A Framework for Smart Production-Logistics Systems based on CPS and Industrial IoT

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***Abstract*—Industrial Internet of Things (IIoT) has received increasing attention from both academia and industry. However, several challenges including excessively long waiting time and a serious waste of energy still exist in the IIoT-based integration between production and logistics in job shops. To address these challenges, a framework depicting the mechanism and methodology of smart production-logistics systems is proposed to implement intelligent modeling of key manufacturing resources and investigate self-organizing configuration mechanisms. A data-driven model based on analytical target cascading is developed to implement the self-organizing configuration. A case study based on a Chinese engine manufacturer is presented to validate the feasibility and evaluate the performance of the proposed framework and the developed method. The results show that the manufacturing time and the energy consumption are reduced and the computing time is reasonable. The presented work potentially enables manufacturers to deploy IIoT-based applications and improve the efficiency of production-logistics systems.**

***Index Terms*— Production-logistics, cyber-physical systems, industrial Internet of Things, analytical target cascading, self-organizing configuration.**

This work was supported in part by the National Science Foundation of China under Grant 51675441, in part by the Fundamental Research Funds for the Central Universities under Grant 3102017jc04001, and in part by the 111 Project Grant of NPU under Grant B13044. Paper no. TII-17-2897. *(Corresponding author: Yingfeng Zhang.)*

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I. INTRODUCTION

The increasing demands for customized products and services as well as frequent market fluctuations have posed challenges to management and control of manufacturing processes. For example, due to external and internal fluctuations, such as production order changes and unexpected equipment failures, production plans and schedules become inefficient or even infeasible. In addition, customized production with a small batch and short production cycle increases the computational complexity and requires more time cost for scheduling. As a consequence of lacking collaboration, excessively long waiting time and large amounts of energy are wasted in production and logistics.

The emergence of advanced technologies, such as Internet of Things (IoT) [1], cloud manufacturing (CMfg) [2], cyber-physical systems (CPS) [3]–[5], and service-oriented technology (SOT) [6], has provided several promising opportunities to address the aforementioned challenges. The rapid development and widespread use of industrial IoT (IIoT) technology in manufacturing industry greatly promote information progress in real-time monitoring, traceability, tracking, transparency, and interaction [7]. Real-time and multi-source manufacturing data generated by embedded devices and sensors have been used to perform operation optimization and decision-making [8]. CPS with integrated computational and physical capabilities has been used to implement the efficient management and utilization of big data [9]. Besides, a variety of IIoT-based models and applications are developed to improve the efficiency of manufacturing industry [10].

With respect to the topic of production and logistics, many researchers and practitioners focus on the simultaneous scheduling of machines and automated guided vehicles (AGVs) [11], [12]. Although a few of them paid attention to the IIoT-based synchronized relationships between production and logistics, which have shown improvements in overall performance of enterprises operations [13]–[15]. However, existing manufacturing paradigms are insufficient to address typical problems of production logistics in job shops. These problems are listed as follows.

(1) For manufacturing resources in the infrastructure layer of job shops, how to achieve manufacturing status perception and intelligent modeling on the key manufacturing resources side, such as machines and

material handling systems?

(2) For manufacturing tasks in the job shop level, how to implement a task-driven smart manufacturing service chain to realize active response and optimization of global interaction and collaboration?

(3) For executive processes of production logistics in job shops, how to conduct real-time performance analysis, exception diagnosis, and self-adaptive conflict resolution to realize real-time interaction and self-organizing configuration between machines, materials, and human?

Here, the authors present a framework for smart production-logistics systems (SPLS) and investigate the mechanism and methodology of SPLS. The investigation is focused on two key problems, namely the intelligent modeling of manufacturing resources in the infrastructure layer and the self-organizing configuration of smart manufacturing service groups. The proposed conceptual framework of SPLS is validated by a case study based on a Chinese engine manufacturer, showing better potentiality than the separated production logistics at each level of manufacturing services. Based on the developed engine manufacturer framework, a comparison is conducted to show the key features of the separated production logistics and SPLS. In Fig. 1, four levels are involved, including equipment level, job shop level, enterprise level, and industry level.

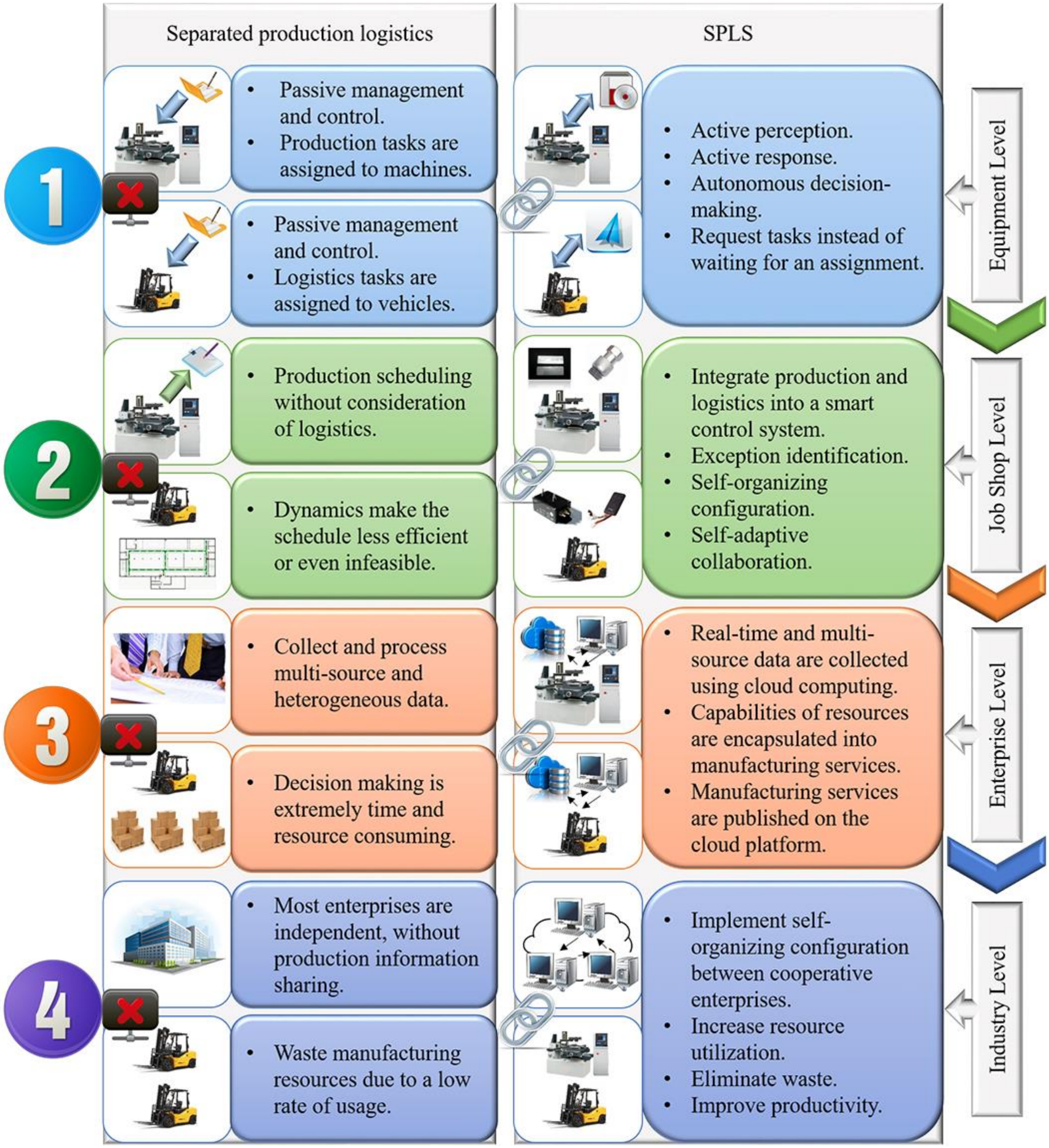

Fig. 1. Comparison between separated production logistics and SPLS.

At the equipment level, for the separated production logistics, machines and material handling systems are managed and controlled in a passive manner, i.e., production tasks are usually assigned to machines. In contrast, SPLS makes machines and material handling systems 'smart' by using CPS and IIoT technology, which are capable of active perception, active response, and autonomous decision-making. For example, machines actively request production tasks instead of waiting for an assignment.

At the job shop level, each individual production and logistics is scheduled separately. To overcome the inefficiency and infeasibility in the scheduling which arises from both external and internal dynamic changes, production and logistics are integrated into a smart control system such that SPLS is capable of exception identification, self-organizing configuration, and self-adaptive collaboration.

At the enterprise level, multi-source and heterogeneous data collected from separated production logistics might require a considerable amount of computational resources to support decision making. Different from separated production logistics, capabilities of manufacturing resources for SPLS are encapsulated into smart manufacturing services using cloud computing technology as well as real-time and multi-source data. Manufacturing services are published on the cloud platform to complete production tasks in an on-demand manner.

At the industry level, most enterprises are independent, whose production information is not shared. As a consequence, separated production logistics might waste manufacturing resources due to a low rate of usage, which causes more manufacturing costs, manufacturing time, and energy consumption. Benefiting from the high degree of integration between production and logistics, SPLS can implement the self-organizing configuration of manufacturing resources not only within a job shop but also between cooperative enterprises, which may increase resource utilization, eliminate waste, and improve productivity in the manufacturing industry.

To summarize, the objectives of this research work are the following: (1) to investigate the mechanism of intelligent modeling and active response of manufacturing resources in the infrastructure layer; (2) to investigate the mechanism of self-organizing configuration for SPLS.

The remainder of this paper is structured in the following way. A review of the existing literature relevant to this study is included in Section II. The overall architecture of SPLS is described in detail in Section III. Section IV explains the intelligent modeling of key manufacturing resources based on CPS and IIoT. The mechanism and methodology of SPLS are presented in Section V. A theory-driven application scenario is given in section VI. Section VII offers conclusion and suggestions for future research.

II. Literature Review

This section reviews the state of the art of this topic, starting from existing manufacturing paradigms and their limitations, enabling technologies and conceptual frameworks, such as CPS and IIoT, and then moving on to innovative properties of production logistics, including self-adaptive collaboration and self-organizing configuration. The main contributions of each work are highlighted.

A. Existing Manufacturing Paradigms and Their Limitations

To achieve the goal of TQCSE, namely fastest time-to-market, highest quality, lowest cost, best service, and cleanest environment, many manufacturing models and technologies have been researched and developed. Originating from the Toyota Production System, lean manufacturing is a multi-dimensional manufacturing approach that includes just-in-time (JIT), quality systems, cellular manufacturing, production smoothing, and setup reduction, which has been widely used in discrete manufacturing [16]. Agile manufacturing is a natural development from lean manufacturing, which is capable of responding quickly to rapidly changing markets driven by customized products and services [17]. Based on lean manufacturing and agile manufacturing, the intelligent modeling of manufacturing resources and services needs further investigation. The supply chain operations reference (SCOR) model is a business process reference model for supply chain management, which provides a standard format to facilitate communication [18]. The SCOR model lacks integration and synchronization, especially the integration between production and internal logistics. Holonic manufacturing is a distributed control paradigm based on autonomous cooperating agents named ‘holons’, which is able to manage production changes and disturbances [19]. Giret et al. proposed a holonic multi-agent methodology to design sustainable intelligent manufacturing systems [20]. Cloud manufacturing is a computing and service oriented manufacturing model that provides manufacturing services in an on-demand manner [21]. In cloud manufacturing, cloud services are managed in a centralized way, which cannot enforce a self-organizing configuration between machines, materials, and human in job shops. A multi-agent system (MAS) is made up of decentralized, distributed, autonomous and intelligent agents that cooperate to achieve the global objectives [22]. Hu, Liu, and Feng proposed a distributed event-triggered control scheme and a self-triggered control scheme to solve the output consensus problem of heterogeneous linear multi-agent systems [23]. Nevertheless, most of the existing approaches regard production and logistics as two independent systems, which lack collaboration between production tasks and logistics tasks. As a consequence, to fulfill the goal of integration between production and logistics, a new manufacturing paradigm is needed to implement the intelligent modeling of manufacturing resources and self-organizing configuration of collaborative production-logistics.

