are defined as a graph $G = (V, E)$ with a finite nonempty set V of vertices (nodes) and a set E of edges representing links between all connected vertices. Figure 3 depicts the network topology of SMCNs, where a few hubs have large degrees, and the great majority of vertices have small degrees. Thus, the scale-free property of SMCNs meets the power law of degree distribution. SMCNs include four types of vertices, namely, systems, cells, machines, and vehicles. In SMCNs, the major system hubs have the highest degree, followed by the cell hubs with lower degrees, and the machine and vehicle vertices have the lowest degree. The vertex set in Fig. 3 can be defined as $V = S \cup C \cup M \cup Veh$, where $S = \{s_1, s_2, ..., s_5\}$ represents a finite set of the system hubs, $C = \{c_1, c_2, ..., c_{11}\}$ represents a finite set of the cell hubs, $M = \{m_1, m_2, ..., m_{24}\}$ represents a finite set of the machine vertices, and $Veh = \{v_1, v_2, ..., v_{12}\}$ represents a finite set of the vehicle vertices. The edge set is defined as $E \subseteq \{(i, j) | i, j \in V\}$, where the interactive links between vertices represent the flows of materials, information, and financial assets. Specifically, the information flow is assumed to be bidirectional between any connected vertices.

The scale-free property of SMCNs is described by the

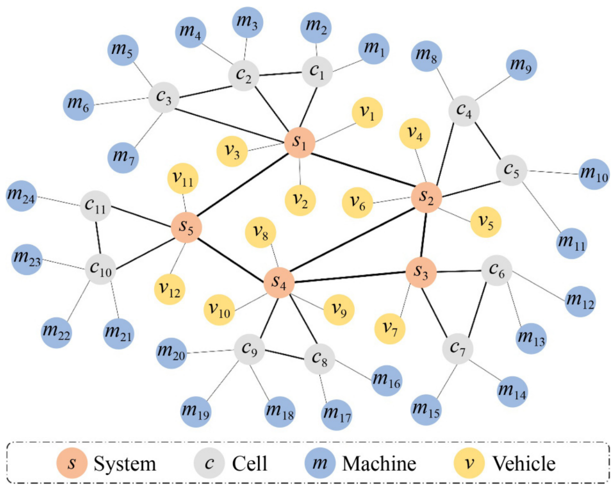


Fig. 3 Network topology of smart manufacturing complex networks.

power law of degree distribution, which can be formulated as follows

$$P(k) \sim k^{-\gamma}, \tag{1}$$

where k denotes the degree, and γ denotes the scaling exponent. In terms of γ with a fixed value, the number of vertices with k degree decreases when the degree k increases.

Based on the feature of hierarchical structure in SMCNs, ATC is used to formulate the processes of self-organizing optimal configuration and self-adaptive collaborative control for multilevel key manufacturing resources. As a model-based collaborative optimization method, ATC has been used for the design optimization of hierarchical multilevel systems (Tosserams et al., 2006). In the case of SMCNs, a three-layer ATC hierarchy model is constructed including the system, cell, and equipment levels. The ATC elements at each level are coupled with target and response variables and connected to their parent (dominator) and/or children ATC elements. Figure 4 illustrates the information flow of the proposed ATC model. The optimization targets are first input into the system-level ATC element while the local problem at the system level is solved using intelligent optimization algorithms. Targets at the system-level ATC element are then decomposed and propagated down to lower-level ATC elements until terminal ATC elements. Responses from lower-level ATC elements are used to rebalance and adjust the target decomposition at upper-level ATC elements iteratively. For instance, if the optimization results of the local problem at lower levels cannot meet the cascaded targets from the upper level, responses are sent to the upper-level ATC element for the redivision and propagation of targets. Thus, collaborative optimization is realized by iteratively minimizing the deviations between the targets from the parent ATC elements and responses from the children ATC elements.

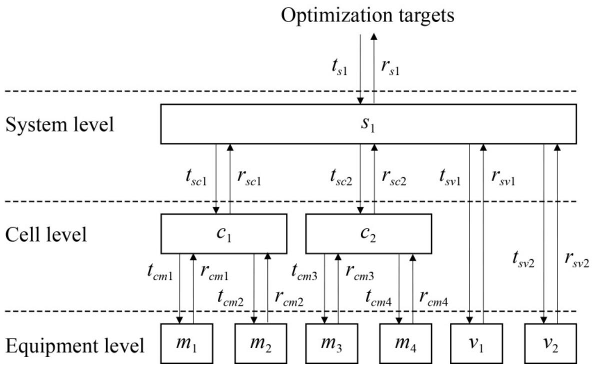


Fig. 4 Information flow of the proposed analytical target cascading model (notes: t represents for the targets, and r stands for the responses).

Considering the actual needs of discrete manufacturing enterprises for the cost, time, efficiency, and sustainability, four KPIs are considered as optimization targets of SMCNs, namely, manufacturing cost, manufacturing time, waiting time, and energy consumption. Waiting time refers to the duration before manufacturing resources are available. For example, the raw materials wait in the input buffer of a machine until the current processing is completed; after processing, WIPs wait in the output buffer of a machine until a vehicle arrives and loads them. During manufacturing execution, each production task can only be processed on one machine every time, and the production task being processed cannot be interrupted. In the case of logistics, each logistics task can only be transported by one vehicle every time.

