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A multi-agent architecture for scheduling in platform-based smart manufacturing systems*

Yong-kui LIU[1], Xue-song ZHANG[‡2], Lin ZHANG[3], Fei TAO[3], Li-hui WANG[4]

[1]*Center for Intelligent Manufacturing Systems and Robots, School of Mechano-Electronic Engineering, Xidian University, Xi'an 710071, China*

[2]*College of Computer Science and Technology, Jilin University, Changchun 130012, China*

[3]*School of Automation Science and Electrical Engineering, Beihang University, Beijing 100191, China*

[4]*Department of Production Engineering, KTH Royal Institute of Technology, Stockholm 11428, Sweden*

E-mail: yongkuiliu@163.com; xs_zhang@126.com; zhanglin@buaa.edu.cn; ftao@buaa.edu.cn; lihuiw@kth.se

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Abstract: During the past years, a number of smart manufacturing concepts have been proposed, such as cloud manufacturing, Industry 4.0, and Industrial Internet. One of their common aims is to optimize the collaborative resource configuration across enterprises by establishing platforms that aggregate distributed resources. In all of these concepts, a complete manufacturing system consists of distributed physical manufacturing systems and a platform containing the virtual manufacturing systems mapped from the physical ones. We call such manufacturing systems platform-based smart manufacturing systems (PSMSs). A PSMS can therefore be regarded as a huge cyber-physical system with the cyber part being the platform and the physical part being the corresponding physical manufacturing system. A significant issue for a PSMS is how to optimally schedule the aggregated resources. Multi-agent technology provides an effective approach for solving this issue. In this paper we propose a multi-agent architecture for scheduling in PSMSs, which consists of a platform-level scheduling multi-agent system (MAS) and an enterprise-level scheduling MAS. Procedures, characteristics, and requirements of scheduling in PSMSs are presented. A model for scheduling in a PSMS based on the architecture is proposed. A case study is conducted to demonstrate the effectiveness of the proposed architecture and model.

Key words: Platform; Smart manufacturing; Multi-agent; Scheduling
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1 Introduction

During the past years, enabled by emerging information and communications technologies such as cloud computing, Internet of Things (IoT), big data, and artificial intelligence, a number of significant smart manufacturing concepts have emerged, with the most prominent ones being cloud manufacturing (Zhang et al., 2014; Kang et al., 2016; Liu and Xu, 2017), Industry 4.0 (Kagermann et al., 2013), and Industrial Internet (Evans and Annunziata, 2012). A common characteristic of them is that a platform is built to connect distributed manufacturing resources, systems, and processes. For example, in a cloud manufacturing system, a cloud platform that facilitates aggregation of distributed resources and capabilities is built for centralized management and operation, so that the aim of delivering on-demand manufacturing services can be achieved. In Industry 4.0, a cyber-physical system (CPS) platform is built to

‡ Corresponding author

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ORCID: Yong-kui LIU, http://orcid.org/0000-0003-2165-775X; Xue-song ZHANG, http://orcid.org/0000-0002-8940-5666

integrate manufacturing resources, systems, and processes from enterprises (or factories) along a value chain (or a value network) so that the IoT and Internet of Services can be achieved. In the Industrial Internet, an Industrial Internet platform needs to be built as a hub for connecting machines, people, and data to achieve an optimized configuration of industrial resources (http://www.miit.gov.cn/n973401/n5993937/n5993968/c6002326/content.html). In all of these platforms, physical manufacturing resources, systems, and processes from different enterprises are transformed into digital entities and pooled in the platforms. Digital entities in cloud manufacturing, Industry 4.0, and Industrial Internet are cloud services, digital twins and services, and micro-services, respectively. Given the critical role of the platform, the manufacturing system in any of the three concepts can be referred to as a platform-based smart manufacturing system (PSMS), which consists of real-world physical manufacturing systems and their virtual digital counterparts. During the operation process of a PSMS, the physical and virtual parts interact with each other in real time to achieve overall optimization of the system. From the perspective of CPS, a PSMS is therefore a huge CPS.

One of the common functions of a PSMS is to facilitate an inter-enterprise optimal collaborative resource configuration. Scheduling is a critical means for this purpose. Thus far, some research efforts have been made towards developing approaches and algorithms for resource scheduling in PSMSs (Liu et al., 2019). Most of the work focuses on cloud manufacturing, and most of the proposed approaches are based on meta-heuristics algorithms such as the genetic algorithm (GA), particle swarm optimization (PSO), and ant colony optimization (ACO). Overall, related research is still in the very early stage, which is reflected by the following fact that scheduling in a PSMS is a highly complex problem, characterized by involvement of numerous autonomous enterprises, large-scale resources/services, wide-area logistics, and highly dynamic and multi-granularity resources and requirements, so the currently proposed meta-heuristics algorithm based centralized scheduling approaches are very likely to fail due to their inefficiency and lack of adaptability. Due to the high complexity of a PSMS, distributed approaches have more advantages than traditional centralized ones in solving the scheduling issue. Multi-agent (MA) technology provides an effective approach in this regard due to its inherent characteristics of distributed, parallel, and intelligent features such as autonomy, reactivity, and adaptability (Liu et al., 2018). Hence, MA technology is used to deal with the scheduling issue in a PSMS. A multi-agent architecture for scheduling in a PSMS is proposed, comprising a platform-level scheduling multi-agent system (MAS) and an enterprise-level scheduling MAS. A specific model based on the architecture is proposed. A case study is conducted to demonstrate the effectiveness of the proposed architecture and model.

The main contributions of this paper are as follows. First and foremost, the concept of PSMS is proposed by extracting common features of cloud manufacturing systems, Industry 4.0, and Industrial Internet, and a detailed and comprehensive MA-based two-layer architecture for scheduling in PSMS is proposed based on the analysis of its procedures, characteristics, and requirements. Second, a new task-modeling approach is proposed that incorporates both manufacturing subtasks and logistics subtasks, taking into account enterprise subtasks and platform subtasks, respectively. Third, a new complex network based logistics modeling approach is proposed, which ensures that different logistics service providers have different logistics networks. All these contributions can provide reference for future research.

2 Literature review

In this section we present a systematic review of the literature pertaining to scheduling in typical PSMSs, including mainly cloud manufacturing systems, Industry 4.0 manufacturing systems, and Industrial Internet based manufacturing systems. Literature on agent-based production scheduling is also reviewed and analyzed.

2.1 Scheduling in cloud manufacturing

Cloud manufacturing is the earliest PSMS concept, and a cloud manufacturing system is a typical PSMS. Existing research on scheduling in PSMSs concerns mainly cloud manufacturing. Thus far, dozens of papers on scheduling in cloud manufacturing have been published, and the research topics have covered scheduling of computing and manufacturing resources in terms of scheduling objects, platform-level and shop-level scheduling in terms of scheduling levels, static and dynamic scheduling in terms of scheduling approaches, cloud service based virtual enterprise-like scheduling and supply chain scheduling in terms of issues addressed, and single- and multi-task scheduling in terms of the number of tasks scheduled at the same time (Liu et al., 2019).

Lin and Chong (2017) addressed resource constraint project scheduling to solve computing resource allocation problems in cloud manufacturing using an improved GA. Laili et al. (2011) dealt with scheduling of collaborative design tasks in cloud manufacturing. Lartigau et al. (2012) proposed a scheduling methodology for production services in cloud manufacturing. Lartigau et al. (2014) proposed a scheduling framework for cloud manufacturing taking into account resource availability. Cao et al. (2016) addressed the service selection and scheduling issue in cloud manufacturing with the consideration of service occupancy over time. Akbaripour et al. (2018) proposed mixed-integer programming models for the service selection optimization and scheduling problem in cloud manufacturing with optimized routing decisions in a given hybrid hub-and-spoke transportation network.

Multi-task scheduling is an important characteristic of cloud manufacturing. Cheng et al. (2014) studied multi-task scheduling in cloud manufacturing taking virtual resource correlations into account. The tasks they considered were of completely identical subtask execution flows. Li et al. (2017) investigated subtask scheduling of distributed robots in the context of cloud manufacturing. The multiple tasks they considered were heterogeneous in terms of subtask type, execution flow, and required resources. Inventory and transportation were also explicitly considered. Liu et al. (2016) proposed an extensible multi-task-oriented service composition and scheduling model for cloud manufacturing. Based on this model, they further investigated workload-based multi-task scheduling in cloud manufacturing (Liu et al., 2017). All of the above works adopted static scheduling approaches (Liu et al., 2019).

Some researchers addressed dynamic scheduling issues in cloud manufacturing. Typically, Tai et al. (2013) dealt with multi-objective dynamic scheduling in cloud manufacturing. In their model, rescheduling is triggered when utility discrepancy between the current schedule and the new schedule exceeds a threshold in the time-domain period. Zhang et al. (2017a) developed a real-time order dispatching mechanism to provide an optimal scheduling plan for cloud services encapsulated from virtual machining services of injection molding machines.

Some researchers focused on workshop scheduling problems in the context of cloud manufacturing. Lu et al. (2017) dealt with mixed-flow, hybrid job shop scheduling problems in cloud manufacturing. Zhang et al. (2017b) proposed a dynamic optimization model for flexible job shop scheduling based on game theory. Yuan et al. (2017) considered the problem of multi-objective optimization scheduling of a reconfigurable assembly line. Li et al. (2018) considered two uniform parallel machine scheduling problems with fixed machine cost in the context of cloud manufacturing.