B. Cyber-Physical Systems and Industrial Internet of Things

In recent years, IIoT technology has been widely used in manufacturing systems, such as radio-frequency identification (RFID), wireless, mobile, and sensor devices. Xu et al. [24] has summarized the state of the art of IIoT in industries systematically. At the same time, national strategies such as Made in China 2025 and Germany’s Industry 4.0 [25] have been put forward to encourage manufacturing enterprises to upgrade factories to become more competitive, innovative, and efficient. In such an environment, a wide range of IIoT applications have been developed and deployed, which provides promising opportunities to solve problems in industries [24]. Zhang et al. [26] presented a real-time information capturing and integration architecture of the internet of manufacturing things. A similar intention is expressed by Fei Tao et al. [21], [27], who designed a resource intelligent perception and access system under CMfg. These hierarchical architectures address the problem of perception and access of manufacturing resources and services. In CMfg, distributed resources are encapsulated into cloud services and managed in a centralized manner. A huge number of real-time and multi-source manufacturing status data are generated by sensors and networked machines. Zhong et al. [28] proposed a RFID-Cuboid model using the production logic and time stamps to manage the RFID data. CPS are physical and engineered systems for which a computing and communication core monitors, coordinates, controls, and integrates the whole operations. A series of works have been focused on CPS design [29], showing that CPS can be further developed to manage big data and provide real-time services. Lee et al. [30] proposed a unified architecture for implementation of CPS, with in which manufacturing information are synchronized between the physical reality and computing infrastructures. Based on aforementioned CPS and IIoT applications, real-time manufacturing information can be perceived and interacted between multiple levels in industrial manufacturing. However, the high level of integration between production and logistics under the support of CPS and IIoT needs further investigation.

C. Self-Adaptive Collaboration and Self-Organizing Configuration Mechanisms

Dynamics-based economics requires enterprises not only to quickly adapt to rapid changes in customers' demands but also to proactively resolve exceptions within manufacturing systems. Traditional integrated manufacturing systems are capable of managing programmable logic controllers and electrical interconnections, control logic, and satisfactory robustness [31]. However, these manufacturing systems cannot meet the demands of diversity and flexibility in production. In order to address the aforementioned problems, manufacturing systems can be made adaptive by using feedback to perceive internal and environmental changes in real time and then adjusting accordingly [32]. Recent research work that includes self-adaptive systems can be found in [33]. In addition, self-organization has been proven to be an efficient way to fulfill the dynamic requirements in distributed systems [34]. The self-organizing architecture presented by Ribeiro et al. [35] dynamically handles the potential rescheduling of the orders based on available resources and their status in a time-efficient manner. Semasinghe et al. [36] proposed an evolutionary game theory based distributed resource allocation scheme to address the problem of resource allocation in self-organizing small cells. To achieve self-organizing logistics systems, many research efforts have been made to develop models based on decentralized management and control, showing that self-organizing methods outperform centralized control methods in speed, accuracy, autonomy, and robustness [37], [38]. Yang and Recker investigated the feasibility of a self-organizing and completely distributed traffic information system based on vehicle-to-vehicle communication technologies [39]. A self-organizing vehicular network has been implemented with vehicles equipped with inter-vehicle communication systems [40]. Nevertheless, the self-organizing configuration of collaborative production-logistics has not received due attention from both researchers and practitioners. The simulation work proposed by Liotta et al. [41] supports the development and optimization of the production logistics with detailed dynamic distribution plans affected by demand uncertainty. Not only simulation and synchronization of production logistics, but dynamics in production logistics systems are discussed by researchers [13]–[15]. Monostori et al. [42] summarized the advantages and disadvantages of cooperative control approaches used in production and logistics. However, a unified framework of production logistics has not been proposed yet. Furthermore, the mechanism and methodology of collaborative relationships between production and logistics lack in-depth studies in existing literature.

III. Overall Architecture of Smart Production-Logistics Systems

In this section, a three-layered conceptual framework of SPLS is built such that collaborative production-logistics are self-organizing. As shown in Fig. 2, the proposed framework consists of the intelligent modeling of key manufacturing resources, smart production-logistics systems, and the self-organizing configuration. The smartness of SPLS appears in two aspects: (1) smart manufacturing resources based on CPS and IIoT; (2) self-organization based on the analytical target cascading (ATC) method.

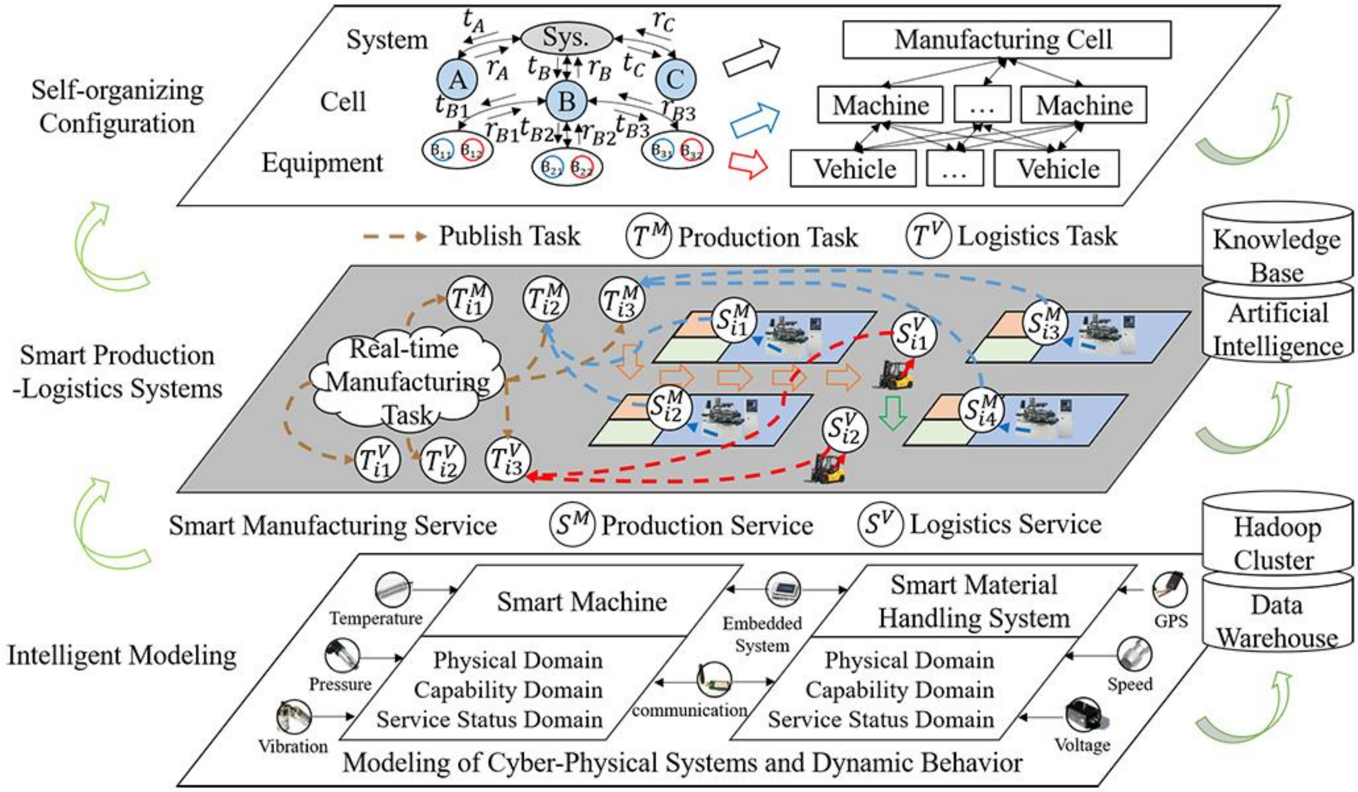

Fig. 2. A conceptual framework for smart production-logistics systems.

In the intelligent modeling layer, by integrating with IoT technology and sensor networks, key manufacturing resources such as machines and material handling systems are made ‘smart’ to perceive real-time status, communicate, and actively respond to production changes and disturbances in an autonomous manner. The CPS model and dynamic behavior model are developed to depict the real-time status of smart machines and smart material handling systems. Three domains, namely physical domain, capability domain, and service status domain, are constructed for intelligent modeling of machines and material handling systems. The physical domain contains the basic information of the equipment. The capability domain contains the functional information of the equipment including production capability and logistics capability. The service status domain contains service status information such as current task pool, service capability, and service satisfaction. As for manufacturing status data storage and management, Hadoop clusters are used to store and process semi-structured and unstructured data, while the data warehouse is used to manage structured data.

In the smart production-logistics systems layer, the task-driven smart manufacturing service chain is introduced for active response, interaction and collaborative optimization of SPLS. By leveraging cloud computing, the production capability of smart machines and the logistics capability of smart material handling systems are encapsulated into smart manufacturing services, namely smart production services and smart logistics services. Real-time manufacturing tasks including production tasks and logistics tasks are published by smart machines and smart material handling systems through the cloud platform. Smart machines or smart material handling systems can actively request the tasks according to their service capabilities. Knowledge bases are constructed to make smart machines and smart material handling systems capable of reasoning and autonomous decision making when faced different manufacturing scenarios.