For simplification, all variables in the proposed ATC model are normalized to eliminate the effect of different units and sizes, which is executed as follows

$$g_l = \frac{g'_l - g_{\min}}{g_{\max} - g_{\min}}, \tag{2}$$

where g_l denotes the lth normalized variable value, and g'_l denotes the lth original variable value. $g_{\max}$ and $g_{\min}$ denote the maximum and minimum of variable g, respectively.

Therefore, the objective function of the proposed ATC model is formulated as follows

$$\min \sum_{i \in S} \left(\omega_{\mathrm{C}} C_i + \omega_{\mathrm{T}} T_i + \omega_{\mathrm{W}} W_i + \omega_{\mathrm{E}} E_i \right), \tag{3}$$

where C_i, T_i, W_i, E_i denote the manufacturing cost, manufacturing time, waiting time, and energy consumption of the system-level ATC element i, respectively. ω_{C}, ω_{T}, ω_{W}, ω_{E} denote the weighting coefficients of the manufacturing cost, manufacturing time, waiting time, and energy consumption, respectively.

At the system-level ATC element i, C_i, T_i, W_i, E_i are formulated as follows

$$C_i = \sum_{j \in \varphi_i \cap C} C_j + \sum_{j \in \varphi_i \cap Veh} \alpha_j C_j, \tag{4}$$

$$T_i = \sum_{j \in \varphi_i \cap C} T_j + \sum_{j \in \varphi_i \cap Veh} \alpha_j T_j, \tag{5}$$

$$W_i = \sum_{j \in \varphi_i \cap C} W_j + \sum_{j \in \varphi_i \cap Veh} \alpha_j W_j, \tag{6}$$

$$E_i = \sum_{j \in \varphi_i \cap C} E_j + \sum_{j \in \varphi_i \cap Veh} \alpha_j E_j, \tag{7}$$

$$\sum_{j \in \varphi_i \cap Veh} \alpha_j = 1, \tag{8}$$

where φ_i denotes a finite set of children vertices to the system-level ATC element i. α_j denotes a Boolean variable of lower-level ATC element j : $\alpha_j = 1$ when vertex j is selected and $\alpha_j = 0$ otherwise.

At the cell-level ATC element i, C_i, T_i, W_i, E_i are formulated as follows

$$C_i = \sum_{j \in \varphi_i} \alpha_j C_j, \tag{9}$$

$$T_i = \sum_{j \in \varphi_i} \alpha_j T_j, \tag{10}$$

$$W_i = \sum_{j \in \varphi_i} \alpha_j W_j, \tag{11}$$

$$E_i = \sum_{j \in \varphi_i} \alpha_j E_j, \tag{12}$$

$$\sum_{j \in \varphi_i} \alpha_j = 1, \tag{13}$$

where φ_i denotes a finite set of children vertices to the cell-level ATC element i. α_j denotes a Boolean variable of lower-level ATC element j : $\alpha_j = 1$ when vertex j is selected and $\alpha_j = 0$ otherwise.

At the equipment-level ATC element i, C_i, T_i, W_i, E_i are formulated as follows

$$C_i = \sum_{ms_{i,h} \in MS_i} \beta_{ms_{i,h}} mc_{ms_{i,h}}, \tag{14}$$

$$T_i = \sum_{ms_{i,h} \in MS_i} \beta_{ms_{i,h}} \left(st_{ms_{i,h}} + mt_{ms_{i,h}} \right), \tag{15}$$

$$W_i = \sum_{ms_{i,h} \in MS_i} \beta_{ms_{i,h}} wt_{ms_{i,h}}, \tag{16}$$

$$E_i = \sum_{ms_{i,h} \in MS_i} \beta_{ms_{i,h}} ec_{ms_{i,h}}, \tag{17}$$

$$\sum_{ms_{i,h} \in MS_i} \beta_{ms_{i,h}} = 1, \tag{18}$$

where MS_i denotes a finite set of manufacturing services to the equipment-level ATC element i, and $ms_{i,h}$ denotes the hth manufacturing service of MS_i. $mc_{ms_{i,h}}$, $st_{ms_{i,h}}$, $mt_{ms_{i,h}}$, $wt_{ms_{i,h}}$, $ec_{ms_{i,h}}$ denote the manufacturing cost, setup time, manufacturing time, waiting time, and energy consumption of manufacturing service $ms_{i,h}$, respectively. $\beta_{ms_{i,h}}$ denotes a Boolean variable of manufacturing service $ms_{i,h}$: $\beta_{ms_{i,h}} = 1$ when service $ms_{i,h}$ is selected and $\beta_{ms_{i,h}} = 0$ otherwise.