Aiming to use surplus capacities of enterprises in cloud manufacturing, Wang et al. (2017) proposed a job shop scheduling method considering idle times. Similarly, some researchers addressed the issue of dynamic or adaptive job shop scheduling in cloud manufacturing workshops. Li et al. (2012) investigated collaborative scheduling technologies between multiple geographically distributed job shops based on dynamic resource capability services. Mourtzis et al. (2015) addressed cloud-based adaptive shop-floor scheduling considering machine tool availability based on gathering of data from a multi- sensory system and machine tool operators.

In particular, Xiao et al. (2015) addressed distributed supply chain scheduling for customization of multiple products. Xiao et al. (2016) reviewed planning and scheduling technologies of supply chain management in cloud manufacturing, encompassing the short-term production planning and scheduling, medium- and long-term plan management problem, and multi-dimensional integration planning and scheduling problems.

Considering the advantages of multi-agent technology in addressing scheduling issues in cloud manufacturing, Ma et al. (2014) proposed the concept of cloud agent and studied adaptive management and scheduling of cloud manufacturing services using an improved contract net mechanism. Very recently, Liu et al. (2018) addressed scheduling issues in cloud manufacturing with dynamic task arrivals using an extended MA contract net protocol.

2.2 Scheduling in Industry 4.0

So far, only a couple of articles have touched upon scheduling in Industry 4.0. Ivanov et al. (2016) proposed a dynamic model and algorithm for short-term supply chain scheduling in smart factories with simultaneous consideration of both machine structure selection and job assignments. Fu et al. (2018) investigated a flow-shop scheduling problem, considering time-dependent processing time and uncertainty in Industry 4.0 based manufacturing systems. Chekired et al. (2018) proposed a hierarchical free open- source ghost (FOG) server deployment approach at the network service layer across different tiers, in which industrial IoT data and requests were divided into high- and low-priority requests with the high-priority requests being urgent/emergency demands that need to be scheduled rapidly. Mourtzis and Vlachou (2018) proposed a cloud-based cyber-physical system for adaptive shop-floor scheduling and condition-based maintenance.

2.3 Scheduling in the context of the Industrial Internet

There are several articles focusing on scheduling in the context of Industrial Internet. Considering a centralized industrial IoT network where the gateway makes frequency allocations and time slot assignments, Ojo et al. (2018) proposed a novel auction-based scheduling mechanism that uses a first-price sealed bids auction to solve the throughput maximizing scheduling problem, for providing an effective scheduling scheme in the IEEE 802.15.4 time slotted channel hopping mode. Tang et al. (2018) presented a mobile cloud based scheduling strategy for the industrial IoT, in which the task scheduling problem was modeled as an energy consumption optimization problem. Genetic algorithms were employed to solve it. Given the fact that the IEEE 802.15.4e standard defines a method for executing a schedule but does not define the scheduling method, Choi and Chung (2017) proposed a quick setup scheduling scheme with minimum control messages, which has three algorithms: quick setup scheduling allocation processing, quick setup scheduling deallocation processing, and quick setup scheduling optimization processing. The traditional backpressure scheduling scheme explores all the possible paths between the source and destination nodes; this is a shortcoming that causes an exceedingly long path for packets. To solve this problem, Qiu et al. (2018) proposed an event-aware backpressure scheduling scheme for IoT emergencies. Comparison of the approach with two existing backpressure scheduling schemes showed that the approach has better performance.

2.4 Agent-based manufacturing or production scheduling

Multi-agent technology has long been used to deal with the manufacturing or production scheduling issue. Shen (2002) gave a comprehensive analysis of distributed manufacturing scheduling using intelligent agents, including agent encapsulation, coordinated and negotiation protocols, architecture, and decision schemes. Shen et al. (2006) reviewed the literature on agent-based manufacturing process planning, scheduling, and their integration, discussed major issues in these research areas, and identified research opportunities and challenges. Ouelhadj and Petrovic (2009) presented a survey of dynamic scheduling in manufacturing systems, pointing out that the multi-agent system is a promising technology for dynamic scheduling. Macchiaroli and Riemma (2002) proposed a negotiation scheme for autonomous agents in job shop scheduling, in which the spread between part proposals and resources drives an iterative re-negotiation process to reach convergence. Xiang and Lee (2008) proposed an approach to dynamic scheduling of a more generic and realistic manufacturing system (with multiple product types, multiple/parallel multi-purpose machines, and various dynamic disturbances) using multi-agent technologies into which ant colony intelligence is incorporated. Similarly, Zhang and Wong (2017) presented a hybrid approach combining multi-agent negotiations with ACO for flexible job shop scheduling/ rescheduling problems in a dynamic environment, taking into account different types of disruptions such as machine failures, tool shortages, and requirement variations. Wong et al. (2006) developed an agent-based approach for dynamic integration of process planning and scheduling functions, in which selection and allocation of manufacturing resources are achieved through negotiation among part agents and machine agents. Zhang and Wang (2016) addressed production scheduling problems in re-entrant manufacturing systems by developing an effective way of formulating production schedules. Wang and Haghighi (2016) presented a novel approach for implementing cyber-physical systems using the combined strength of holons, agents, and function blocks.

The literature review above indicates that although multi-agent technology has been widely used to deal with scheduling issues in various manufacturing systems, it has rarely been used in PSMSs. As a result, there is a need to explore multi-agent-based approaches for effectively addressing scheduling problems in PSMSs. This paper represents an early effort in this regard.

3 Procedure, characteristics, and requirements of scheduling in a PSMS

In this section we present the procedure, characteristics, and requirements of scheduling in a public PSMS.

3.1 Procedure

As shown in Fig. 1, production planning, scheduling, and control in a PSMS take place at the platform and enterprise levels simultaneously. The overall procedure is as follows:

1. Platform-level order submission and classification. Platform consumers, including enterprises involved/uninvolved in the platform and end-product consumers, submit their orders to the platform. According to a subsequent execution procedure, orders can be classified into long-term orders and urgent orders (e.g., urgent individualized requirements).

2. Platform-level production planning. For long-term orders, the platform planning system first makes production plans and then sends the plans to the platform scheduling system for further scheduling, while urgent orders go to the platform scheduling system directly. Some long-term orders may also be sent to the enterprise production planning system for direct processing without undergoing the scheduling phase in the platform (Wang and Shen, 2007; Cai et al., 2009).

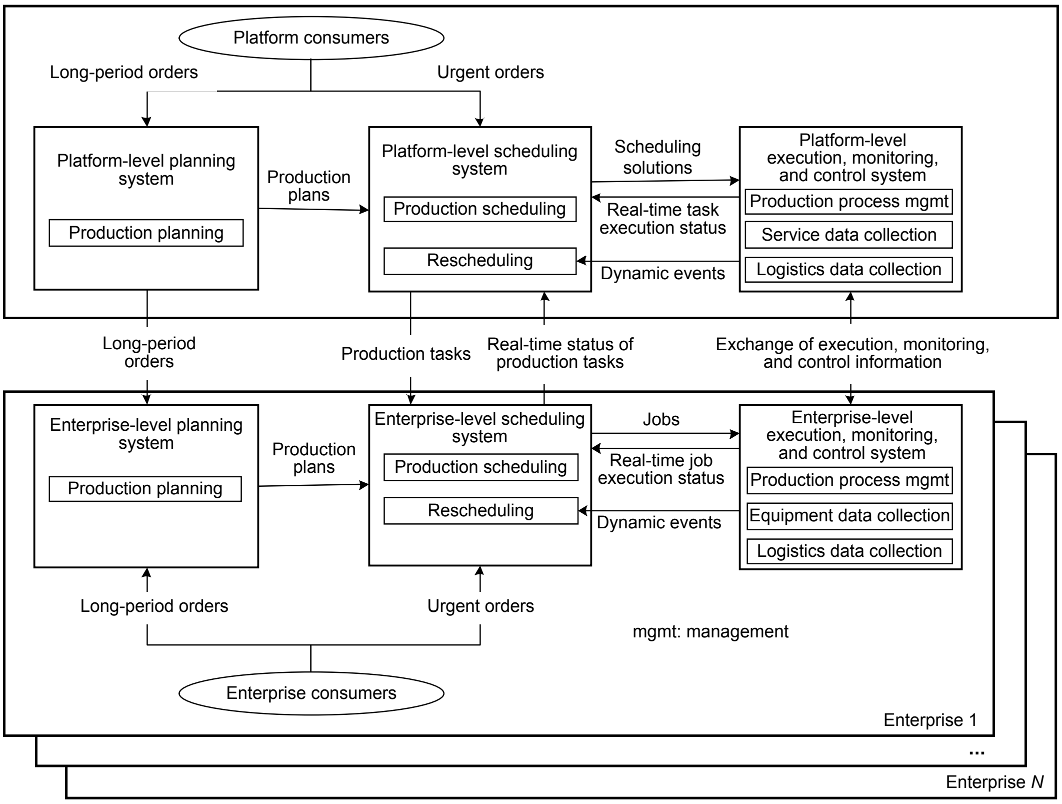

Fig. 1 Operation principle of a platform-based smart manufacturing system (PSMS)

3. Platform-level production scheduling. The platform scheduling system generates schedules and then sends them to, and at the same time receives feedback (e.g., real-time task execution status and various dynamic events) from, the platform execution, monitoring, and control system and the enterprise scheduling system. The enterprise scheduling system is responsible for executing production tasks that are dispatched from the platform scheduling system.