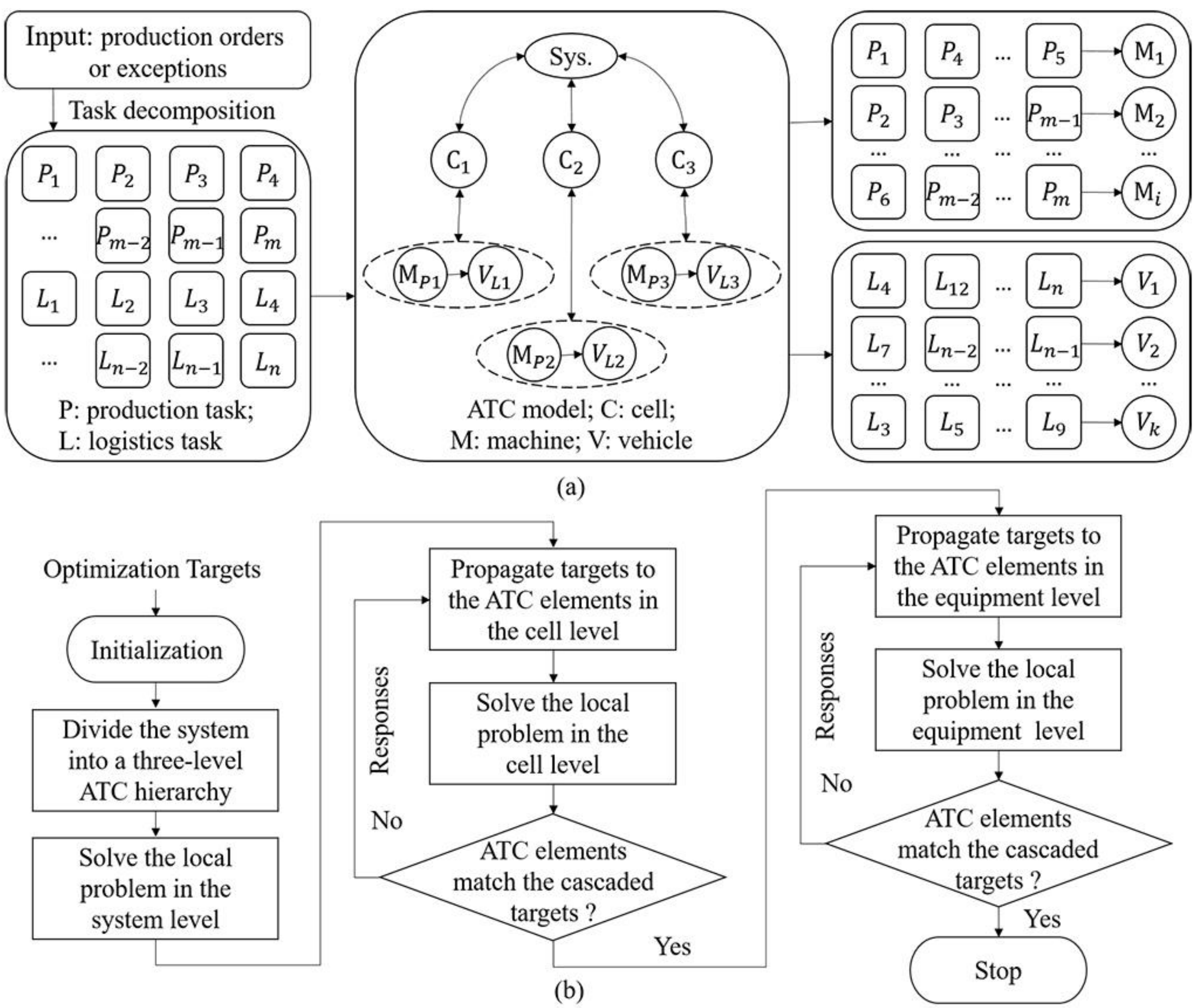

Fig. 3. Self-organizing configuration based on the analytical target cascading.

In the self-organizing configuration layer, as shown in Fig. 3 (a), once production orders or exceptions are input, self-organization is triggered. Firstly, the input is decomposed into production tasks and logistics tasks. Secondly, the manufacturing system is partitioned into a three-level ATC hierarchy composed of ATC elements. The proposed ATC model is used to configure the manufacturing resources including machines and material handling systems composed of vehicles, according to the processing constraints and the optimization goal such as cost, time, and energy. Fig. 3 (b) introduces the flow chart of self-organizing configuration based on the ATC method. Beginning from the system level element, local problems are solved and targets for their children elements are sequentially cascaded down until reaching elements in the bottom level. As a consequence, the whole manufacturing system converges to a consistent configuration. Details of the ATC model are given in Section V. The self-organizing configuration is implemented for production planning, while collaboration is in place between production and logistics during execution. As shown in Fig. 4, the logistics is triggered by the production when a job is being processed on a machine. The machine publishes a logistics task on the cloud platform, which can be actively requested and assigned to the nearest and available vehicle by the material handling systems. The logistics triggers the production when the vehicle unloads the pallet to the next machine.

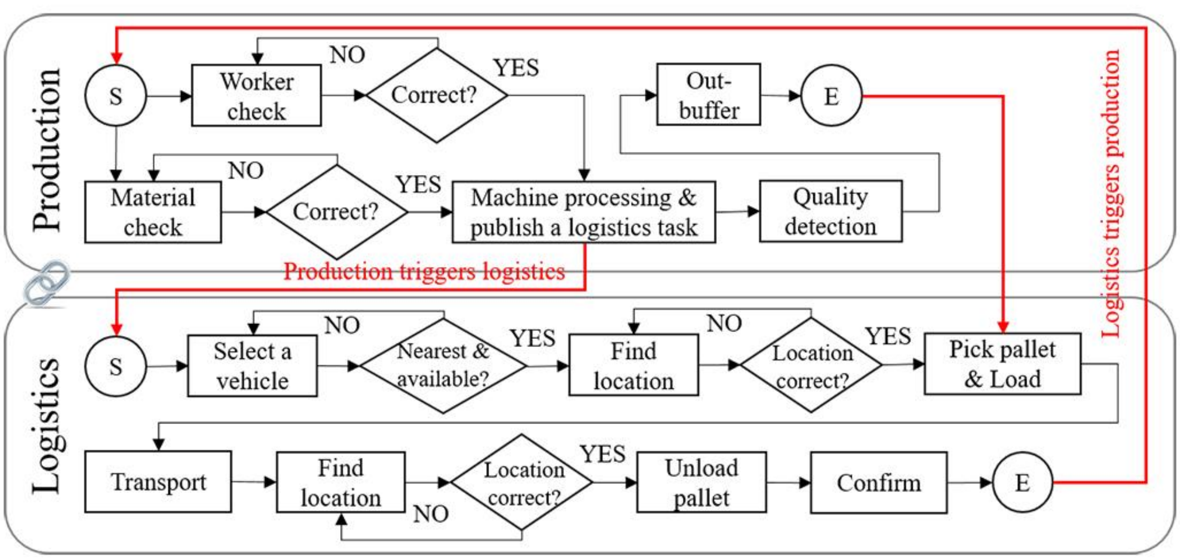

Fig. 4. Collaboration between production and logistics in SPLS.

For the data communication between key manufacturing resources and cloud servers, several standards and protocols of wireless communication technologies such as ISA100.11a [43] and IEEE 802.11e [44] can be used to implement the proposed framework. Clock synchronization protocols are used to accurately synchronize manufacturing resources and cloud servers [45], [46]. Real-time requirements are satisfied by conducting incremental scheduling, distributed scheduling, and concurrent scheduling [47]. High-performance computation is implemented with the support of large-scale server clusters and high-speed internet connection. As a consequence, the proposed SPLS and the data-driven ATC model can be packaged as cloud services and integrated with embedded devices or mobile devices such as smartphones and tablet computers.

The deep integration of CPS and IIoT in SPLS increases security threats to both the cyber domain and the physical domain, such as eavesdropping attacks and arbitrary attacks on the physical process. To protect security and privacy of SPLS, intrusion detection approaches [48] are used as the initial protective barrier, while cryptographic encryption methods and physical layer security techniques [49] are used to enhance secrecy of wireless communications. Two intrusion detection approaches are used to identify known and new attacks. Signature-based methods use the database or fixed signatures to identify known attacks while anomaly-based methods detect new attacks by monitoring behaviors of physical systems.

IV. Intelligent Modeling of Key Manufacturing Resources Based on CPS and IIoT

This section introduces the intelligent modeling of key manufacturing resources based on CPS and IIoT, which provides the basis for the implementation of SPLS.

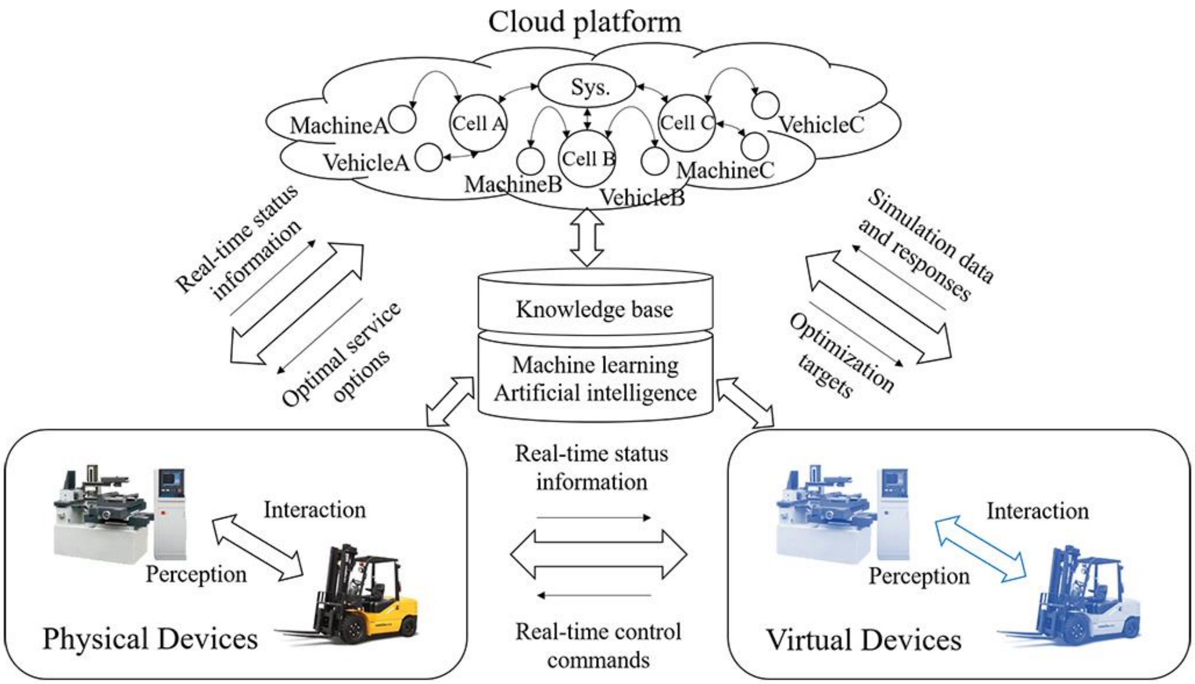

Fig. 5. The modeling of cyber-physical systems and dynamic behaviors.

Fig. 5 shows the modeling of CPS and its dynamic behaviors. CPS is composed of three parts: physical devices, virtual devices, and the cloud platform. Active perception is firstly realized by collecting real-time status information of physical devices which are actual devices in the physical world and are responsible for perceiving the environment, publishing and request tasks, and executing commands to process or transport materials. Virtual devices are then constructed based on real-time status information of physical devices, which can simulate self-organizing configuration and transmit optimization targets to the ATC model while physical devices respond actively to real-time control commands from virtual devices. Intelligent decision-making is finally realized based on the knowledge base as well as the ATC model in the cloud platform. Optimal service options are selected by analyzing real-time status information of physical devices.