Collaborative optimization is realized by the rebalance and adjustment between targets and responses for multi-level ATC elements. To minimize the deviations between optimization targets from the parent (dominator) ATC element and responses from lower-level ATC elements, the objective function of the local problem at each ATC element is formulated as follows

$$\min\left\|\omega_{\mathrm{C}}\left(t_i^{\mathrm{C}}-r_i^{\mathrm{C}}\right),\ \omega_{\mathrm{T}}\left(t_i^{\mathrm{T}}-r_i^{\mathrm{T}}\right),\ \omega_{\mathrm{W}}\left(t_i^{\mathrm{W}}-r_i^{\mathrm{W}}\right),\ \omega_{\mathrm{E}}\left(t_i^{\mathrm{E}}-r_i^{\mathrm{E}}\right)\right\|_2^2 + \sum_{j\in\varphi_i}\left(\varepsilon_j^{\mathrm{C}}+\varepsilon_j^{\mathrm{T}}+\varepsilon_j^{\mathrm{W}}+\varepsilon_j^{\mathrm{E}}\right) \tag{19}$$

$$\textit{subject to}\quad r_i^{\mathrm{C}}=C_i,\ r_i^{\mathrm{T}}=T_i,\ r_i^{\mathrm{W}}=W_i,\ r_i^{\mathrm{E}}=E_i, \tag{20}$$

$$r_j^{\mathrm{C}}=C_j,\ r_j^{\mathrm{T}}=T_j,\ r_j^{\mathrm{W}}=W_j,\ r_j^{\mathrm{E}}=E_j, \tag{21}$$

$$\left\|t_j^{\mathrm{C}}-r_j^{\mathrm{C}}\right\|_2^2 \leqslant \varepsilon_j^{\mathrm{C}},\ j\in\varphi_i, \tag{22}$$

$$\left\|t_j^{\mathrm{T}}-r_j^{\mathrm{T}}\right\|_2^2 \leqslant \varepsilon_j^{\mathrm{T}},\ j\in\varphi_i, \tag{23}$$

$$\left\|t_j^{\mathrm{W}}-r_j^{\mathrm{W}}\right\|_2^2 \leqslant \varepsilon_j^{\mathrm{W}},\ j\in\varphi_i, \tag{24}$$

$$\left\|t_j^{\mathrm{E}}-r_j^{\mathrm{E}}\right\|_2^2 \leqslant \varepsilon_j^{\mathrm{E}},\ j\in\varphi_i, \tag{25}$$

$$r_j^{\mathrm{C}},\ r_j^{\mathrm{T}},\ r_j^{\mathrm{W}},\ r_j^{\mathrm{E}} \geqslant 0,\ j\in\varphi_i, \tag{26}$$

where $\left(t_i^{\mathrm{C}}, t_i^{\mathrm{T}}, t_i^{\mathrm{W}}, t_i^{\mathrm{E}}\right)$ and $\left(r_i^{\mathrm{C}}, r_i^{\mathrm{T}}, r_i^{\mathrm{W}}, r_i^{\mathrm{E}}\right)$ denote the target/response variables of the ATC element i including manufacturing cost, manufacturing time, waiting time, and energy consumption, respectively, and $\left(\varepsilon_j^{\mathrm{C}}, \varepsilon_j^{\mathrm{T}}, \varepsilon_j^{\mathrm{W}}, \varepsilon_j^{\mathrm{E}}\right)$ denotes small positive thresholds.

Intelligent optimization algorithms can be used to solve the local problems at ATC elements (network vertices). For example, as a stochastic population-based optimization technique, PSO has been used to tackle discrete optimization problems (Rezaee Jordehi and Jasni, 2015). The PSO method is initialized with a swarm of particles in a multi-dimensional search space. Each particle represents a candidate solution for the optimization problems characterized by four attributes, namely, position x_i, velocity vc_i, individual best position p_{id} found by the particle, and global best position p_{gd} found by the whole swarm. During the search, the velocity and position of each particle in the nth iteration are updated using Eqs. (27) and (28), respectively.

$$vc_i^{n+1} = \omega vc_i^n + ct_1 rd_1\left(p_{\mathrm{id}}^n - x_i^n\right) + ct_2 rd_2\left(p_{\mathrm{gd}}^n - x_i^n\right), \tag{27}$$

$$x_i^{n+1} = x_i^n + vc_i^{n+1}, \tag{28}$$

where ω denotes the inertia weight, ct_1 and ct_2 are constants, and rd_1 and rd_2 are random numbers with a uniform distribution, rd_1, $rd_2 \in [0, 1]$.

Additionally, twofold termination criteria are used to ensure a feasible computational time of the proposed ATC model, namely, the maximum number of iterations and the relative error of objective function values. Once a termination criterion is fulfilled, the iteration of rebalance and adjustment between targets and responses is stopped. The relative error of objective function values is given as follows

$$\frac{\left|f_i^n - f_i^{n-1}\right|}{f_i^{n-1}} \leqslant \varepsilon_i, \tag{29}$$

where f_i^n denotes the objective function value of the local problem at ATC element i in the nth iteration, and ε_i denotes a small positive threshold.

5 Case study

To demonstrate the feasibility and efficiency of the proposed model and method for handling typical exceptions, an industrial case is introduced based on a Chinese engine factory. This factory is a discrete manufacturing enterprise, owning multiple job shops for engine production and assembly. Based on the investigation and real-life scenarios of the collaborative enterprise, the proof-of-concept prototype systems of the job shop is constructed, as shown in Fig. 5. The physical infrastructure resources include seven types of machines, three types of vehicles, and an automated storage and retrieval system. Raw materials and WIPs are processed on machines and transported by vehicles between production cells. The real-time status information of equipment and the location information of materials are collected using RFID devices including RFID readers and tags as well as infrared sensors. The control of machines and vehicles and the data transmission and reception are executed by the embedded STM32F103ZET6 processors with 512 kB flash and 64 kB SRAM. An edge-cloud collaborative system is constructed to integrate heterogeneous manufacturing resources with computational resources, where equipment can publish manufacturing services based on their capabilities and actively request manufacturing tasks.