4. Platform-level execution, monitoring, and control. The platform execution, monitoring, and control system is responsible for managing the production process, including executing schedules, collecting service and logistics data, analyzing the data, identifying discrepancies, reporting various dynamic events, and exerting feedback control as needed. Apart from the function above, it interacts and communicates with the enterprise counterpart to obtain necessary data and information about equipment, logistics, quality, etc.

5. Enterprise-level order submission, planning, and scheduling. In addition to the orders/tasks from the platform, enterprises receive orders/tasks from other channels, and carry out in-house planning and scheduling. Similarly, long-term orders/tasks undergo the stages of planning and scheduling, whereas urgent orders/tasks can be scheduled directly.

3.2 Characteristics and requirements

Typically, a public PSMS is a huge manufacturing system that aggregates large-scale manufacturing resources from numerous enterprises. The characteristics of the PSMS and associated requirements for scheduling are summarized in Table 1.

4 Multi-agent architecture for scheduling in a PSMS

In this section we present a multi-agent architecture for scheduling in a PSMS (Fig. 2). A scenario with centralized management and operation like cloud manufacturing is considered, which is actually also the most common scenario for PSMSs. As shown in Fig. 2, the MA architecture overall consists of two parts: platform-level scheduling MAS and enterprise-level scheduling MAS.

4.1 Multi-agent architecture

4.1.1 Platform-level scheduling MAS

The platform-level scheduling MAS consists of five modules (Fig. 3). In the following, the responsibilities of the modules are described in detail.

1. Platform customer and order management MAS (PCOM-MAS). The main functions of this module include: (1) managing consumers and their orders, maintaining associated information, and performing necessary functions (e.g., consumer registration and order/task decomposition), (2) interacting with the PMC-MAS module to obtain real-time order information to achieve dynamic information updates, (3) interacting with the EOJM-MAS module to obtain

Table 1 Characteristics and requirements of scheduling in a public platform-based smart manufacturing system (PSMS) (Liu et al., 2019)

No.	Characteristic	Requirement
1	Autonomy and preferences of providers	Providers' autonomy and preferences need to be taken into account
2	Numerous enterprises and large-scale resources	Highly efficient scheduling approaches/algorithms and big data analytics are required
3	Highly dynamic environment	Dynamic, adaptive scheduling approaches are required
4	Wide-area logistics	Wide-area logistics should be considered
5	Multi-granularity resources	Multi-granularity matching and scheduling of resources should be considered
6	Many-to-many scheduling	Multiple tasks may exist in a PSMS and need to be scheduled at the same time
7	Huge volumes of data	Big data analytics and artificial intelligence technologies are required
8	Composite tasks	Composite scheduling (i.e., multiple services need to be combined during scheduling for optimality)
9	Highly individualized consumers' requirements	Individualized preferences of consumers should be considered
10	Knowledge	Knowledge should be effectively used during scheduling

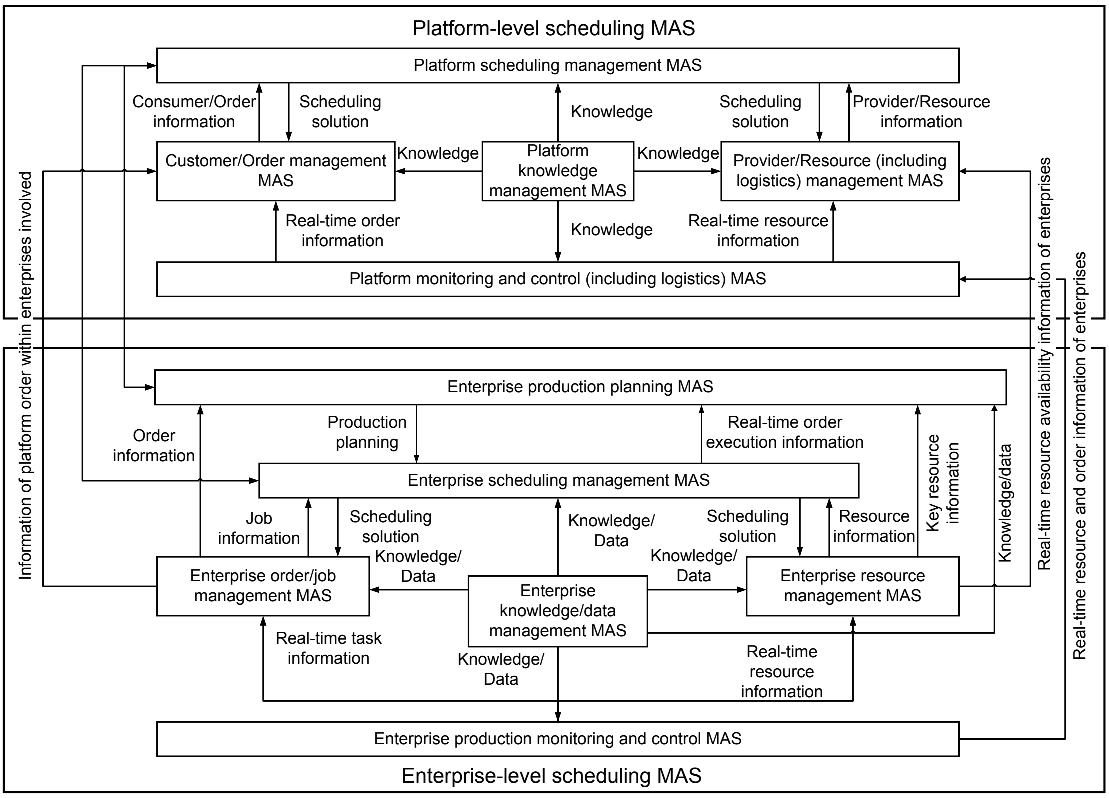

Fig. 2 A multi-agent architecture for scheduling in a platform-based smart manufacturing system (PSMS)

real-time information on the tasks that are dispatched to enterprises from the platform, (4) providing static or dynamic information on consumers and their orders to the PSM-MAS module to facilitate scheduling, (5) receiving scheduling solutions from the PSM-MAS module and performing scheduling in collaboration with it, and (6) interacting with the PKM-MAS module to obtain the knowledge necessary for consumers and order management (e.g., order/task decomposition). In this module, each consumer is modeled as an agent to facilitate separate management, and each task is modeled as an agent for separate processing, taking into account the fact that orders/tasks in a PSMS are usually highly individualized. As there are a large number of enterprises and also large-scale resources in a PSMS, the consumer management agent and order/task management agent are introduced for efficient management of consumers and tasks.

2. Platform provider and resource management MAS (PPRM-MAS). The main functions of this module include: (1) managing providers and their resources (including logistics resources), maintaining associated information, and performing necessary functions (e.g., provider registration and resource publication, pricing, and transactions), (2) interacting with the PMC-MAS module to obtain real-time resource information to achieve dynamic information update, (3) interacting with the ERM-MAS module to obtain enterprises' real-time resource availability information and their status, (4) providing static or dynamic information on providers and their resources to the PSM-MAS module to facilitate scheduling, (5) receiving scheduling solutions from the PSM-MAS module and performing scheduling in collaboration with it, and (6) interacting with the PKM-MAS module to obtain the knowledge necessary for providers and resource management. In this module, each provider is modeled as an agent, and each type of resource from each provider is modeled as an agent. Similarly, considering that there are a large number of providers and large-scale resources in a PSMS, the provider management agent(s) and service management agent(s) are introduced for efficient management of providers and their resources.