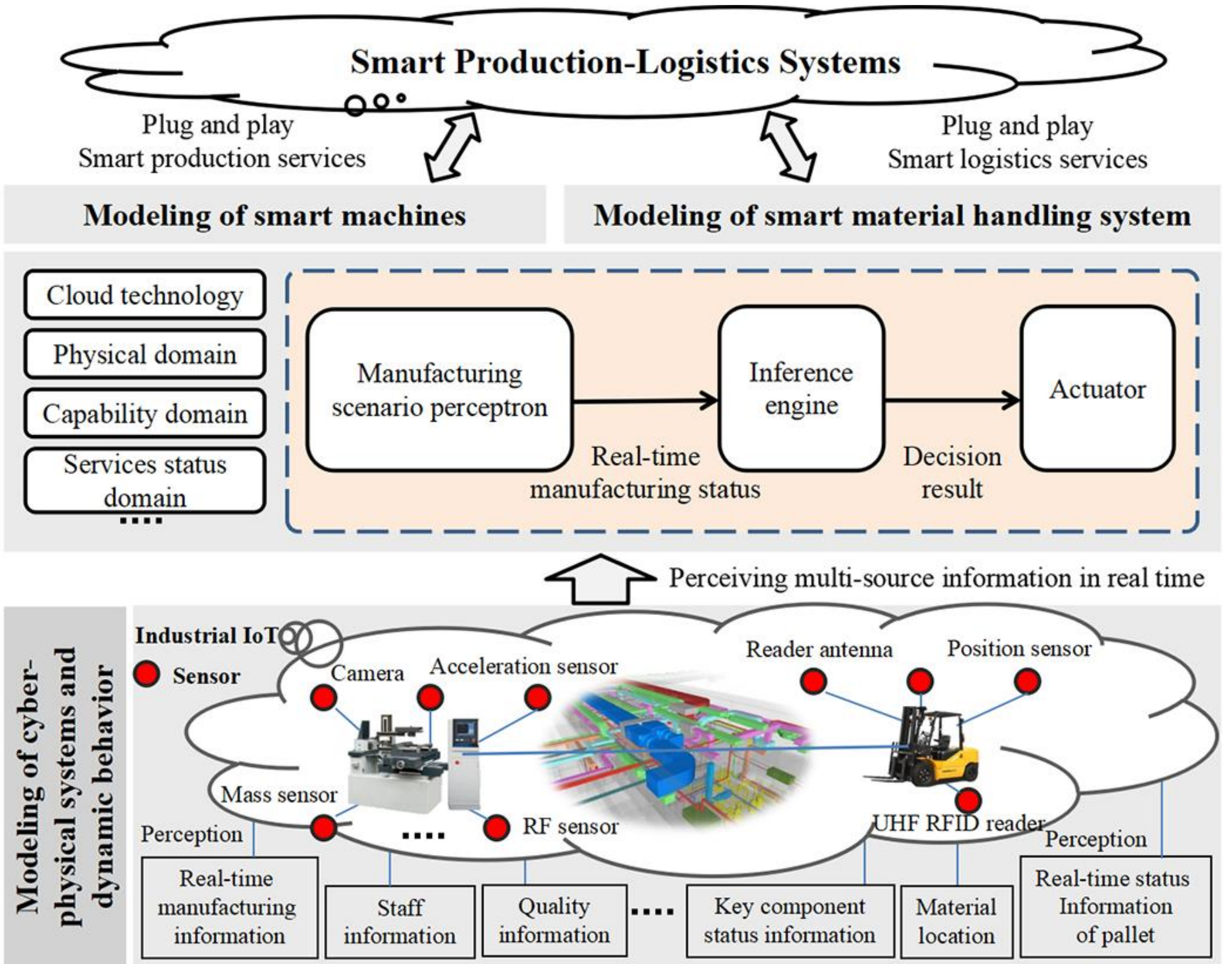

Fig. 6. Intelligent modeling of key manufacturing resources.

The intelligent modeling of key manufacturing resources is shown in Fig. 6. An awareness space is established based on real-time, multi-source, and multi-dimensional manufacturing status. A sensor network is modeled and configured based on set and graph theory such that multi-source manufacturing information on the equipment end can be actively collected. As a consequence, manufacturing physical resources including machines and material handling systems are able to provide manufacturing services which can be perceived. Multi-level event models are then used to interpret the mapping relation between real-time manufacturing status, perception events, and dynamic behaviors. Real-time manufacturing status includes production status, logistics status, inventory status, exception detection, dynamic queue, service load, service process status, energy consumption, and processing quality. Discrete and continuous behaviors of machines and material handling systems are formalized using hybrid automata and relevant differential equations.

Therefore, real-time perception events are transformed into dynamic behaviors which can be understood by manufacturing systems. Finally, manufacturing physical resources are integrated with information networks.

Perception is the foundation for intelligent modeling of key manufacturing resources including machines and material handling systems. Here, the manufacturing cost is the fixed cost of producing products, including the cost of raw materials and maintenance costs. Setup times between manufacturing parts involves installing and clamping workpieces, and therefore the setup times are dependent on manufacturing service options and sequence-independent. In order to better manage the real-time status data, status information models of machines and material handling systems are developed as follows.

The status of machines is characterized by six nodes, including equipment number, service option, manufacturing cost, setup time, manufacturing time, and energy consumption, which are stored in the matrix M.

$$M = \begin{bmatrix} EID_{m1} & S_{m1}^{1} & c_{S_{m1}^{1}} & st_{S_{m1}^{1}} & t_{S_{m1}^{1}} & e_{S_{m1}^{1}} \\ EID_{m2} & S_{m2}^{1} & c_{S_{m2}^{1}} & st_{S_{m2}^{1}} & t_{S_{m2}^{1}} & e_{S_{m2}^{1}} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ EID_{i} & S_{i}^{j} & c_{S_{i}^{j}} & st_{S_{i}^{j}} & t_{S_{i}^{j}} & e_{S_{i}^{j}} \end{bmatrix} \tag{1}$$

where EID_i denotes the equipment number of machine i, S_i^j denotes the jth production service of machine i, $c_{S_i^j}$ denotes the manufacturing cost of service option S_i^j, $st_{S_i^j}$ denotes the setup time of service option S_i^j, $t_{S_i^j}$ denotes the manufacturing time of service option S_i^j, $e_{S_i^j}$ denotes the energy consumption of service option S_i^j.

The status of material handling systems is also characterized by six nodes, which are equipment number, service option, manufacturing cost, setup time, manufacturing time, and energy consumption. The information is stored in the matrix V.

$$V = \begin{bmatrix} EID_{v1} & S_{v1}^{1} & c_{S_{v1}^{1}} & st_{S_{v1}^{1}} & t_{S_{v1}^{1}} & e_{S_{v1}^{1}} \\ EID_{v2} & S_{v2}^{1} & c_{S_{v2}^{1}} & st_{S_{v2}^{1}} & t_{S_{v2}^{1}} & e_{S_{v2}^{1}} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ EID_{k} & S_{k}^{j} & c_{S_{k}^{j}} & st_{S_{k}^{j}} & t_{S_{k}^{j}} & e_{S_{k}^{j}} \end{bmatrix} \tag{2}$$

where EID_k denotes the equipment number of vehicle k, S_k^j denotes the jth production service of vehicle k, $c_{S_k^j}$ denotes the manufacturing cost of service option S_k^j, $st_{S_k^j}$ denotes the setup time of service option S_k^j, $t_{S_k^j}$ denotes the manufacturing time of service option S_k^j, $e_{S_k^j}$ denotes the energy consumption of service option S_k^j.

In order to make key manufacturing resources including machines and material handling systems more intelligent, manufacturing services including production services and logistics services are formulated based on the modeling of CPS and dynamic behaviors. Using appropriate sensor installations, multi-source and real-time status information of machines and material handling systems can be perceived and stored in the cloud platform for further data mining. To further improve transparency and productivity of SPLS, a CPS model is developed using a knowledge base and related machine learning and artificial intelligence techniques to represent dynamic behaviors in the physical world. Meaningful information from big data are extracted for intelligent decision-making based on the knowledge base which represents dynamic behavior and collaboration mechanisms. The knowledge base is automatically populated using machine learning and artificial intelligence algorithms. Once the self-organizing configuration is triggered, the knowledge base provides the necessary information for decision making. Three domains including physical domain, capability domain, and service status domain are constructed for smart machines and smart material handling systems. By integrating with cloud technology, smart manufacturing services inherently assures flexibility and scalability for the functionality on a 'plug and play' basis.

V. Self-Organizing Configuration Mechanism and Methodology of SPLS

In this section, the collaborative production-logistics service chain is introduced to depict self-organizing configuration mechanism and methodology of SPLS, as shown in Fig. 7. In the service chain, task nodes, time, and process-level tasks are graphically represented by circles, rectangles, and squares respectively.

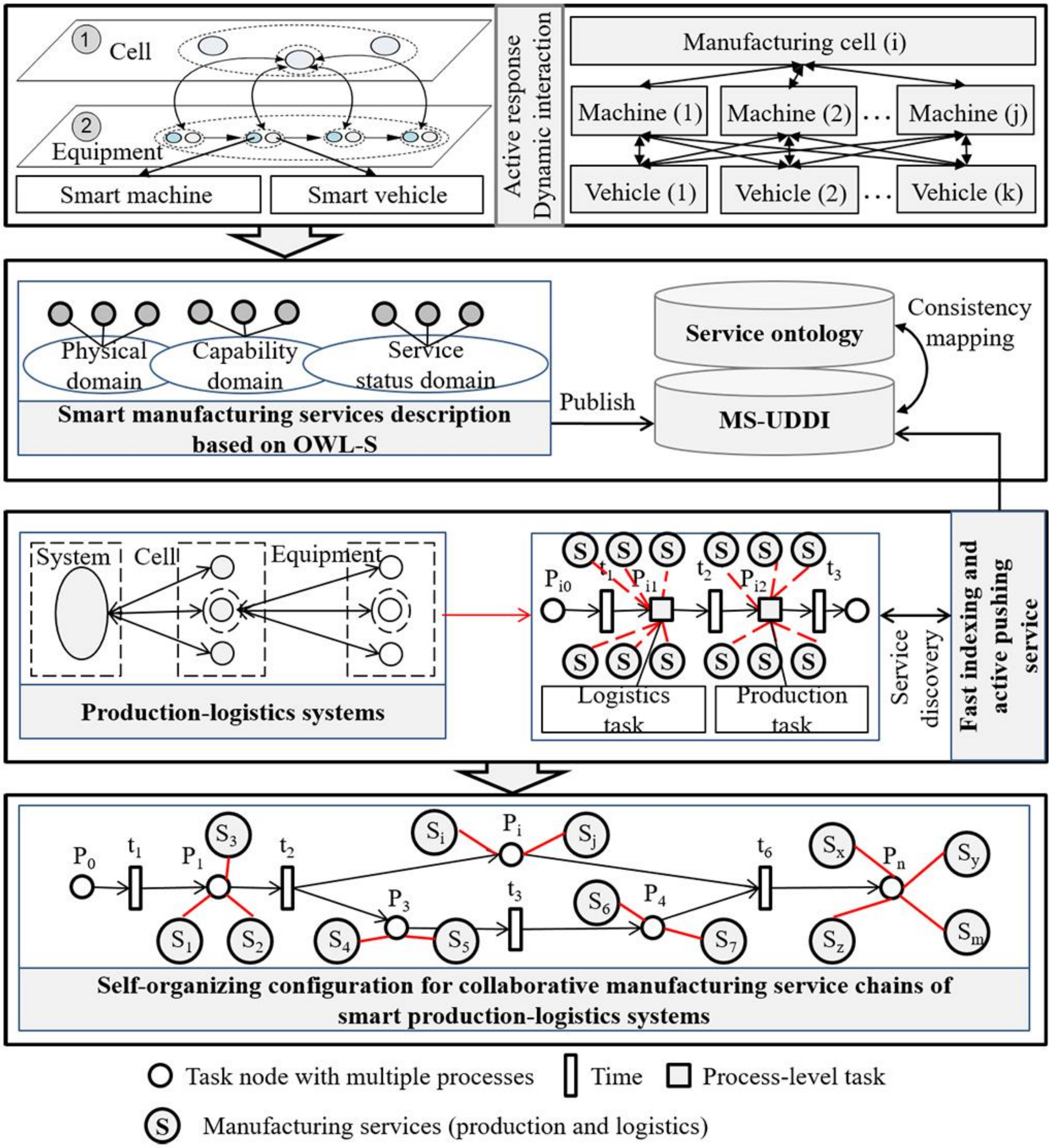

Fig. 7. Self-organizing configuration mechanism and methodology.