To scale up the proof-of-concept prototype systems, a general model of SMCNs is constructed using scale-free networks based on network topology in Fig. 3, which includes 5 job shop systems, 11 production cells, 24 machines, and 12 vehicles. In SMCNs, network vertices

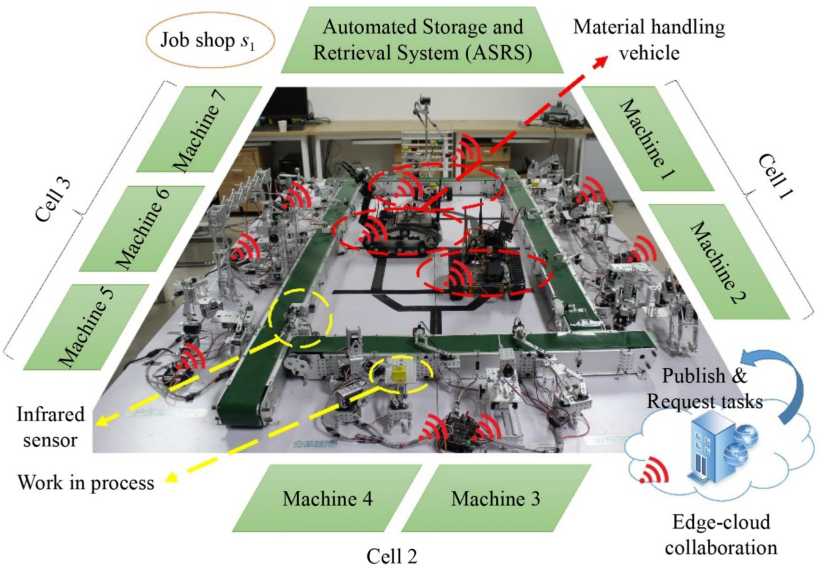


Fig. 5 Proof-of-concept prototype systems.

represent heterogeneous manufacturing resources including systems, cells, machines, and vehicles. Materials, information, and financial assets are passed through interactive links across the networks. The real-time status information of machine and vehicle vertices is given in Table 1.

Typical exceptions and disturbances in discrete manufacturing processes can be classified into two categories: 1) external exceptions without any change in the network topology of SMCNs such as new job arrivals and order changes; and 2) internal exceptions changing the network topology of SMCNs such as equipment failures, maintenance, and procurement. For the former, the proposed self-organization and self-adaption mechanisms can be used directly to handle external exceptions. For the latter, internal exceptions can be expressed as removing and adding vertices in SMCNs. For example, when a failure occurs, the virtual representation in cyber space can perceive the real-time status of the corresponding equipment; thus, the corresponding vertex is removed from the SMCNs. If the equipment maintenance or procurement is completed, the virtual representation in cyber space can synchronize its real-time status and behaviors of the physical entity, and then the corresponding vertex is added in SMCNs. The network topology of SMCNs and the finite set of optional manufacturing services are updated in a timely manner.

In this case study, the real-time information of machine and vehicle vertices added from Cases 1–5 is given in Table 2, whereas the real-time information of machine and vehicle vertices removed from Cases 6–10 is given in Table 3. Different types of the equipment belong to the corresponding production cells as a result of the layout of function in job shops. In SMCNs, the corresponding vertices are connected or disconnected to certain parent (dominator) vertices.

Computational experiments were conducted using R-4.2.0 for Windows (64-bit) on a computer with an AMD A10 processor and 8 GB RAM. In SMCNs, the optimization targets (t^{C}, t^{T}, t^{W}, t^{E}) were set to (0, 0, 0, 0), and the weighting coefficients (ω_{C}, ω_{T}, ω_{W}, ω_{E}) were set to (0.3, 0.3, 0.2, 0.2). Generally, event-triggered rescheduling methods have been widely used to handle exceptions in discrete manufacturing environments (Cheng et al., 2021). Three comparison experiments between event-triggered rescheduling and the proposed self-organization and self-adaption method were conducted based on the original SMCNs, SMCNs adding vertices from Cases 1–5, and SMCNs removing vertices from Cases 6–10. The results of the comparison experiments are shown in Fig. 6. The computational time was around 2 s, which demonstrates the efficiency of the proposed method to be implemented in real-life manufacturing environments.

For the event-triggered rescheduling method without consideration of self-organization and self-adaption, system stability is one of the most important KPIs to prevent internal exceptions. In this context, the set of optimal manufacturing services was $\{ms_{m_2,1}, ms_{m_4,2}, ms_{m_7,2}, ms_{m_9,1}, ms_{m_{11},1}, ms_{m_{12},2}, ms_{m_{14},2}, ms_{m_{16},2}, ms_{m_{18},1}, ms_{m_{22},1}, ms_{m_{24},3}, ms_{v_1,1}, ms_{v_5,2}, ms_{v_7,1}, ms_{v_{10},1}, ms_{v_{12},2}\}$. The total manufacturing cost was \$899, whereas the total manufacturing time was 30765 s. The total waiting time was 14290 s, and the total energy consumption was 520 kW. The value of the objective function was 9.41.