3. Platform scheduling management MAS

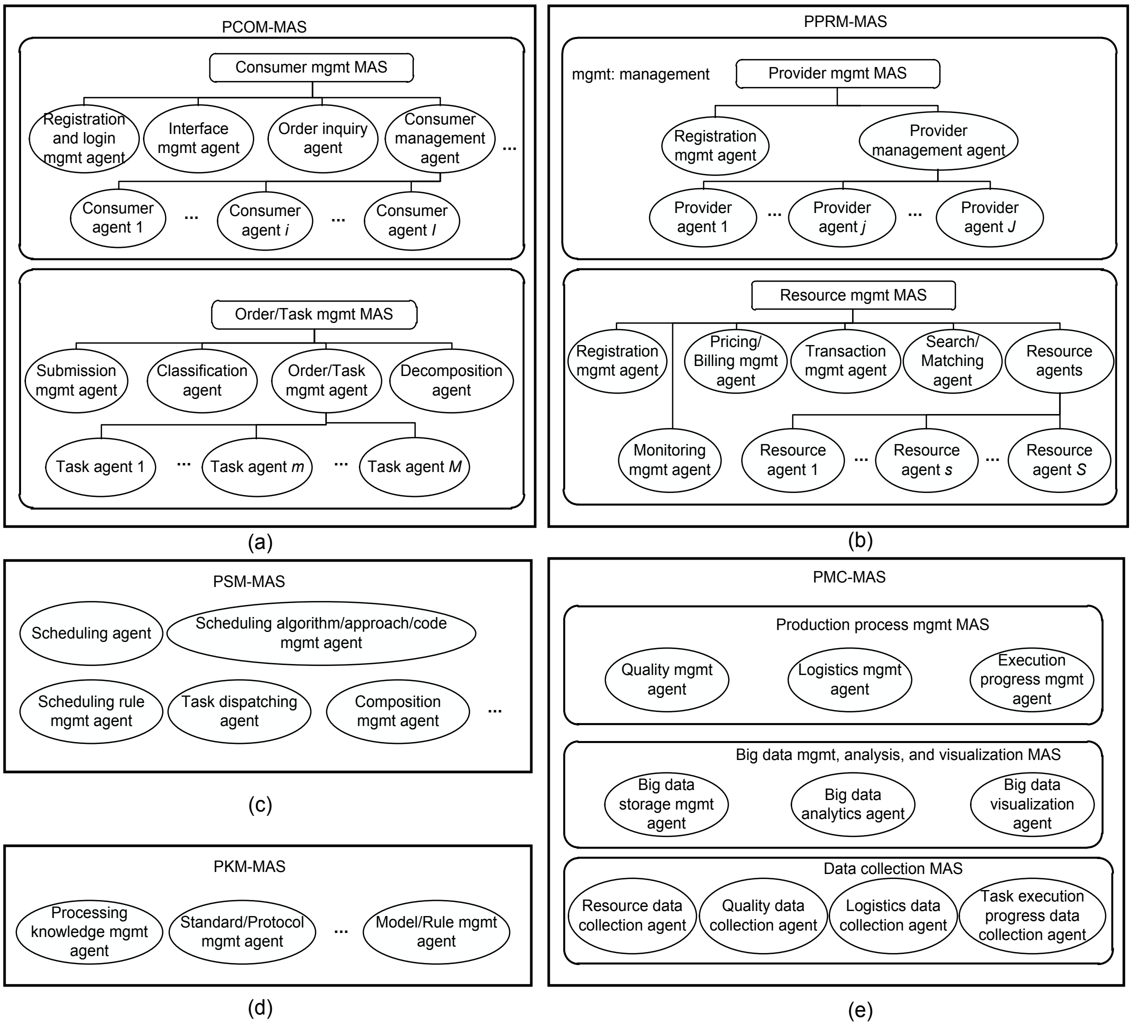

Fig. 3 Modules of the platform-level scheduling multi-agent system (MAS) of a platform-based smart manufacturing system (PSMS): (a) PCOM-MAS; (b) PPRM-MAS; (c) PSM-MAS; (d) PKM-MAS; (e) PMC-MAS

(PSM-MAS). PSM-MAS is a core module, whose functions include: (1) interacting with the PCOM-MAS module to obtain information on consumers and orders/tasks necessary for generating schedules, (2) interacting with the PPRM-MAS module to obtain information on providers and resources necessary for generating schedules, (3) interacting with the PKM-MAS module to obtain the knowledge necessary for generating schedules, (4) managing scheduling rules, approaches, algorithms, etc., (5) generating schedules, dispatching tasks to enterprises, and managing the execution process in collaboration with the PCOM-MAS and PPRM-MAS modules, and (6) interacting with the EPP-MAS and ESM-MAS modules to achieve scheduling collaboration between a platform and the enterprises involved. Major agents in this module are shown in Fig. 3c.

4. Platform monitoring and control MAS (PMC-MAS). The main functions of this module include: (1) monitoring the order, resource, and logistics status in real time, collecting related data, analyzing and visualizing the data, and managing production and logistics processes, (2) interacting with the PKM-MAS module to obtain the knowledge necessary for monitoring and control, (3) providing real-time order information to the PCOM-MAS module, (4) providing real-time resource information to the PPRM-MAS module, and (5) interacting with the EMC-MAS module to obtain real-time information on resources on shop floors (including various dynamic events that

trigger rescheduling).

5. Platform knowledge management MAS (PKM-MAS). This is a core supporting module for scheduling in a PSMS. Its functions include: (1) managing various types of knowledge such as process knowledge, models, rules, standards, and protocols, which are very important for many activities and processes such as task management, service management, scheduling management, and monitoring and control, and (2) providing necessary knowledge to the PCOM-MAS, PPRM-MAS, PSM-MAS, and PMC-MAS modules.

4.1.2 Enterprise-level scheduling MAS

The enterprise-level scheduling MAS is composed of six modules (Fig. 4). In the following, the responsibilities of the modules are described in detail.

1. Enterprise order/job management MAS (EOJM-MAS). The functions of this module include: (1) managing orders and jobs and maintaining their information, (2) providing order information to the EPP-MAS module to make production plans, (3) providing job information to the ESM-MAS module, (4) receiving schedules from the ESM-MAS module, and generating and performing the schedules in collaboration with it, (5) providing real-time information on jobs dispatched from the platform to the PCOM-MAS module, and (6) interacting with the EKDM-MAS module to obtain the knowledge/data necessary for order/job management.

2. Enterprise resource management MAS (ERM-MAS). The functions of this module include: (1) managing resources and maintaining their information, (2) providing critical resource information to the EPP-MAS module for generating plans, (3) providing resource information to the ESM-MAS module for generating schedules, (4) receiving schedules from the ESM-MAS module, and generating and performing the schedules in collaboration with it, (5) providing real-time resource availability information to the PPRM-MAS module, and (6) interacting with the EKDM-MAS module to obtain the knowledge/data necessary for resource management.

3. Enterprise production planning MAS (EPP-MAS). The functions of this module include: (1) generating plans according to the order information provided by the EOJM-MAS module and critical resource information provided by the ERM-MAS

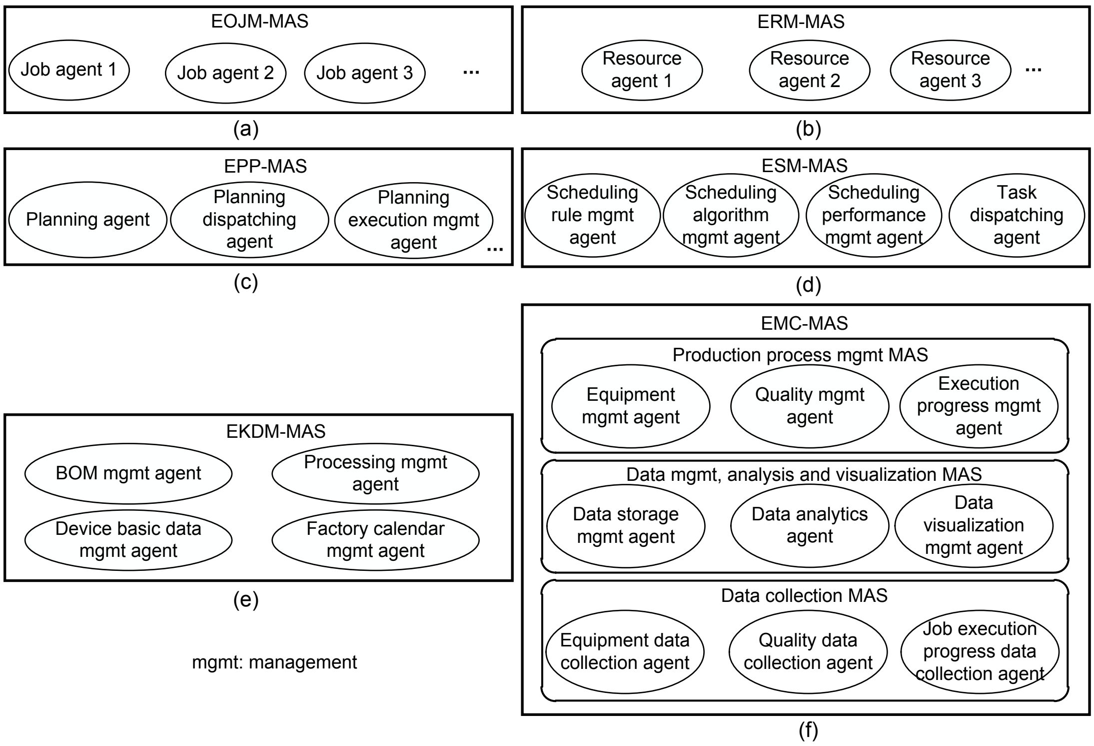

Fig. 4 Modules of the enterprise-level scheduling multi-agent system (MAS) of a platform-based smart manufacturing system (PSMS): (a) EOJM-MAS; (b) ERM-MAS; (c) EPP-MAS; (d) ESM-MAS; (e) EKDM-MAS; (f) EMC-MAS

module, (2) dispatching the plan to the ESM-MAS module, and receiving order execution information from the ESM-MAS module, (3) interacting with the EOJM-MAS and ERM-MAS modules to obtain order and critical resource information, and (4) interacting with the EKDM-MAS module to obtain the knowledge and data necessary for making plans.

4. Enterprise scheduling management MAS (ESM-MAS). The functions of this module include: (1) receiving production plans from the EPP-MAS module, (2) collecting job information from the EOJM-MAS module, (3) collecting resource information from the ERM-MAS module, (4) managing scheduling rules, approaches, and algorithms, (5) generating schedules, (6) dispatching schedules to the EOJM- MAS and ERM-MAS modules, and (7) interacting with the PSM-MAS module for scheduling collaboration.

5. Enterprise monitoring and control MAS (EMC-MAS). This module is responsible mainly for (1) collecting data on jobs and resources in real time, analyzing and visualizing the data, and managing the production process, and (2) providing real-time job and resource information to the EOJM-MAS and ERM-MAS modules.

6. Enterprise knowledge/data management MAS (EKDM-MAS). This module is responsible mainly for managing knowledge and data such as process knowledge, equipment data, and bill of materials.

4.2 Operation models

In this section we present the platform- and enterprise-level MAS operation models, which interact with each other according to Fig. 2.

4.2.1 Operation model of the platform-level MAS

The overall operation model of the platform-level MAS is as follows (Fig. 5):

Step 1: Providers register in the platform through the PPRM-MAS module, and publish their resources to the platform. At the same time, consumers register in the platform through the PCOM-MAS module, and publish their requirements to the platform.