First, the ATC model is developed based on smart machines and smart material handling systems to implement the self-organizing configuration at both the manufacturing cell level and the equipment level. Nodes in the ATC model which are capable of active response and dynamic interaction are used to implement self-organizing configuration for collaborative production-logistics service chains.

Then, based on universal description discovery and integration (UDDI), manufacturing services UDDI

(MS-UDDI) is proposed as a platform-independent framework for describing and discovering services by the Internet [50]. The consistency mapping between MS-UDDI and the manufacturing services' physical domain, capability domain, and service status domain is established by using ontology web language for services (OWL-S).

Subsequently, the process flow of production tasks is developed based on the topology and morphology model to form the initial network for collaborative production-logistics service chains. On the basis of the requirements domain of production-logistics services on each node of ATC model, the bi-directional matching relation is established between the requirements domain and manufacturing services' physical domain, capability domain, and service status domain. Fast indexing of heuristic recommendation algorithm based on computational intelligence is used for the establishment of the matching relation to actively push high-quality smart manufacturing services. As a consequence, a potential smart manufacturing service group with production and logistics capabilities is autonomously formed.

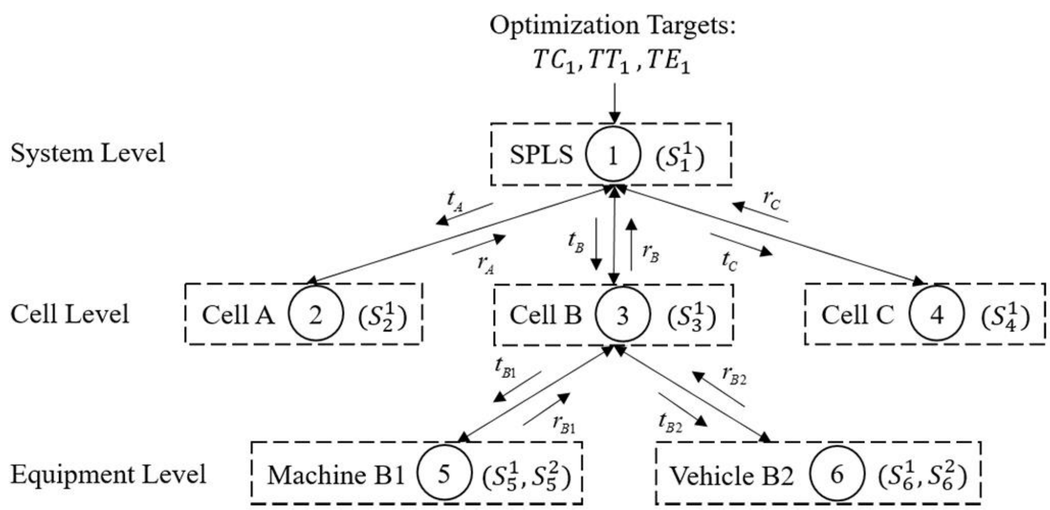

Fig. 8. Partitioning and information flow of the analytical target cascading process for smart production-logistics systems.

Partitioning and information flow of the ATC process of SPLS is illustrated in Fig. 8. ATC is an effective model-based and multilevel optimization method for hierarchical systems design [51], [52]. In the ATC hierarchy, the overall targets of SPLS are propagated down to lower-level elements. Firstly, the ATC model of SPLS in a job shop is a three-level hierarchy composed of system level, manufacturing cell level, and equipment level. In each level, manufacturing resources are represented by ATC elements that are capable of active response and autonomous decision making. Secondly, key links between ATC elements are identified with the target (*t*) and response (*r*) variables. Thirdly, objective functions of ATC elements are formulated to minimize the deviation between target and response variables. From the top-level element to the bottom level elements, target cascading proceeds to lower levels in a coordinated manner.

The notation used in the ATC model and throughout the paper is the following.

i: ATC element;

j: manufacturing service;

S_i: a finite set of candidate services for element i;

S_i^j: jth manufacturing service for element i;

φ_i: a finite set of children elements for element i;

TC_i: total manufacturing cost for element i;

TT_i: total manufacturing time for element i;

TE_i: total energy consumption for element i;

C_i: local manufacturing cost for element i;

T_i: local manufacturing time for element i;

E_i: local energy consumption for element i;

$c_{S_i^j}$: manufacturing cost of service option S_i^j;

$st_{S_i^j}$: setup time of service option S_i^j;

$t_{S_i^j}$: manufacturing time of service option S_i^j;

$e_{S_i^j}$: energy consumption of service option S_i^j;

$l_{S_i^j}$: the Boolean variable, $l_{S_i^j}$=1, when service S_i^j is selected; otherwise, $l_{S_i^j}$=0;

w^C: manufacturing cost weighting coefficient;

w^T: manufacturing time weighting coefficient;

w^E: energy consumption weighting coefficient;

t_i^C: manufacturing cost target from parents of element i;

t_i^T: manufacturing time target from parents of element i;

t_i^E: energy consumption target from parents of element i.

In order to focus on the ATC model and simply the simulation, the value of manufacturing cost represents the cost of raw materials or maintenance costs, while values of setup time and manufacturing time represent the cost of wages and other related costs associated with the processing time. The value of energy consumption represents the cost of electricity or other forms of energy. Thus, units for manufacturing cost, manufacturing time, and energy consumption are the same and objective functions can be obtained by adding them together.

The objective of the proposed ATC model is to minimize the sum of weighted total manufacturing cost, total manufacturing time, and total energy consumption, which can be formulated as follows.

$$\min w^C \cdot TC_1 + w^T \cdot TT_1 + w^E \cdot TE_1 \tag{3}$$

subject to $$TC_i = C_i + \sum_{k\in\varphi_i} TC_k \tag{4}$$

$$TT_i = \begin{cases} T_i + \max\{TT_k | k \in \varphi_i\}, & for\ system\ level\ set \\ T_i + \sum_{k\in\varphi_i} TT_k, & otherwise \end{cases} \tag{5}$$

$$TE_i = E_i + \sum_{k\in\varphi_i} TE_k \tag{6}$$

$$C_i = \sum_{s_i^j \in S_i} l_{s_i^j} \cdot c_{s_i^j} \tag{7}$$

$$T_i = \sum_{s_i^j \in S_i} l_{s_i^j} \cdot (st_{s_i^j} + t_{s_i^j}) \tag{8}$$

$$E_i = \sum_{s_i^j \in S_i} l_{s_i^j} \cdot e_{s_i^j} \tag{9}$$

$$\sum_{s_i^j \in S_i} l_{s_i^j} = 1 \tag{10}$$

At the system level, the ATC model aims at minimizing the deviation between ATC element responses and manufacturing targets. The ATC element 1 in Fig. 8 is used as an illustration, which can be formulated as follows.

$$\min \parallel w^C \cdot (TC_1 - t_1^C) + w^T \cdot (TT_1 - t_1^T) + w^E \cdot (TE_1 - t_1^E) \parallel_2^2 + \sum_{i=1}^{7} \varepsilon_1^i \quad (11)$$

where $TC_1 = C_1 + TC_2 + TC_3 + TC_4$ (12)

$$TT_1 = T_1 + \max\{TT_2, TT_3, TT_4\} \quad (13)$$

$$TE_1 = E_1 + TE_2 + TE_3 + TE_4 \quad (14)$$

$$C_1 = \sum_{j=1}^{2} l_{S_1^j} \cdot c_{S_1^j} \quad (15)$$

$$T_1 = \sum_{j=1}^{2} l_{S_1^j} \cdot (st_{S_1^j} + t_{S_1^j}) \quad (16)$$

$$E_1 = \sum_{j=1}^{2} l_{S_1^j} \cdot e_{S_1^j} \quad (17)$$

$$l_{S_1^j} = \begin{cases} 1, if\ service\ S_1^j\ is\ selected \\ 0, otherwise \end{cases} \text{ and } \sum_{j=1}^{2} l_{S_1^j} = 1 \quad (18)$$

subject to $\parallel TC_2 - t_2^C \parallel_2^2 \leq \varepsilon_1^1, \parallel TC_3 - t_3^C \parallel_2^2 \leq \varepsilon_1^2, \parallel TC_4 - t_4^C \parallel_2^2 \leq \varepsilon_1^3$ (19)

$$\parallel \max\{TT_2, TT_3, TT_4\} - \max\{t_2^T, t_3^T, t_4^T\} \parallel_2^2 \leq \varepsilon_1^4 \quad (20)$$

$$\parallel TE_2 - t_2^E \parallel_2^2 \leq \varepsilon_1^5, \parallel TE_3 - t_3^E \parallel_2^2 \leq \varepsilon_1^6, \parallel TE_4 - t_4^E \parallel_2^2 \leq \varepsilon_1^7 \quad (21)$$

$$TC_2, TC_3, TC_4, TT_2, TT_3, TT_4, TE_2, TE_3, TE_4 \geq 0 \quad (22)$$

At the cell level, the ATC model aims at minimizing the deviation between ATC element responses and targets from parents. The ATC element 3 in Fig. 8 is used as an illustration, the objective function can be formulated as follows.

$$\min \parallel w^C \cdot (TC_3 - t_3^C) + w^T \cdot (TT_3 - t_3^T) + w^E \cdot (TE_3 - t_3^E) \parallel_2^2 + \sum_{i=1}^{6} \varepsilon_3^i \quad (23)$$

where $TC_3 = C_3 + TC_5 + TC_6$ (24)

$$TT_3 = T_3 + TT_5 + TT_6 \quad (25)$$

$$TE_3 = E_3 + TE_5 + TE_6 \quad (26)$$

$$C_3 = \sum_{j=1}^{2} l_{S_3^j} \cdot c_{S_3^j} \quad (27)$$

$$T_3 = \sum_{j=1}^{2} l_{S_3^j} \cdot (st_{S_3^j} + t_{S_3^j}) \tag{28}$$

$$E_3 = \sum_{j=1}^{2} l_{S_3^j} \cdot e_{S_3^j} \tag{29}$$

$$l_{S_3^j} = \begin{cases} 1, if\ service\ S_3^j\ is\ selected \\ 0, otherwise \end{cases} \text{ and } \sum_{j=1}^{2} l_{S_3^j} = 1 \tag{30}$$

subject to $\| TC_5 - t_5^C \|_2^2 \leq \varepsilon_3^1, \| TC_6 - t_6^C \|_2^2 \leq \varepsilon_3^2$ (31)

$$\| TT_5 - t_5^T \|_2^2 \leq \varepsilon_3^3, \| TT_6 - t_6^T \|_2^2 \leq \varepsilon_3^4 \tag{32}$$

$$\| TE_5 - t_5^E \|_2^2 \leq \varepsilon_3^5, \| TE_6 - t_6^E \|_2^2 \leq \varepsilon_3^6 \tag{33}$$

$$TC_5, TC_6, TT_5, TT_6, TE_5, TE_6 \geq 0 \tag{34}$$

At the equipment level, the ATC model aims at minimizing the deviation between ATC element responses and targets from parents. Taking ATC element 5 in Fig. 8 as an illustration, the objective function can be formulated as follows.