For the first simulation experiment based on the original SMCNs, the set of optimal manufacturing services for the proposed method was $\{ms_{m_1,3}, ms_{m_4,1}, ms_{m_6,2}, ms_{m_8,1}, ms_{m_{10},2}, ms_{m_{13},2}, ms_{m_{15},2}, ms_{m_{17},2}, ms_{m_{19},1}, ms_{m_{21},1}, ms_{m_{24},2}, ms_{v_3,1}, ms_{v_4,1}, ms_{v_7,3}, ms_{v_8,2}, ms_{v_{11},1}\}$. The total manufacturing cost was \$530, approximately 41% lower than that of the

Table 1 Real-time information of machine and vehicle vertices

Vertex	Parent vertex	Manuf. service	Manuf. cost ($)	Setup time (s)	Manuf. time (s)	Waiting time (s)	Energy cons. (kW)
m_1	c_1	$ms_{m_1,1}$	48	185	1436	1087	34
		$ms_{m_1,2}$	62	208	1720	909	23
		$ms_{m_1,3}$	35	137	1818	1187	31
m_2	c_1	$ms_{m_2,1}$	93	234	2142	1102	42
		$ms_{m_2,2}$	41	91	2170	1396	32
m_3	c_2	$ms_{m_3,1}$	46	210	1574	822	54
		$ms_{m_3,2}$	43	172	2216	823	35
m_4	c_2	$ms_{m_4,1}$	52	156	1596	1022	31
		$ms_{m_4,2}$	35	184	2278	1267	49
…	…	…	…	…	…	…	…
m_{10}	c_5	$ms_{m_{10},1}$	78	98	1445	726	24
		$ms_{m_{10},2}$	21	147	1210	993	30
m_{11}	c_5	$ms_{m_{11},1}$	71	153	2634	889	53
		$ms_{m_{11},2}$	37	145	2355	1289	41
…	…	…	…	…	…	…	…
m_{21}	c_{10}	$ms_{m_{21},1}$	23	218	975	790	26
		$ms_{m_{21},2}$	45	226	1774	1324	23
m_{22}	c_{10}	$ms_{m_{22},1}$	92	185	2644	1261	33
		$ms_{m_{22},2}$	69	144	2007	939	36
m_{23}	c_{10}	$ms_{m_{23},1}$	45	92	1915	1058	34
		$ms_{m_{23},2}$	63	223	2603	968	30
m_{24}	c_{11}	$ms_{m_{24},1}$	99	174	1008	1432	55
		$ms_{m_{24},2}$	58	101	2090	1281	40
		$ms_{m_{24},3}$	91	211	2469	1465	33
v_1	s_1	$ms_{v_1,1}$	15	61	498	127	2.8
		$ms_{v_1,2}$	7	64	494	179	2.9
v_2	s_1	$ms_{v_2,1}$	9	80	388	112	2.3
		$ms_{v_2,2}$	6	76	373	202	2.5
v_3	s_1	$ms_{v_3,1}$	5	65	351	175	1.9
		$ms_{v_3,2}$	8	74	436	112	2.4
…	…	…	…	…	…	…	…
v_6	s_2	$ms_{v_6,1}$	13	87	383	134	2.5
		$ms_{v_6,2}$	13	64	337	167	1.9
v_7	s_3	$ms_{v_7,1}$	12	63	481	180	2.4
		$ms_{v_7,2}$	11	90	453	100	1.5
		$ms_{v_7,3}$	9	74	455	100	2.0
v_8	s_4	$ms_{v_8,1}$	14	88	315	134	1.8
		$ms_{v_8,2}$	12	60	378	130	1.6
v_9	s_4	$ms_{v_9,1}$	9	80	489	157	2.4
		$ms_{v_9,2}$	8	67	444	168	1.9
v_{10}	s_4	$ms_{v_{10},1}$	9	69	431	235	2.6
		$ms_{v_{10},2}$	11	76	358	204	1.8
v_{11}	s_5	$ms_{v_{11},1}$	5	71	369	138	3.0
		$ms_{v_{11},2}$	14	60	428	131	2.9
v_{12}	s_5	$ms_{v_{12},1}$	13	64	469	175	2.0
		$ms_{v_{12},2}$	15	88	436	218	1.5

Table 2 Real-time information of machine and vehicle vertices added from Cases 1–5

Case number	Vertex	Parent vertex	Manuf. service	Manuf. cost ($)	Setup time (s)	Manuf. time (s)	Waiting time (s)	Energy cons. (kW)
Case 1	m_{25}	c_1	$ms_{m_{25},1}$	66	96	1531	558	35
			$ms_{m_{25},2}$	25	114	616	563	27
			$ms_{m_{25},3}$	61	132	860	302	22
Case 2	m_{26}	c_5	$ms_{m_{26},1}$	27	100	1577	325	49
			$ms_{m_{26},2}$	62	119	852	448	28
Case 3	m_{27}	c_{11}	$ms_{m_{27},1}$	61	99	1037	368	37
			$ms_{m_{27},2}$	72	101	660	414	47
Case 4	v_{13}	s_3	$ms_{v_{13},1}$	14	86	290	94	1.8
			$ms_{v_{13},2}$	10	69	280	96	1.7
Case 5	v_{14}	s_5	$ms_{v_{14},1}$	6	62	244	119	1.8
			$ms_{v_{14},2}$	8	76	277	91	2.0

Table 3 Real-time information of machine and vehicle vertices removed from Cases 6–10

Case number	Vertex	Parent vertex	Failure cause
Case 6	m_1	c_1	Equipment failure
Case 7	m_{10}	c_5	Maintenance
Case 8	m_{21}	c_{10}	Maintenance
Case 9	v_6	s_2	Equipment failure
Case 10	v_8	s_4	Maintenance

event-triggered rescheduling method. The total manufacturing time was 18744 s, about 39% shorter than that of the event-triggered rescheduling method. The total waiting time was 11451 s, approximately 20% shorter than that of the event-triggered rescheduling method. The total energy consumption was 417.6 kW, approximately 20% lower than that of the event-triggered rescheduling method. The value of the objective function was 6.38.