Step 2: The PPRM-MAS and PCOM-MAS modules interact with the PKM-MAS module to obtain the knowledge necessary for resource and requirement management, and then perform provider and resource management, and consumer and order management, separately, based on that knowledge.

Step 3: The PSM-MAS module generates schedules based on the provider and resource information provided by the PPRM-MAS module, the

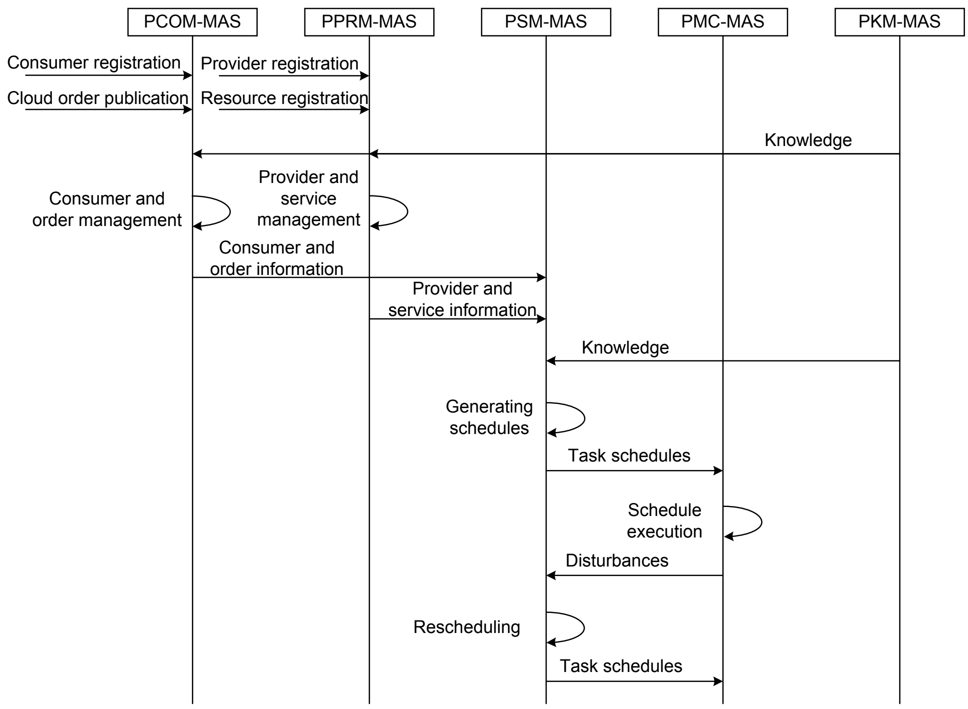

Fig. 5 Operation mode of the platform-level scheduling multi-agent system (MAS)

consumer and order information provided by the PCOM-MAS module, and the knowledge obtained from the PKM-MAS module.

Step 4: Scheduling solutions are sent to the PMC-MAS module for execution.

Step 5: When disturbances occur, the PMC-MAS module informs the PSM-MAS module of the dynamic real-time events. Then the PSM-MAS module generates rescheduling solutions and sends them to the PMC-MAS module.

4.2.2 Operation model of the enterprise-level MAS

The enterprise-level MAS has an operation model similar to the platform-level MAS (Fig. 6). The procedure is as follows:

Step 1: Customers submit their orders to the EPP-MAS module of the enterprise systems.

Step 2: The EPP-MAS module generates production plans according to the critical resource information provided by the ERM-MAS module and the knowledge (e.g., process knowledge) obtained from the EKDM-MAS module, and then sends the production plans to the ESM-MAS module for generating schedules.

Step 3: The ESM-MAS module generates schedules according to the production plans, the resource information provided by the ERM-MAS module, and the process knowledge obtained from the EKDM-MAS module, and then sends the job schedules to the EMC-MAS module for execution.

Step 4: The EMC-MAS module sends production orders to the physical manufacturing environment (PHE) for production execution, gathers data on materials and equipment, etc., and performs necessary production control. In addition, during the process of production execution, the EMC-MAS module sends real-time information about resources and jobs to the ERM-MAS and EOJM-MAS modules, respectively.

Step 5: When disturbances occur, the EMC-MAS module sends associated real-time information to facilitate rescheduling, which is performed by the ESM-MAS module.

5 Model

A multi-agent scheduling model is presented according to the architecture proposed in Section 4.

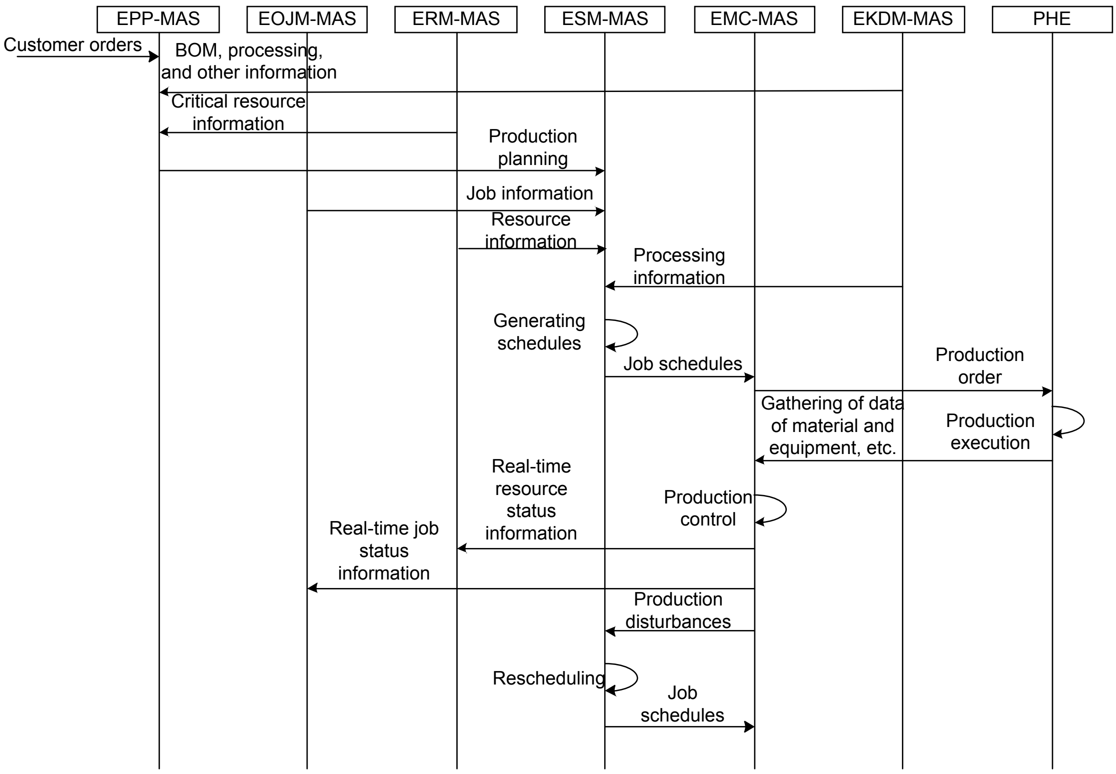

Fig. 6 Operation mode of the enterprise-level scheduling multi-agent system (MAS)

The notations used in this paper is given in the appendix.

5.1 Providers and resources

We consider a PSMS that involves I_{m} registered manufacturing service providers (i.e., enterprises) $P^{\mathrm{m}}=\{P_1^{\mathrm{m}}, P_2^{\mathrm{m}}, \cdots, P_{I_{\mathrm{m}}}^{\mathrm{m}}\}$ and I_{l} registered logistics service providers (i.e., enterprises) $P^{\mathrm{l}}=\{P_1^{\mathrm{l}}, P_2^{\mathrm{l}}, \cdots, P_{I_{\mathrm{l}}}^{\mathrm{l}}\}$. When a provider, P_i^{m} or P_i^{l}, registers in the system through the registration management agent, a provider agent, $\mathrm{PA}_i^{\mathrm{m}}$ or $\mathrm{PA}_i^{\mathrm{l}}$, is created. All of the provider agents are managed by the provider management agent. Totally there are M types of manufacturing resources $r=\{r_1, r_2, \ldots, r_M\}$ in the PSMS and the resources altogether can perform F types of functions. Resources are registered to the system through the resource registration management agent and managed by the resource agents.

P_i^{m} can be described as follows:

$$P_i^{\mathrm{m}}=\{\mathrm{Loc}_i^{\mathrm{m}}, \mathrm{Rep}_i^{\mathrm{m}}, R_i^{\mathrm{m}}\}, \tag{1}$$

where $\mathrm{Loc}_i^{\mathrm{m}}$ and $\mathrm{Rep}_i^{\mathrm{m}}$ represent the location and reputation of P_i^{m}, respectively, and R_i^{m} is the manufacturing resource set offered by P_i^{m}.

R_i^{m} can be described as follows:

$$R_i^{\mathrm{m}}=\{R_{i,1}^{\mathrm{m}}, R_{i,2}^{\mathrm{m}}, \ldots, R_{i,K_i}^{\mathrm{m}}\}, \tag{2}$$

where $R_{i,k}^{\mathrm{m}}$ is the k^{th} type of resource offered by P_i^{m}, and K_i ($1\le K_i \le M$) is the total number of types of manufacturing resources offered by P_i^{m}.