$$\min \| w^C \cdot (TC_5 - t_5^C) + w^T \cdot (TT_5 - t_5^T) + w^E \cdot (TE_5 - t_5^E) \|_2^2 \tag{35}$$

where $TC_5 = C_5, TT_5 = T_5, TE_5 = E_5$ (36)

subject to $C_5 = \sum_{j=1}^{2} l_{S_5^j} \cdot c_{S_5^j}$ (37)

$$T_5 = \sum_{j=1}^{2} l_{S_5^j} \cdot (st_{S_5^j} + t_{S_5^j}) \tag{38}$$

$$E_5 = \sum_{j=1}^{2} l_{S_5^j} \cdot e_{S_5^j} \tag{39}$$

$$l_{S_5^j} = \begin{cases} 1, if\ service\ S_5^j\ is\ selected \\ 0, otherwise \end{cases} \text{ and } \sum_{j=1}^{2} l_{S_5^j} = 1 \tag{40}$$

The convergence criterion requires that the relative change in the values of objective function for ATC element i is smaller than a user-specified small positive threshold ε_i:

$$\left| f_i^k - f_i^{k-1} \right| / f_i^{k-1} \leq \varepsilon_i \tag{41}$$

where f_i^k denotes the local objective function of iteration k for ATC element i.

With respect to the defined local problem of ATC elements, a variety of optimization algorithms has been proposed, such as genetic algorithms (GA) [53], ant colony optimization (ACO) [54], and particle swarm optimization (PSO) [55]. There is no restriction on the optimization method for each ATC element. As a consequence, the local solution method is chosen according to the application specifics. In the case of small-scale problems, the optimal solution is calculated by using traversal algorithms. For large-scale problems, in order to reduce the computation complexity and time, the advanced artificial intelligence search algorithms such as GA, ACO, and PSO are used to obtain a suboptimal solution.

VI. An Application Scenario of SPLS

This section validates the feasibility and evaluates the performance of the proposed framework and the developed method. An industrial case from an engine manufacturing company in Xi'an is introduced. The company is a typical discrete manufacturer of aviation engine production and maintenance. Engine components are processed on a series of machines on the given process route. A material handling system is used to transport components between manufacturing cells. However, due to external and internal exceptions, production changes and disturbances arise constantly in real production, which makes the production plan and schedules less efficient or even infeasible. As a consequence, the company is in great need of self-organizing configuration solutions to implement collaborative optimization for production-logistics systems. By using the cloud computing information architecture, a prototype system is designed based on the engine manufacturer framework. A simulation experiment is also conducted in the laboratory to demonstrate the proposed SPLS.

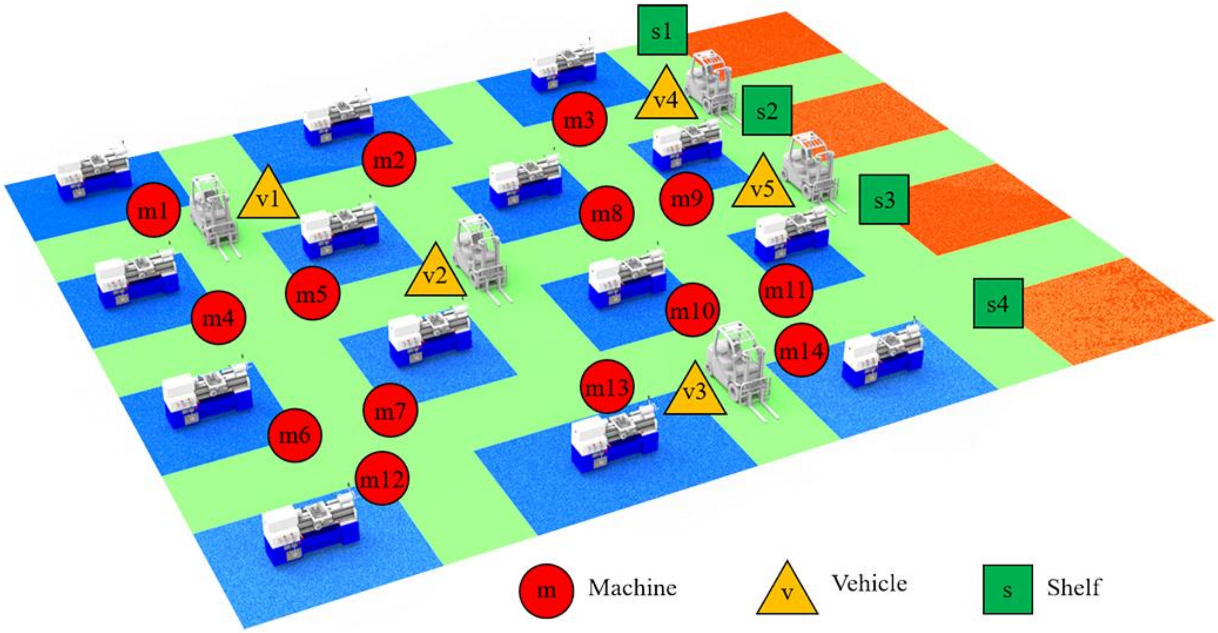

Fig. 9. The layout of the case scenario.

The layout of the job shop is shown in Fig. 9. The job shop consists of four manufacturing cells, a logistics cell, a warehouse, fourteen machines, and a material handling system with five vehicles. Machines *m1* to *m3* belong to manufacturing cell *C1*. Machines *m4* to *m7* belong to manufacturing cell *C2*. Machines *m8* to *m11* belong to manufacturing cell *C3*. Machines *m12* to *m14* belong to manufacturing cell *C4*. Logistics cell *V1* consists of vehicles *v1* to *v5*. The warehouse consists of shelves *s1* to *s4*. The experimental system is composed of two industrial personal computers (IPCs), six RFID readers, twenty-three antennas, and twenty RFID tags. RFID readers are connected to the IPC and antennas are connected to RFID readers. RFID tags are attached to manufacturing resources, including machines, material handling systems, materials, and buffers. Antennas are used to perceive real-time manufacturing status and location information collected by RFID tags.

A. Prototype System Design based on Cloud Computing Information Architecture

In this part, cloud computing information architecture is used to develop the prototype system of SPLS based on CPS and IIoT. A variety of cloud services such as Amazon Web Services (AWS) and Aliyun are provided by Internet companies. In this research, Aliyun is used to develop the prototype system, as shown in Fig. 10.

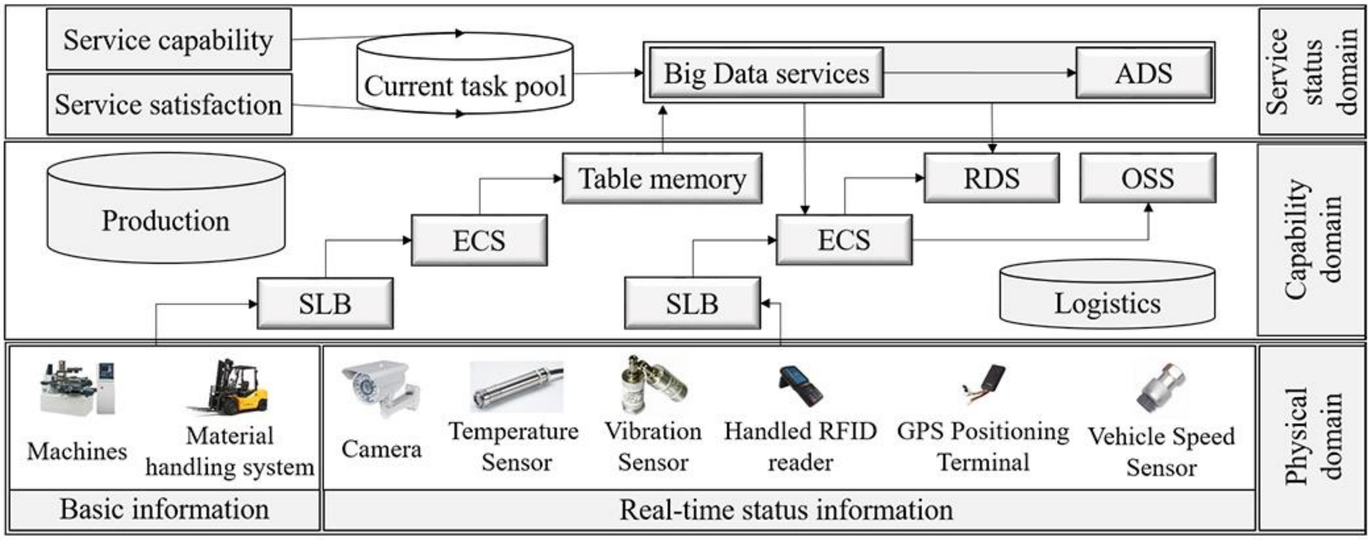

Fig. 10. The prototype system of smart production-logistics systems.

In the prototype system, six elastic compute service (ECS) cloud servers, a relational database service (RDS) cloud database, an analysis database service (ADS), two server load balancers (SLB), and an object storage service (OSS) are used. The detailed information is given in Table I.

TABLE I
INFORMATION OF RESOURCES USED IN THE PROTOTYPE SYSTEM

Product		Specification	Quantity
ECS	Cloud Server	8 cores CPU, 16G memory	6
RDS	Cloud Database	8 cores CPU, 2000G memory	1
ADS	Analysis Database	-	1
SLB	Load Balancing	-	2
OSS	Object Storage	1T memory	1

The physical domain is composed of smart machines, smart material handling systems, and sensors. Sensors are used to collect real-time status information of machines, material handling systems, and materials. The basic information of equipment is perceived within the physical domain and transmitted to cloud servers. The capability domain is based on cloud servers and cloud databases. Real-time status information of production and logistics are stored and processed within the capability domain. The service status domain consists of big data services and the ADS analysis database. Current task pool, service capability, and service satisfaction are provided in the service status domain. The other two modules, namely safety protection, cloud management and monitoring, have protective effects against hostile attacks and maintain system stability.

B. Simulation Study of Theory-Driven Application Scenario

Based on the designed prototype system, simulation experiments are introduced to validate the applicability of the proposed SPLS. Three key performance indicators (KPI) are considered in the comparison study, including manufacturing cost, manufacturing time, and energy consumption.