For the second simulation experiment based on SMCNs adding vertices from Cases 1–5, the set of optimal manufacturing services for the proposed method was $\{ms_{m_{25},2}$, $ms_{m_4,1}$, $ms_{m_6,2}$, $ms_{m_8,1}$, $ms_{m_{10},2}$, $ms_{m_{13},2}$, $ms_{m_{15},2}$, $ms_{m_{17},2}$, $ms_{m_{19},1}$, $ms_{m_{21},1}$, $ms_{m_{27},1}$, $ms_{v_3,1}$, $ms_{v_4,1}$, $ms_{v_{13},2}$, $ms_{v_8,2}$, $ms_{v_{14},1}\}$. The total manufacturing cost was $525, slightly lower than

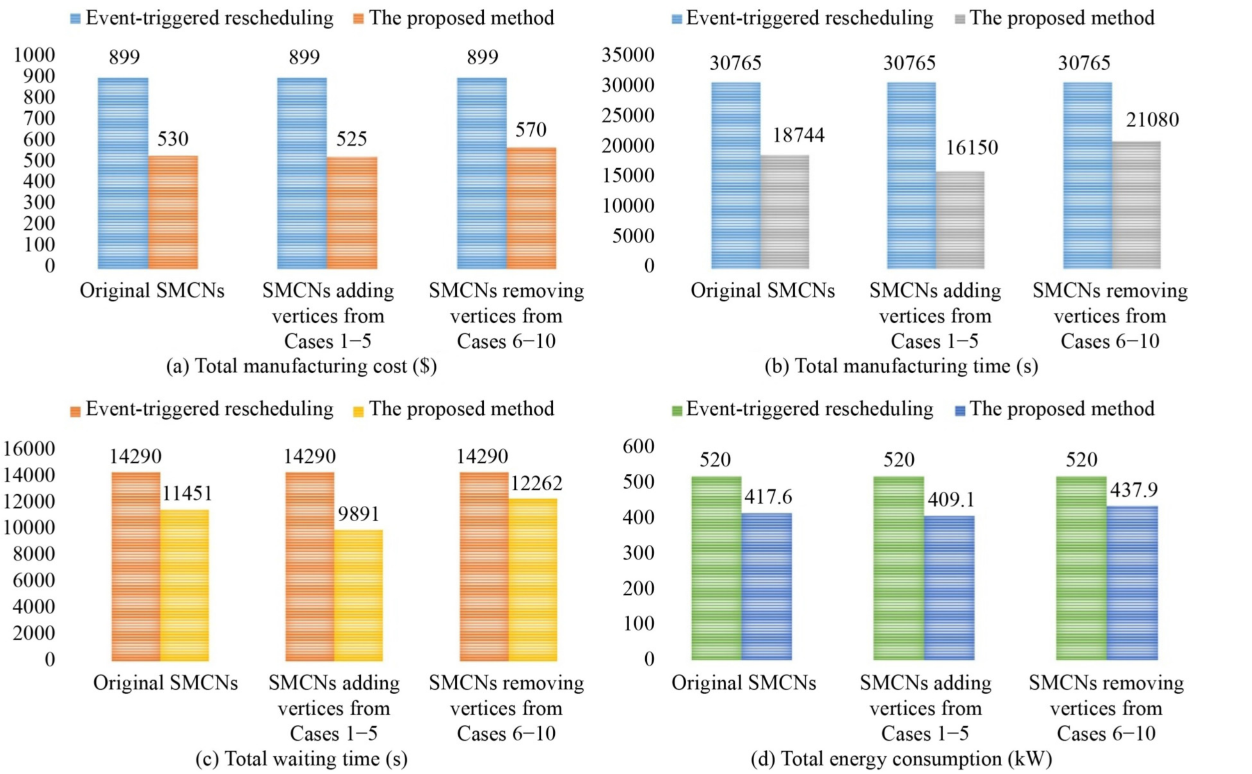


Fig. 6 Comparison experiment results of event-triggered rescheduling and the proposed method.

that of the original SMCNs. The total manufacturing time was 16150 s, around 14% shorter than that of the original SMCNs. The total waiting time was 9891 s, about 14% shorter than that of the original SMCNs. The total energy consumption was 409.1 kW, about 2% lower than that of the original SMCNs. The value of the objective function was 5.87. As the newly added machine and vehicle vertices in SMCNs provided more manufacturing service options and enlarged the optional service group for the optimal configuration, the set of optimal manufacturing services for manufacturing tasks was updated with lower manufacturing cost, manufacturing time, waiting time, and energy consumption.