$R_{i,k}^{\mathrm{m}}$ can be described as follows:

$$R_{i,k}^{\mathrm{m}}=\{r_{i,k}^{\mathrm{m}}, F_{i,k}^{\mathrm{m}}, A_{i,k}^{\mathrm{m}}, p_{i,k}^{\mathrm{m}}, \alpha_{i,k}^{\mathrm{m}}, \mathrm{rel}_{i,k}^{\mathrm{m}}\}, \tag{3}$$

where $r_{i,k}^{\mathrm{m}}$ is the resource type of $R_{i,k}^{\mathrm{m}}$, $F_{i,k}^{\mathrm{m}}=\{f_{i,k,1}^{\mathrm{m}}, f_{i,k,2}^{\mathrm{m}}, \cdots, f_{i,k,z_{i,k}^{\mathrm{m}}}^{\mathrm{m}}\}$ represents the function set of $R_{i,k}^{\mathrm{m}}$ ($z_{i,k}^{\mathrm{m}}$ is the number of types of functions of $R_{i,k}^{\mathrm{m}}$, and $1\le z_{i,k}^{\mathrm{m}} \le F$), $A_{i,k}^{\mathrm{m}}$ is the resource quantity of $R_{i,k}^{\mathrm{m}}$, $p_{i,k}^{\mathrm{m}}$, which is managed by the pricing/billing management agent, is the price of $R_{i,k}^{\mathrm{m}}$ for using a unit amount of manufacturing service for unit time, $\alpha_{i,k}^{\mathrm{m}}$ is its efficiency coefficient of $R_{i,k}^{\mathrm{m}}$, and $\mathrm{rel}_{i,k}^{\mathrm{m}}$ represents the reliability of $R_{i,k}^{\mathrm{m}}$ (measured in the pass rate). An agent $\mathrm{RA}_{i,k}^{\mathrm{m}}$ is created for each type of resource $R_{i,k}^{\mathrm{m}}$ for managing all the resources of this type. All resource agents encapsulated from P_i^{m}'s resources are managed by $\mathrm{PA}_i^{\mathrm{m}}$.

P_i^{l} can be described as

$$P_i^{\mathrm{l}}=\{\mathrm{Rep}_i^{\mathrm{l}}, R_i^{\mathrm{l}}\}, \tag{4}$$

where $\mathrm{Rep}_i^{\mathrm{l}}$ is the reputation of P_i^{l}, and R_i^{l} is the logistics resource set offered by P_i^{l}. There are different logistics methods such as water, land, or air. For simplicity, but without loss of generality, only the road logistics is considered, and only one type of logistics resource (e.g., trucks) is assumed in the PSMS. An agent $\mathrm{RA}_i^{\mathrm{l}}$ is created for managing the logistics resource R_i^{l} of P_i^{l}.

R_i^{l} can be described as follows:

$$R_i^{\mathrm{l}}=\{p_i^{\mathrm{l}}, t_i^{\mathrm{l}}, \mathrm{sc}_i^{\mathrm{l}}\}, \tag{5}$$

where p_i^{l} is the price of transporting a unit weight of parts/blanks for unit distance, t_i^{l} is the time required for unit distance, and $\mathrm{sc}_i^{\mathrm{l}}$ denotes the safety coefficient of R_i^{l}.

5.2 Consumers and tasks

There are J consumers $C=\{C_1, C_2, \ldots, C_J\}$ that are registered to the system considered through the registration management agent, and consumer C_j ($1\le j\le J$) is modeled as an agent CA_j. All of the consumers are managed by the consumer management agent. Each of them submits a task to the PSMS through the order submission agent with probability p_{t} at each time step (p_{t} is called the task arrival probability hereafter). There are J tasks in the system in total, which are managed by the order/task management agent. Orders/tasks are classified by the order/task classification agent according to their types and resource requirements. Some of the tasks are submitted to the platform, while some of the tasks are submitted to resource providers directly, which are hereafter called platform tasks (PTs) and enterprise tasks (ETs), respectively (Fig. 7). The probability of tasks to be submitted to the platform is p_1, and with the rest probability $1-p_1$, tasks are submitted to the I_m enterprises. In the latter case, the probability for a provider to receive a task is $(1-p_1)/I_m$.

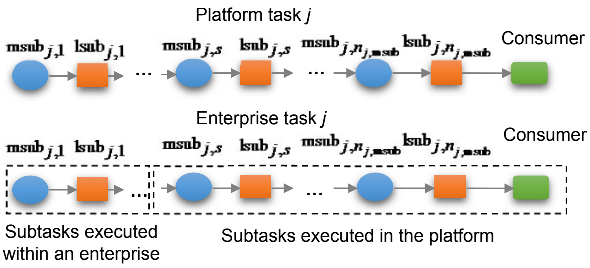

Fig. 7 Schematic of a platform task and an enterprise task

C_j can be described as follows:

$$C_j = \{\mathrm{Loc}_j^{\mathrm{c}}, \mathrm{Rep}_j^{\mathrm{c}}, T_j\}, \tag{6}$$

where $\mathrm{Loc}_j^{\mathrm{c}}$ is the location of C_j, $\mathrm{Rep}_j^{\mathrm{c}}$ is the preference of C_j toward providers' reputation, and T_j denotes its requirement task.

Tasks are labeled according to the order in which they enter the system $T=\{T_1, T_2, \ldots, T_J\}$. An agent TA_j is created dynamically when task T_j enters the system and removes after completion. T_j can be described as follows:

$$T_j = \{C_j, \mathrm{AT}_j, \mathrm{DT}_j, \mathrm{mss}_j, \mathrm{lss}_j, \mathrm{Stru}_j, \mathrm{mwl}_j, \mathrm{Cons}_j^{\mathrm{QoS}}\}, \tag{7}$$

where C_j is the consumer to which T_j belongs, AT_j and DT_j are the arrival time and due time, respectively, $\mathrm{mss}_j = \{\mathrm{msub}_{j,1}, \mathrm{msub}_{j,2}, \cdots, \mathrm{msub}_{j,n_{j,\mathrm{msub}}}\}$ is the machining subtask set of T_j ($n_{j,\mathrm{msub}}$ is the number of machining subtasks in T_j), $\mathrm{lss}_j=\{\mathrm{lsub}_{j,1}, \mathrm{lsub}_{j,2}, \ldots, \mathrm{lsub}_{j,n_{j,\mathrm{msub}}}\}$ is the possible logistics subtask set of T_j (the number of logistics subtasks in T_j is also $n_{j,\mathrm{msub}}$, see Fig. 7), Stru_j represents T_j's subtask structure (typically, sequential, parallel, circular, selective, or their combination, which specifies the machining flow of T_j), mwl_j is the machining workload of T_j, and $\mathrm{Cons}_j^{\mathrm{QoS}}$ represents the QoS constraints in terms of time, cost, and reliability. $\mathrm{Cons}_j^{\mathrm{QoS}}$ can be defined as follows:

$$\mathrm{Cons}_j^{\mathrm{QoS}}=\{\mathrm{Cons}_j^{\mathrm{time}}, \mathrm{Cons}_j^{\mathrm{cost}}, \mathrm{Cons}_j^{\mathrm{rel}}\}, \tag{8}$$

where $\mathrm{Cons}_j^{\mathrm{time}}$, $\mathrm{Cons}_j^{\mathrm{cost}}$, and $\mathrm{Cons}_j^{\mathrm{rel}}$ denote the maximum acceptable time, maximum acceptable cost, and minimum acceptable reliability constraints, respectively. $\mathrm{Cons}_j^{\mathrm{time}}$ is expressed as $\mathrm{DT}_j-\mathrm{AT}_j$, $\mathrm{Cons}_j^{\mathrm{cost}}$ is actually BUD_j (i.e., the budget of T_j), and $\mathrm{Cons}_j^{\mathrm{rel}}$ is denoted by REL_j (i.e., the overall reliability of resources used to perform T_j). Delayed completion (i.e., the actual completion time exceeds the time constraint $\mathrm{Cons}_j^{\mathrm{cost}}$) of T_j will incur a penalty, which is expressed as PEN_j.

$\mathrm{msub}_{j,s}$ can be described as follows:

$$\mathrm{msub}_{j,s} = \left\{h_{j,s}, \mathrm{mu}_{j,s}, \mathrm{mswl}_{j,s}, \mathrm{wght}_{j,s}\right\}, \tag{9}$$

where $h_{j,s}$ is the number of parts/blanks to be machined for $\mathrm{msub}_{j,s}$ (which is equal to that of T_j), $\mathrm{mu}_{j,s}$ is the functional type required for performing $\mathrm{msub}_{j,s}$, $\mathrm{mswl}_{j,s}$ is the workload of $\mathrm{msub}_{j,s}$, and $\mathrm{wght}_{j,s}$ is the weight of the parts/blanks to be produced for $\mathrm{msub}_{j,s}$.

$\mathrm{mswl}_{j,s}$ can be defined as follows:

$$\mathrm{mswl}_{j,s} = \alpha_0 h_{j,s} \mathrm{pt}_{j,s}^{\mathrm{m}} u_{j,s}, \tag{10}$$

where $\alpha_0=1.0$ is the benchmark efficiency coefficient, $\mathrm{pt}_{j,s}^{\mathrm{m}}$ is the time required to complete a part/blank in $\mathrm{msub}_{j,s}$ using a unit amount of matched service with the benchmark efficiency coefficient, and $u_{j,s}$ represents the unit amount of matched service for $\mathrm{msub}_{j,s}$. The workload mwl_j of T_j can thus be calculated by summing the workloads of all manufacturing subtasks of T_j:

$$\mathrm{mwl}_j = \sum_{s=1}^{n_{j,\mathrm{msub}}} \mathrm{mswl}_{j,s}. \tag{11}$$

Given the fact that materials are continuously removed from the parts/blanks during the machining process, the weight of parts/blanks for $\text{msub}_{j,s}$ is calculated as follows: $\text{wght}_{j,s} = \alpha_{\text{d}}^{s-1}\text{wght}_{j,1}$, where $\text{wght}_{j,1}$ represents the weight of the parts/blanks of $\text{msub}_{j,1}$, and $0<\alpha_{\text{d}}<1.0$ is a discounting factor.