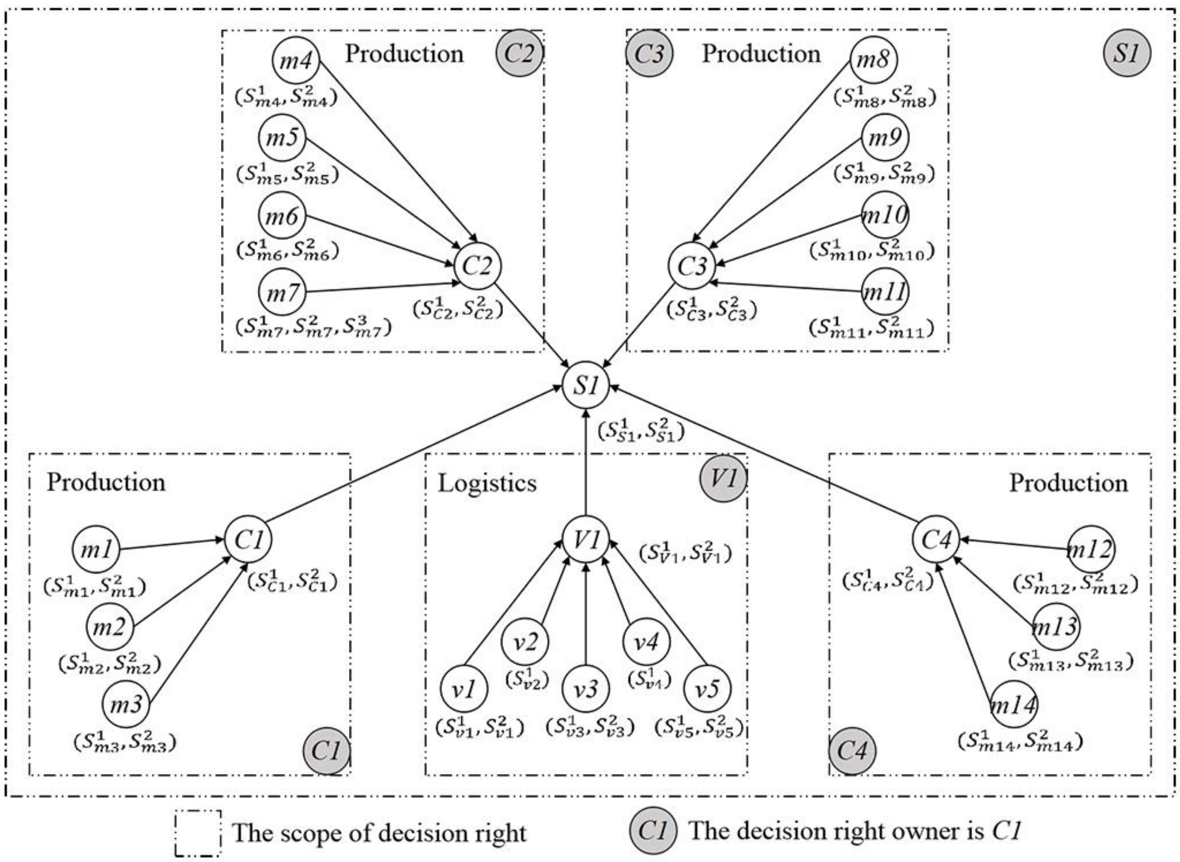

Fig. 11. The analytical target cascading model of the job shop case.

As seen in Fig. 11, the ATC model of the job shop case is constructed. The production process can be divided into three levels: system level, cell level, and equipment level. The ATC element *S1* is responsible for the configuration decisions of system level. The elements *C1* to *C4* are responsible for the production cell level and the element *V1* is responsible for the logistics cell level. Each machine and each vehicle are responsible for their own configuration decisions. The material handling system includes all kinds of vehicles used for materials handling including motorized vehicles and AGVs, which are considered as limited resources. Materials are transported to manufacturing cells by smart material handling systems. Next, materials are processed on smart machines and logistics tasks are published by smart machines through the cloud platform. Then, smart material handling systems actively request the logistics tasks and the optimal vehicle is selected.

The information of all service options for each ATC element is given in Table II. These data are all without units but they are associated with money. Actually, they are transformed from real-life data of the collaborative company. Based on different manufacturing resources and their processing time, the value of manufacturing cost ranges from 0 to 500, while the value of setup time ranges from 0 to 20 and the value of manufacturing time ranges from 0 to 180. Besides, the value of energy consumption ranges from 0 to 220.

Computational experiments were conducted by R-3.4.2 for (Mac) OS X (64-bit) in a computer with an Intel Core i5 processor and 8 GB 1600 MHz DDR3 RAM. The combination of weighted manufacturing cost, manufacturing time, and energy consumption is considered as the optimization objective. Input parameters in the ATC model include the manufacturing targets (t^C, t^T, t^E) and weighting coefficients (w^C, w^T, w^E). The manufacturing targets were respectively set as zero. According to different application scenarios, three manufacturing patterns were tested, including cost-saving pattern, time-saving pattern, and energy-saving pattern. Three sets of weighting coefficients were respectively set as (0.5,0.3,0.2), (0.2,0.5,0.3), and (0.2,03,0.5). The ATC model started running while the production and logistics were executed. Real-time manufacturing status data were transmitted to the IPC through RFID reader ports. Based on the collected data, objective functions were calculated by R-3.4.2 in the computer. A traversal algorithm was used to solve the local optimization problem of ATC elements. Table III shows the optimization results of ATC method under three patterns.

TABLE II
INFORMATION OF ALL SERVICE OPTIONS FOR EACH ELEMENT

Element		Service information					
No.	Set	Option	SC	MC	ST	MT	EC
S1	SLS	S_{S1}^1	S	100.0	2.0	18.0	45.0
		S_{S1}^2	S	150.0	1.0	9.0	35.0
C1	CLS	S_{C1}^1	C	120.0	1.0	9.0	50.0
		S_{C1}^2	C	135.0	0.5	4.5	40.0
C2	CLS	S_{C2}^1	C	130.0	1.5	13.5	65.0
		S_{C2}^2	C	150.0	1.0	9.0	50.0
C3	CLS	S_{C3}^1	C	100.0	3.0	27.0	75.0
		S_{C3}^2	C	120.0	2.5	22.5	55.0
C4	CLS	S_{C4}^1	C	90.0	2.5	22.5	45.0
		S_{C4}^2	C	115.0	1.0	9.0	35.0

V1	CLS	S_{V1}^{1}	C	150.0	5.0	45.0	85.0
		S_{V1}^{2}	C	220.0	3.0	27.0	65.0
m1	ELS	S_{m1}^{1}	P	255.0	10.0	90.0	150.0
		S_{m1}^{2}	P	275.0	6.5	58.5	110.0
m2	ELS	S_{m2}^{1}	P	300.0	7.5	67.5	120.0
		S_{m2}^{2}	P	345.0	4.0	36.0	85.0
m3	ELS	S_{m3}^{1}	P	350.0	5.0	45.0	100.0
		S_{m3}^{2}	P	400.0	3.5	31.5	70.0
m4	ELS	S_{m4}^{1}	P	225.0	8.0	72.0	135.0
		S_{m4}^{2}	P	300.0	4.5	40.5	95.0
m5	ELS	S_{m5}^{1}	P	240.0	6.5	58.5	110.0
		S_{m5}^{2}	P	325.0	4.0	36.0	75.0
m6	ELS	S_{m6}^{1}	P	255.0	5.5	49.5	100.0
		S_{m6}^{2}	P	325.0	2.0	18.0	45.0
m7	ELS	S_{m7}^{1}	P	265.0	7.5	67.5	85.0
		S_{m7}^{2}	P	340.0	6.5	58.5	45.0
		S_{m7}^{3}	P	385.0	1.5	13.5	60.0
m8	ELS	S_{m8}^{1}	P	230.0	9.5	85.5	150.0
		S_{m8}^{2}	P	310.0	5.0	45.0	85.0
m9	ELS	S_{m9}^{1}	P	245.0	7.5	67.5	130.0
		S_{m9}^{2}	P	345.0	3.5	31.5	70.0
m10	ELS	S_{m10}^{1}	P	275.0	6.0	54.0	115.0
		S_{m10}^{2}	P	370.0	2.5	22.5	50.0
m11	ELS	S_{m11}^{1}	P	300.0	4.5	40.5	80.0
		S_{m11}^{2}	P	350.0	2.0	18.0	40.0
m12	ELS	S_{m12}^{1}	P	195.0	18.0	162.0	220.0
		S_{m12}^{2}	P	285.0	9.0	81.0	145.0
m13	ELS	S_{m13}^{1}	P	260.0	10.5	94.5	170.0
		S_{m13}^{2}	P	340.0	4.5	40.5	80.0
m14	ELS	S_{m14}^{1}	P	355.0	6.0	54.0	95.0
		S_{m14}^{2}	P	460.0	2.0	18.0	50.0
v1	ELS	S_{v1}^{1}	L	115.0	1.5	13.5	40.0
		S_{v1}^{2}	L	210.0	0.5	4.5	20.0
v2	ELS	S_{v2}^{1}	L	120.0	1.0	9.0	35.0
v3	ELS	S_{v3}^{1}	L	130.0	1.0	9.0	20.0
		S_{v3}^{2}	L	230.0	0.5	4.5	10.0
v4	ELS	S_{v4}^{1}	L	135.0	0.5	4.5	15.0
v5	ELS	S_{v5}^{1}	L	150.0	0.5	4.5	10.0
		S_{v5}^{2}	L	240.0	0.2	1.8	5.0

SLS: System level set; CLS: Cell level set; ELS: Equipment level set;
SC: Service category; S: System; C: Cell; P: Production; L: Logistics;
MC: Manufacturing Cost; ST: Setup Time; MT: Manufacturing Time;
EC: Energy Consumption.