For the third simulation experiment based on SMCNs removing vertices from Cases 6–10, the set of optimal manufacturing services for the proposed method was $\{ms_{m_2,2}, ms_{m_4,1}, ms_{m_6,2}, ms_{m_8,1}, ms_{m_{11},2}, ms_{m_{13},2}, ms_{m_{15},2}, ms_{m_{17},2}, ms_{m_{19},1}, ms_{m_{23},1}, ms_{m_{24},2}, ms_{v_3,1}, ms_{v_4,1}, ms_{v_7,3}, ms_{v_9,2}, ms_{v_{11},1}\}$. The total manufacturing cost was \$570, about 8% higher than that of the original SMCNs. The total manufacturing time was 21080 s, around 12% longer than that of the original SMCNs. The total waiting time was 12262 s, approximately 7% longer than that of the original SMCNs. The total energy consumption was 437.9 kW, about 5% higher than that of the original SMCNs. The value of the objective function was 6.91. As machine and vehicle vertices were removed from the SMCNs due to various exceptions such as random failures and regular maintenance, the set of optimal manufacturing services for manufacturing tasks was updated with the remaining manufacturing services. However, these removed machine and vehicle vertices may contain manufacturing service options with lower manufacturing cost, manufacturing time, waiting time, and energy consumption.

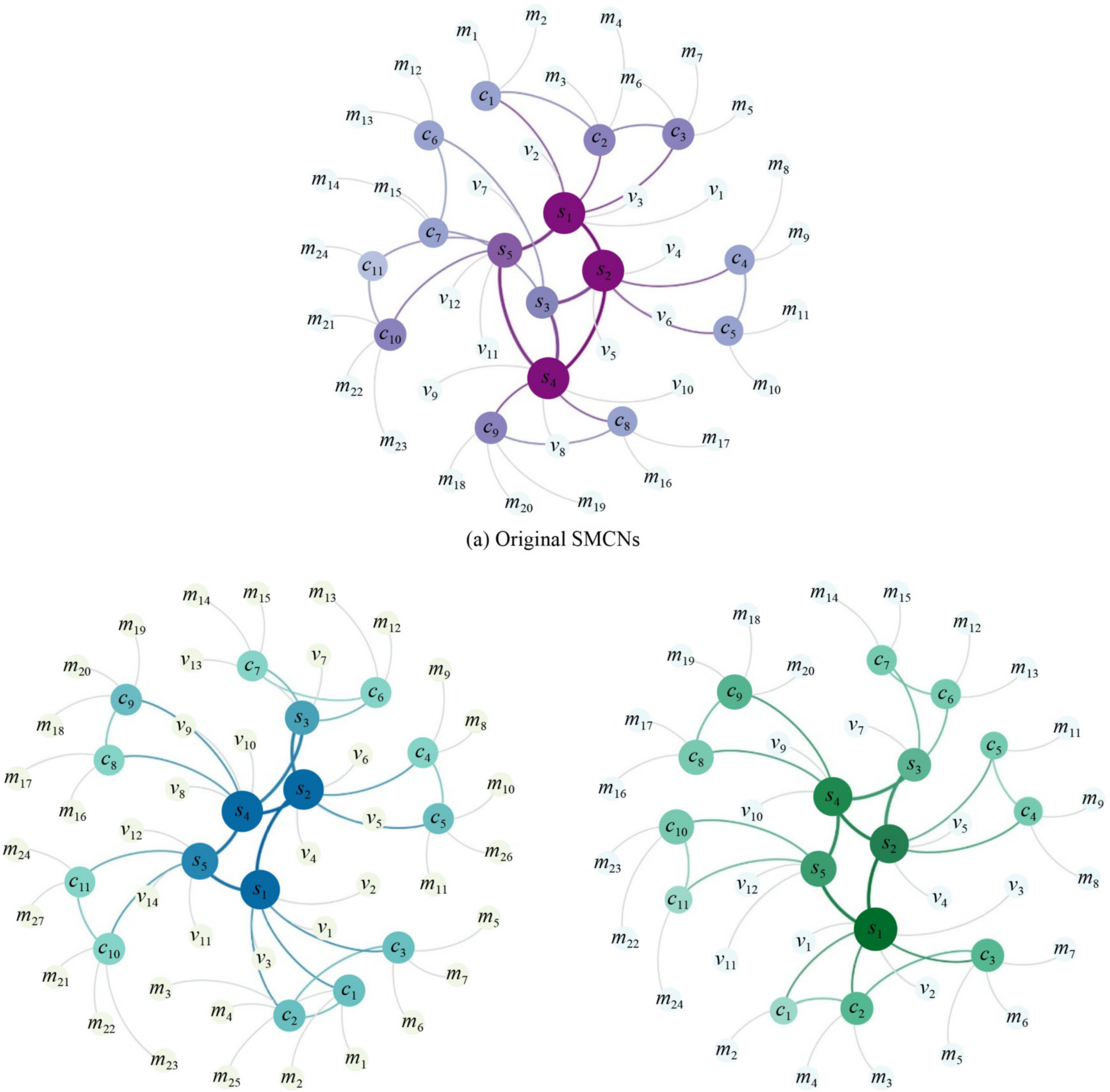
Based on the results of comparison experiments, Table 4 illustrates the numerical analysis of SMCNs in the three simulation experiments. Six types of network characteristics were considered, namely, vertex number, edge number, average degree, diameter, density, and average clustering coefficient. Specifically, in the original SMCNs, the number of vertices was 52, the number of edges was 59, the average degree was 2.27, the diameter was 6, the density was 0.04, and the average clustering coefficient was 0.15. However, the number of both vertices and edges in SMCNs adding vertices from Cases 1–5 increased by 5. As the degrees of the added machine and vehicle vertices were lower than the average degree of the original SMCNs, the average degree and average clustering coefficient of SMCNs adding vertices from Cases 1–5 were lower than those of the original SMCNs. On the contrary, the number of vertices and edges in SMCNs removing vertices from cases 6–10 decreased to 47 and 54, respectively, while the average degree, density, and average clustering coefficient of SMCNs removing vertices from Cases 6–10 were higher than those of the original SMCNs because the removed machine and vehicle vertices had lower degrees than the average degree of the original SMCNs.