The number of manufacturing subtasks $n_{j,\text{msub}}$ is uniformly distributed within $[N_{\min}, N_{\max}]$, irrespective of PTs and ETs. For PTs, the function required for each subtask is randomly selected from the F types of functions in the entire PSMS. However, in generating ETs, P_i^{m} is first chosen randomly, and then a random number sn_i uniformly distributed within $[1, F_i]$ ($F_i = \sum_{k=1}^{K_i} z_{i,k}^{\text{m}}$) is generated; at the same time, a number sn_0 uniformly distributed within $[n_{j,\text{msub}}-\text{sn}_i, N_{\max}]$ ($n_{j,\text{msub}}-\text{sn}_i>0$) is generated; that is, the types of functions for the former sn_i subtasks are randomly selected from all the types of functions of resources provided by P_i^{m}, and the types of functions required by the remaining subtasks are randomly selected from the other $F-F_i$ types of functions that are different from the resources of P_i^{m}. Hence, scheduling of PTs is completely managed by the platform, whereas for ETs, some of the subtasks are executed within the corresponding enterprise, but the subtasks beyond the capability of the enterprise are submitted to and executed in the cloud platform.

5.3 Logistics network

Logistics is an important factor that significantly affects the performance of the scheduling system. Logistics modeling includes logistics service modeling and logistics network modeling. The former has been addressed in Section 5.1, and here we focus on the latter. Given the fact that different logistics service providers have different logistics networks, the following two-step approach is employed to generate logistics networks of different providers. First, a square lattice is generated, in which the number of nodes is equal to the number of manufacturing resource providers I_{m}, and the edge between any two directly connected enterprises characterizes the geographical distance between them. The geographical distance d_{adj} of each edge is a randomly generated integer that follows the uniform distribution within a certain interval. Second, three scale-free networks are generated according to the Barabási–Albert network model (Albert and Barabási, 2002). During the network generation process, the geographical distance between any two providers is computed according to the square lattice; i.e., the distance is equal to that of the shortest path between the corresponding two enterprises in the square lattice. In this manner, the geographical distance between any two enterprises in the logistics networks of different logistics enterprises can be guaranteed to be the same, because the square lattice provides a common reference for generating all of them.

5.4 Scheduling

The scheduling process is managed by the PSM-MAS and ESM-MAS modules for tasks that are executed in the platform and within enterprises, respectively. Scheduling solutions are generated through contract net protocol based negotiations between different types of agents, including consumer agents, task agents, provider agents, and resource agents. The scheduling process of each task consists of five major phases: (1) task announcement, (2) bid preparation, (3) bid collection and evaluation, (4) task offer acceptance, and (5) schedule execution.

5.4.1 Task announcement

The negotiation process is initialized and driven by a task announcement. When a task is announced, all of its subtasks (including manufacturing subtasks and logistics subtasks) are announced to all resource agents at the same time, so that all of the subtasks can solicit bids from all resource agents (Fig. 7).

5.4.2 Bid preparation

After receiving a task announcement, all resource agents, including manufacturing resource agents and logistics resource agents, prepare bids for the subtasks. To reduce the number of messages and increase the scheduling efficiency in the presence of large-scale resources in a PSMS, task (or subtask) information on T_j is not broadcast directly to all resource agents. Instead, the information is sent to the resource management agent (RMA) in the PPRM-MAS module, and the RMA then transfers the information to the resource agents it manages. As an intermediary between resource agents and task agents, the RMA plays an important role in the task bidding process. For example, it can determine how many resource agents have the final chance to bid for subtasks by performing resource agent optimal selection.

After receiving the information, each resource agent checks the requirements of the subtasks, its capability, and status (e.g., load) to determine whether to submit a bid. It will bid for one or more subtasks if it is able to and desires to undertake the subtask(s). If a resource agent decides to submit a bid, it will prepare a bid and send it to the RMA. Otherwise, no action is taken.

The bidding procedure for $\mathrm{msub}_{j,s}$ or $\mathrm{lsub}_{j,s}$ is as follows: (1) $\mathrm{RA}_{i,k}^{\mathrm{m}}$ checks whether $\mathrm{mu}_{j,s} \in F_{i,k}^{\mathrm{m}}$ (i.e., whether $\mathrm{RA}_{i,k}^{\mathrm{m}}$ is able to perform the function required by $\mathrm{msub}_{j,s}$). For $\mathrm{lsub}_{j,s}$, this step is not needed because only one type of logistics resource is assumed and logistics resource agents are thus always able to undertake the subtask. (2) $\mathrm{PA}_i^{\mathrm{m}}$ or $\mathrm{PA}_i^{\mathrm{l}}$ checks whether $\mathrm{Rep}_i^{\mathrm{m}} \geq \mathrm{Rep}_j^{\mathrm{c}}$. (3) If the answers to the two questions are both yes, then $\mathrm{RA}_{i,k}^{\mathrm{m}}$ or $\mathrm{RA}_i^{\mathrm{l}}$ will continue to calculate the values of the associated metrics to complete $\mathrm{msub}_{j,s}$ or $\mathrm{lsub}_{j,s}$. Here metrics of time, cost, and reliability are considered for evaluating the system performance (Liu et al., 2019).

The time required for $R_{i,k}^{\mathrm{m}}$ to complete $\mathrm{msub}_{j,s}$ depends on three factors: the workload $\mathrm{mswl}_{j,s}$ of $\mathrm{msub}_{j,s}$, the capability of $R_{i,k}^{\mathrm{m}}$ (which is defined as $A_{i,k}^{\mathrm{m}}\alpha_{i,k}^{\mathrm{m}}$), and its load (e.g., the number of subtasks in its subtask queue). The time required for $R_{i,k}^{\mathrm{m}}$ to complete $\mathrm{msub}_{j,s}$ without considering the subtasks in the subtask queue can be computed as follows:

$$\mathrm{pt}_{j,s,\mathrm{m}}^{i,k} = \frac{\mathrm{mswl}_{j,s}}{A_{i,k}^{\mathrm{m}}\alpha_{i,k}^{\mathrm{m}}}, \tag{12}$$

where $\mathrm{pt}_{j,s,\mathrm{m}}^{i,k}$ is usually a decimal. For convenience of representation (e.g., plotting the Gantt chart), $\mathrm{pt}_{j,s,\mathrm{m}}^{i,k}$ is rounded to the smallest integer greater than or equal to the decimal in this work.

During the scheduling process, there may be several subtasks in the subtask queue of $R_{i,k}^{\mathrm{m}}$. Therefore, according to the first-in-first-out dispatching rule, the current subtask $\mathrm{msub}_{j,s}$ needs to wait for all the subtasks in the subtask queue (i.e., the buffer) to be finished; i.e., the current subtask $\mathrm{msub}_{j,s}$ will be addressed after all subtasks in the current subtask queue of $R_{i,k}^{\mathrm{m}}$ are completed. As a result, the waiting time in this case can be calculated as follows:

$$\mathrm{wt}_{j,s,\mathrm{m}}^{i,k} = \sum_{\mathrm{msub}_{j,s} \in \Omega} \mathrm{pt}_{j,s,\mathrm{m}}^{i,k}, \tag{13}$$

where Ω represents the subtask set in the subtask queue of $R_{i,k}^{\mathrm{m}}$.

The logistics time $\mathrm{lt}_{j,s,\mathrm{l}}^{i}$ for R_i^{l} to undertake $\mathrm{lsub}_{j,s}$ (i.e., the logistics task between $\mathrm{msub}_{j,s}$ and $\mathrm{msub}_{j,s+1}$) depends mainly on two factors: the chosen logistics service and the shortest geographical distance between the two enterprises (e.g., P_i^{m} and $P_{i'}^{\mathrm{m}}$) undertaking the two adjacent subtasks (as the logistics networks for different logistics service providers cover different areas, the shortest distances for different providers are probably different), which can be calculated as follows (without considering the waiting time):

$$\mathrm{lt}_{j,s,\mathrm{l}}^{i} = \begin{cases} t_i^{\mathrm{l}} d_{s,s+1}^{\min}, & \mathrm{Loc}_i^{\mathrm{m}} \neq \mathrm{Loc}_{i'}^{\mathrm{m}}, \\ 0, & \mathrm{Loc}_i^{\mathrm{m}} = \mathrm{Loc}_{i'}^{\mathrm{m}}, \end{cases} \tag{14}$$

where $d_{s,s+1}^{\min}$ denotes the shortest geographical distance of all possible logistics paths between P_i^{m} and $P_{i'}^{\mathrm{m}}$ that undertake $\mathrm{msub}_{j,s}$ and $\mathrm{msub}_{j,s+1}$.

The waiting time for R_i^{l} to process $\mathrm{lsub}_{j,s}$ can be calculated as follows:

$$\mathrm{wt}_{j,s,l}^{i} = \sum_{\mathrm{lsub}_{j,s} \in \Omega} \mathrm{lt}_{j,s,l}^{i}, \tag{15}$$

where Ω represents all the subtasks in the logistics subtask queue of R_i^{l}.