TABLE III
OPTIMIZATION RESULTS OF ATC METHOD UNDER THREE PATTERNS

Pattern	Cost-saving	Time-saving	Energy-saving
(w^C, w^T, w^E)	(0.5, 0.3, 0.2)	(0.2, 0.5, 0.3)	(0.2, 03, 0.5)
Service Option	$S_{S1}^1, S_{C1}^1, S_{C2}^1, S_{C3}^1, S_{C4}^1, S_{V1}^1, S_{m1}^2, S_{m2}^1, S_{m3}^1, S_{m4}^1, S_{m5}^1, S_{m6}^1, S_{m7}^1, S_{m8}^1, S_{m9}^1, S_{m10}^1, S_{m11}^1, S_{m12}^1, S_{m13}^1, S_{m14}^1, S_{v1}^1, S_{v2}^1, S_{v3}^1, S_{v4}^1, S_{v5}^1$	$S_{S1}^1, S_{C1}^2, S_{C2}^2, S_{C3}^2, S_{C4}^2, S_{V1}^2, S_{m1}^2, S_{m2}^2, S_{m3}^2, S_{m4}^2, S_{m5}^2, S_{m6}^2, S_{m7}^3, S_{m8}^2, S_{m9}^2, S_{m10}^2, S_{m11}^2, S_{m12}^2, S_{m13}^2, S_{m14}^2, S_{v1}^1, S_{v2}^1, S_{v3}^1, S_{v4}^1, S_{v5}^1$	$S_{S1}^1, S_{C1}^2, S_{C2}^2, S_{C3}^2, S_{C4}^2, S_{V1}^2, S_{m1}^2, S_{m2}^2, S_{m3}^2, S_{m4}^2, S_{m5}^2, S_{m6}^2, S_{m7}^2, S_{m8}^2, S_{m9}^2, S_{m10}^2, S_{m11}^2, S_{m12}^2, S_{m13}^2, S_{m14}^2, S_{v1}^1, S_{v2}^1, S_{v3}^1, S_{v4}^1, S_{v5}^1$
Total Manufacturing Cost	5110.0	6305.0	6260.0
Total Manufacturing Time	390.0	185.0	200.0
Total Energy Consumption	2205.0	1470.0	1455.0
Value of Objective Function	3113.0	1794.5	2039.5
Computation Time (s)	0.006	0.006	0.006

For the cost-saving pattern, the set of optimal service option is (S_{S1}^1, S_{C1}^1, S_{C2}^1, S_{C3}^1, S_{C4}^1, S_{V1}^1, S_{m1}^2, S_{m2}^1, S_{m3}^1, S_{m4}^1, S_{m5}^1, S_{m6}^1, S_{m7}^1, S_{m8}^1, S_{m9}^1, S_{m10}^1, S_{m11}^1, S_{m12}^1, S_{m13}^1, S_{m14}^1, S_{v1}^1, S_{v2}^1, S_{v3}^1, S_{v4}^1, S_{v5}^1). This pattern can be used for general production. The total manufacturing cost is 5110.0. The total manufacturing time is 390.0. The total energy consumption is 2205.0. The value of the objective function is 3113.0.

For the time-saving pattern, the set of optimal service option is (S^1_{S1}, S^2_{C1}, S^2_{C2}, S^2_{C3}, S^2_{C4}, S^2_{V1}, S^2_{m1}, S^2_{m2}, S^2_{m3}, S^2_{m4}, S^2_{m5}, S^2_{m6}, S^3_{m7}, S^2_{m8}, S^2_{m9}, S^2_{m10}, S^2_{m11}, S^2_{m12}, S^2_{m13}, S^2_{m14}, S^1_{v1}, S^1_{v2}, S^1_{v3}, S^1_{v4}, S^1_{v5}). This pattern can be used for urgent tasks. The total manufacturing cost is 6305.0. The total manufacturing time is 185.0, which is roughly 52% shorter than that of the cost-saving pattern. The total energy consumption is 1470.0. The value of the objective function is 1794.5.

For the energy-saving pattern, the set of optimal service option is (S^1_{S1}, S^2_{C1}, S^2_{C2}, S^2_{C3}, S^2_{C4}, S^2_{V1}, S^2_{m1}, S^2_{m2}, S^2_{m3}, S^2_{m4}, S^2_{m5}, S^2_{m6}, S^2_{m7}, S^2_{m8}, S^2_{m9}, S^2_{m10}, S^2_{m11}, S^2_{m12}, S^2_{m13}, S^2_{m14}, S^1_{v1}, S^1_{v2}, S^1_{v3}, S^1_{v4}, S^1_{v5}). This pattern can be used for energy-intensive industries, such as the ceramic industry. The total manufacturing cost is 6260.0, roughly 22% higher than that of the cost-saving pattern. The total manufacturing time is 200.0, roughly 8% higher than that of the time-saving pattern. The total energy consumption is 1455.0, which is roughly 34% less than that of the cost-saving pattern. The value of the objective function is 2039.5.

The efficiency of SPLS is verified and the result shows that the computing time is less than 0.01s, which is reasonable to implement SPLS in real production.

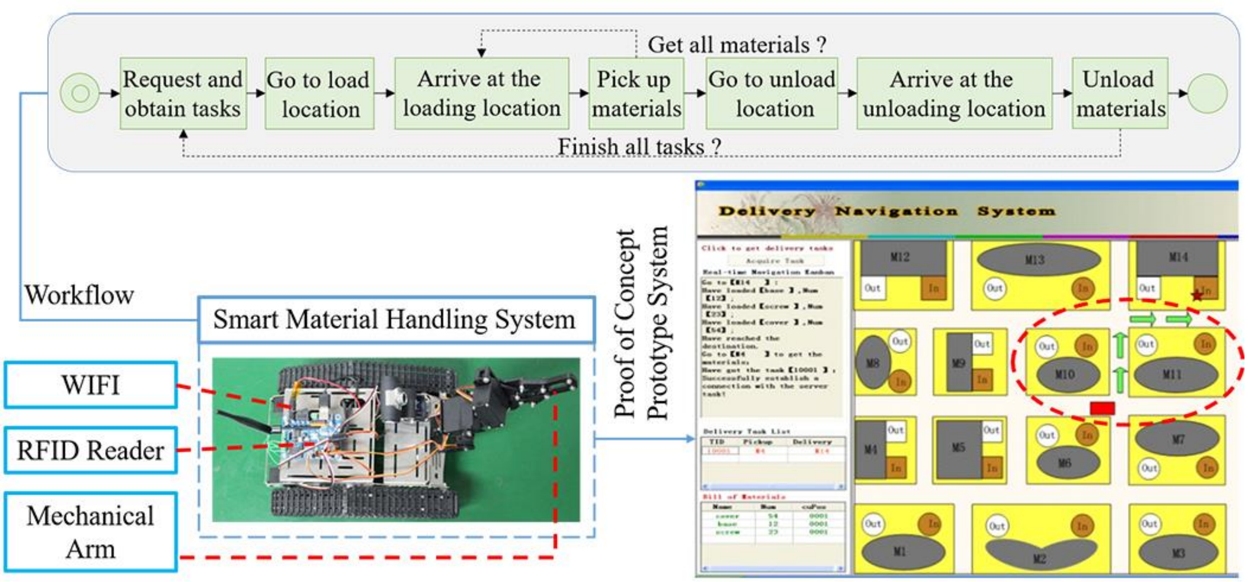

Fig. 12. A proof of the concept prototype system.

Then, a proof of the concept prototype system is introduced. A vehicle of material handling systems is taken as an example, as shown in Fig. 12. The system aims to make the material handling system capable of active perception, active response, and intelligent decision-making. Firstly, in order to provide the active perception capability for the smart material handling system, some hardware devices are used to capture the real-time data, including the WIFI module, the RFID reader, and the antennas. The RFID reader and antennas are used to sense the real-time status of manufacturing resources attached to RFID tags, such as the equipment number, current location, and service options. For example, the RFID tags are used to store the locations information in the shop floor, while an RFID reader is installed at the vehicle side for capturing the real-time location information. Secondly, the process of active response for smart material handling systems can be described as follows. When a new task or an abnormal task is published by the cloud platform, the real-time status of idle vehicles will be sent as an XML-based schema to the cloud platform, including equipment number, current location, service options, transport cost, transport time, and energy consumption. Then, the optimal service options will be chosen by the ATC model based on the configuration target. Thirdly, to implement intelligent decision-making for smart material handling systems, a workflow is introduced to this component. As shown at the top of Fig. 12, the topology of key processes includes seven steps: (1) request and obtain task, (2) go to load location, (3) arrive at the loading location, (4) pick up materials, (5) go to unload location, (6) arrive at the unloading location, and (7) unload materials. When the logistics task contains multi load locations or multi unload locations, the flow (2) to (4) or flow (5) to (7) are repeated.

A simulation-based comparison experiment was conducted by R-3.4.2 for (Mac) OS X (64-bit) to compare the separated production logistics with SPLS. Depending on the features of separated production logistics as well as the investigation of collaborative companies, the set of service option for the separated production logistics was assumed to be (S_{S1}^{1}, S_{C1}^{1}, S_{C2}^{1}, S_{C3}^{1}, S_{C4}^{1}, S_{V1}^{1}, S_{m1}^{1}, S_{m2}^{1}, S_{m3}^{1}, S_{m4}^{1}, S_{m5}^{1}, S_{m6}^{1}, S_{m7}^{1}, S_{m8}^{1}, S_{m9}^{1}, S_{m10}^{1}, S_{m11}^{1}, S_{m12}^{1}, S_{m13}^{1}, S_{m14}^{1}, S_{v1}^{1}, S_{v2}^{1}, S_{v3}^{1}, S_{v4}^{1}, S_{v5}^{1}), which was inefficient to adjust for exceptions. Table IV shows the results of the comparative study. The total manufacturing cost of the separated production logistics is 5090.0, which is around 22% less than the total manufacturing cost of SPLS. The total manufacturing time of the separated production logistics is 390.0 and the total energy consumption of it is 2245.0. In contrast, the results show that SPLS reduces the total manufacturing time by around 51% and the total energy consumption by around 37%.

TABLE IV
THE RESULTS OF THE COMPARATIVE STUDY

KPI	Separated Production Logistics	SPLS
Manufacturing Cost	5090.0	6595.0
Manufacturing Time	390.0	190.0
Energy Consumption	2245.0	1410.0

According to the investigation, in the separated production logistics scenario, production is scheduled without consideration of logistics, namely production schedule belongs to one system while logistics schedule belongs to another system. In such case, it is very difficult to handle exceptions from either the production side or the logistics side during execution. To solve the aforementioned problems, SPLS integrates production and logistics into a smart control system such that it is capable of exception identification, self-organizing configuration, and self-adaptive collaboration. As a consequence, SPLS can overcome the inefficiency and infeasibility in the scheduling which arises from both external and internal dynamic changes, so that SPLS can help manufacturing companies improve production efficiency and energy efficiency.

VII. CONCLUSION

In order to cope with frequent changes and disturbances, discrete manufacturing systems require a high level of integration between production and logistics. This paper introduces a conceptual framework of SPLS and the mechanism and methodology of self-organizing configuration for collaborative production-logistics. Two problems in the field of manufacturing are addressed, including the intelligent modeling of manufacturing resources in the infrastructure layer and the self-organizing configuration of smart manufacturing service groups.

The research is carried out to achieve the self-organizing configuration of SPLS based on CPS and IIoT. In the proposed SPLS, manufacturing resources at all levels are capable of responding to disturbances actively and coordinating intelligently. Bi-directional interaction of production-logistics and collaborative relationships between machines, materials, and human are achieved based on the proposed self-organizing configuration mechanism. As a consequence, production-logistics systems can be optimized adaptively and collaboratively when exceptions occur.

A prototype system is presented in the industrial case, which adopts the cloud computing information architecture. Using the proposed mechanism and methodology, the functionality of the developed prototype system is evaluated by applying a theory-driven application scenario. Computational experiments are conducted to validate the feasibility and verify the efficiency of the proposed SPLS. The results show that SPLS can meet different requirements and the computing time is reasonable to implement the SPLS in real production. A comparative study shows that SPLS can help manufacturing companies save manufacturing time and energy consumption.

As future work, some attention could be paid to the development of self-organizing configuration models using other algorithms. Furthermore, the proposed prototype system may be applied in a real-life environment.

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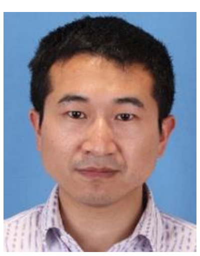

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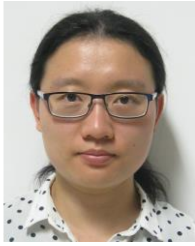

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