In the context of IIoT-based manufacturing environments, by leveraging advanced technologies such as CPSs and DTs, the mapping relationships between virtual vertices and the real-time status of physical entities are established. Figure 7 illustrates the changing processes of the network topology for SMCNs in the three simulation experiments. The size of vertices and the thickness of edges correspond to the degrees. Figure 7(a) shows the network topology of the original SMCNs. When the equipment maintenance or procurement was completed, new corresponding vertices were added to the SMCNs. Figure 7(b) shows the network topology of SMCNs adding vertices from Cases 1–5, where machine vertices m_{25}, m_{26}, m_{27} and vehicle vertices v_{13}, v_{14} were added to cell vertices c_1, c_5, c_{11} and system vertices s_3, s_5, respectively. When machines and vehicles were out of operation due to equipment failures or maintenance, the corresponding vertices were removed from the SMCNs. Figure 7(c) shows the network topology of SMCNs removing vertices from Cases 6–10, where machine vertices m_1, m_{10}, m_{21} and vehicle vertices v_6, v_8 were removed from cell vertices c_1, c_5, c_{10} and system vertices s_2, s_4, respectively. Thus, the real-time status of physical entities was reflected in the topology changes of SMCNs.

Overall, the feasibility and efficiency of the proposed model and method were validated based on an industrial case of a Chinese engine factory. The simulation results show the proposed method can effectively use the real-time status information of physical manufacturing resources to handle typical exceptions efficiently with reductions in manufacturing cost, manufacturing time, waiting time, and energy consumption. Despite its

Table 4 Numerical analysis of smart manufacturing complex networks in three simulation experiments

Network characteristics	Original SMCNs	SMCNs adding vertices from Cases 1–5	SMCNs removing vertices from Cases 6–10
Vertex number	52	57	47
Edge number	59	64	54
Average degree	2.27	2.25	2.30
Diameter	6	6	6
Density	0.04	0.04	0.05
Average clustering coefficient	0.15	0.12	0.17



(a) Original SMCNs

(b) SMCNs adding vertices from Cases 1−5

(c) SMCNs removing vertices from Cases 6−10

Fig. 7 Changing processes of the network topology for smart manufacturing complex networks.

advantages, sub second response time is required for high production efficiency in real-life manufacturing environments. Therefore, this work potentially enables managers and practitioners to implement active perception, active response, self-organization, and self-adaption solutions in discrete manufacturing enterprises.

6 Conclusions and future research

To deal with unpredictive dynamic uncertainties including external and internal exceptions in manufacturing environments, this paper studies the mechanisms and methodology of self-organization and self-adaption for SMCNs to tackle exceptions and disturbances in discrete manufacturing processes. The main contributions of this paper include three aspects: 1) A general model of SMCNs is developed using scale-free networks to interconnect heterogeneous manufacturing resources represented by network vertices at multiple levels. Materials, information, and financial assets are passed through interactive links across the networks. 2) The capabilities of physical manufacturing resources are encapsulated into virtual manufacturing services using cloud technology, which can be added to or removed from the networks in a plug-and-play manner. 3) Subsequently, ATC is used to formulate the processes of self-organizing optimal configuration and self-adaptive collaborative control for multilevel key manufacturing resources, whereas PSO is used to solve local problems on network vertices.

Recent advances in IIoT and the widespread use of embedded processors and sensors in factories enable collecting real-time manufacturing status data and building CPSs for smart, flexible, and resilient manufacturing systems. Self-organization can form a stable network structure with vertices passing materials, information, and financial assets through interactive links across SMCNs. Self-adaption can deal with typical exceptions and dynamics such as new job arrivals, order changes, and equipment failures. When a failure occurs, the virtual representation in cyber space can perceive the real-time status of the corresponding equipment. Thus, the corresponding vertex is removed from SMCNs. If the equipment maintenance or procurement is completed, the virtual representation can synchronize its real-time status and behaviors of the physical entity, and then the corresponding vertex is added in the SMCNs. To validate the feasibility and efficiency of the proposed model and method, an industrial case based on a Chinese engine factory is presented to handle typical exceptions. The simulation results show that the proposed mechanism and method outperform the event-triggered rescheduling method, reducing manufacturing cost, manufacturing time, waiting time, and energy consumption with reasonable computational time. This work potentially enables managers and practitioners to implement active perception, active response, self-organization, and self-adaption solutions in discrete manufacturing enterprises.

For future research, other types of complex network models will be studied and developed for SMCNs. The proposed model and method will be implemented in real-life manufacturing environments.

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