$\mathrm{lsub}_{j,n_{j,\mathrm{msub}}}$ is the logistics task to deliver the parts/blanks of $\mathrm{msub}_{j,n_{j,\mathrm{msub}}}$ to C_j, and the time required for fulfilling it using R_i^{l} can be calculated as follows:

$$\mathrm{lt}_{n_{j,\mathrm{lsub}},c_j,\mathrm{l}}=\begin{cases} t_i^{\mathrm{l}} d_{n_{j,\mathrm{msub}},c_j}^{\min}, & \mathrm{Loc}_i^{\mathrm{m}} \neq \mathrm{Loc}_j^{\mathrm{c}}, \\ 0, & \mathrm{Loc}_i^{\mathrm{m}} = \mathrm{Loc}_j^{\mathrm{c}}, \end{cases} \tag{16}$$

where $d_{n_{j,\mathrm{msub}},c_j}^{\min}$ is the shortest geographical distance of all possible paths between the provider undertaking $\mathrm{lsub}_{j,n_{j,\mathrm{msub}}}$ and C_j.

The waiting time for R_i^{l} to complete $\mathrm{lsub}_{j,n_{j,\mathrm{msub}}}$ is

$$\mathrm{wt}_{j,n_{j,\mathrm{msub}},l}^{i}=\sum_{\mathrm{lsub}_{j,s}\in\Omega} \mathrm{lt}_{j,s,l}^{i}, \tag{17}$$

where Ω represents all the subtasks in the buffer of R_i^{l}.

The total time for T_j to be completed can therefore be calculated as follows:

$$\begin{aligned} t_{T_j} = & \sum_{i=1}^{I_{\mathrm{m}}}\sum_{k=1}^{K_i}\sum_{s=1}^{n_{j,\mathrm{msub}}}\left(\mathrm{pt}_{j,s,\mathrm{m}}^{i,k}+\mathrm{wt}_{j,s,\mathrm{m}}^{i,k}\right)x_{ikjs} \\ & +\sum_{i=1}^{I_{\mathrm{l}}}\sum_{s=1}^{n_{j,\mathrm{msub}}-1}\left(\mathrm{lt}_{j,s,\mathrm{l}}^{i}+\mathrm{wt}_{j,s,\mathrm{l}}^{i}\right)y_{ijs} \\ & +\sum_{i=1}^{I_{\mathrm{l}}}\left(\mathrm{lt}_{n_{j,\mathrm{msub}},c_j,\mathrm{l}}+\mathrm{wt}_{j,n_{j,\mathrm{msub}},\mathrm{l}}^{i}\right)z_{ijn_{j,\mathrm{msub}}}. \end{aligned} \tag{18}$$

The cost for $R_{i,k}^{\mathrm{m}}$ to complete $\mathrm{msub}_{j,s}$ consists of machining cost, logistics cost, and a possible penalty for the delay in delivery. The machining cost can be calculated as follows:

$$\mathrm{mc}_{j,s,\mathrm{m}}^{i,k}=p_{i,k}^{\mathrm{m}}A_{i,k}^{\mathrm{m}}\mathrm{pt}_{j,s,\mathrm{m}}^{i,k}. \tag{19}$$

The logistics cost can be calculated as follows:

$$\mathrm{lc}_{j,s,\mathrm{l}}^{i}=\begin{cases} p_i^{\mathrm{l}} d_{s,s+1}^{\min}\mathrm{wght}_{j,s}, & \mathrm{Loc}_i^{\mathrm{m}} \neq \mathrm{Loc}_{i'}^{\mathrm{m}}, \\ 0, & \mathrm{Loc}_i^{\mathrm{m}} = \mathrm{Loc}_{i'}^{\mathrm{m}}, \end{cases} \tag{20}$$

where $\mathrm{wght}_{j,s}$ represents the total weight of parts/blanks of $\mathrm{msub}_{j,s}$.

The cost for R_i^{l} to deliver the product (or semi-product) to C_j is

$$\mathrm{lc}_{n_{j,\mathrm{msub}},c_j,\mathrm{l}}^{i}=\begin{cases} p_i^{\mathrm{l}} d_{n_{j,\mathrm{msub}},c_j}^{\min}\mathrm{wght}_{j,n_{j,\mathrm{msub}}}, & \mathrm{Loc}_i^{\mathrm{m}} \neq \mathrm{Loc}_j^{\mathrm{c}}, \\ 0, & \mathrm{Loc}_i^{\mathrm{m}} = \mathrm{Loc}_j^{\mathrm{c}}, \end{cases} \tag{21}$$

where $d_{n_{j,\mathrm{msub}},c_j}^{\min}$ is the minimum geographical distance among all possible paths between the enterprise that undertakes $\mathrm{msub}_{j,n_{j,\mathrm{msub}}}$ and C_j, and $\mathrm{wght}_{j,n_{j,\mathrm{msub}}}$ represents the corresponding weight of parts/blanks of $\mathrm{msub}_{j,n_{j,\mathrm{msub}}}$.

The possible penalty PEN_j of T_j for delay in delivery can be calculated as follows:

$$\mathrm{PEN}_j=\begin{cases} \beta_j\mathrm{Cost}_j\mathrm{XT}_j, & \mathrm{XT}_j>0, \\ 0, & \mathrm{XT}_j\le 0, \end{cases} \tag{22}$$

where β_j is a coefficient, Cost_j is the cost of using services in the composition solution obtained to fulfill T_j, and $\mathrm{XT}_j=\mathrm{CT}_j-(\mathrm{DT}_j-\mathrm{AT}_j)$ is the amount of time that exceeds the due time.

As a result, the total cost for completing all the subtasks of T_j can be calculated as follows:

$$\begin{aligned} c_{T_j} = & \sum_{i=1}^{I_{\mathrm{m}}}\sum_{k=1}^{K_i}\sum_{s=1}^{n_{j,\mathrm{msub}}}\mathrm{mc}_{j,s,\mathrm{m}}^{i,k}x_{ikjs}+\sum_{i=1}^{I_{\mathrm{l}}}\sum_{s=1}^{n_{j,\mathrm{msub}}-1}\mathrm{lc}_{j,s,\mathrm{l}}^{i}y_{ijs} \\ & +\sum_{i=1}^{I_{\mathrm{l}}}\mathrm{lc}_{j,n_{j,\mathrm{msub}},\mathrm{l}}^{i}z_{ijn_{j,\mathrm{msub}}}+\mathrm{PEN}_j. \end{aligned} \tag{23}$$

Similarly, the reliability of fulfilling T_j comprises machining reliability and logistics reliability (i.e., logistics safety):

$$\begin{aligned} \mathrm{rel}_{T_j} = & \sum_{i=1}^{I_{\mathrm{m}}}\sum_{k=1}^{K_i}\sum_{s=1}^{n_{j,\mathrm{msub}}}(\mathrm{rel}_{j,s}^{i,k}x_{ikjs}) \\ & \cdot\sum_{i=1}^{I_l}\sum_{s=1}^{n_{j,\mathrm{msub}}-1}\left(\mathrm{sc}_{j,s}^{i,l}y_{ijs}\right)\sum_{i=1}^{I_{\mathrm{l}}}\mathrm{sc}_{i,n_{j,\mathrm{msub}}}^{i,1}, \end{aligned} \tag{24}$$

where $\mathrm{rel}_{j,s}^{i,k}$ is the pass rate for service $R_{i,k}^{\mathrm{m}}$ to process $\mathrm{msub}_{j,s}$, and $\mathrm{sc}_{j,s}^{i,l}$ is the safety coefficient for logistics service R_i^{l} to process $\mathrm{lsub}_{j,s}$, and $\mathrm{sc}_{i,n_{j,\mathrm{msub}}}^{i,\mathrm{l}}$ is the safety coefficient for R_i^{l} to process the logistics task $\mathrm{lsub}_{j,n_{j,\mathrm{msub}}}$. Note that if the starting and ending locations of the logistics are the same, then the logistics reliability is 1.0.

In Eqs. (18), (23), and (24),

$$x_{ikjs}=\begin{cases}1, & \text{if } R_{i,k}^{\mathrm{m}} \text{ is chosen for } \mathrm{msub}_{j,s},\\ 0, & \text{otherwise},\end{cases} \tag{25}$$

$$y_{ijs}=\begin{cases}1, & \text{if } R_i^{\mathrm{l}} \text{ is chosen for } \mathrm{lsub}_{j,s},\\ 0, & \text{otherwise},\end{cases} \tag{26}$$

$$z_{ijn_{j,\mathrm{msub}}}=\begin{cases}1, & \text{if } R_i^{\mathrm{l}} \text{ is chosen for } \mathrm{lsub}_{j,n_{j,\mathrm{msub}}},\\ 0, & \text{otherwise}.\end{cases} \tag{27}$$

5.4.3 Bid collection and evaluation

After the bidding, an eligible resource set is collected for each subtask of T_j. Then, the composition management agent performs optimal resource and their combination selection using heuristic or metaheuristic algorithms such as GA, ACO, and PSO embedded in it (Liu et al., 2019). As mentioned earlier, scheduling in the PSMS involves multiple objectives, including minimization of time and cost to complete the task, and maximization of reliability to complete the task; the overall objective is the linear weighted combination of the above sub-objectives:

$$Q_j=w_{\mathrm{t}}Q_j^{\mathrm{t}}+w_{\mathrm{c}}Q_j^{\mathrm{c}}+w_{\mathrm{rel}}Q_j^{\mathrm{rel}}, \tag{28}$$

where

$$Q_j^{\mathrm{t}}=\begin{cases}\dfrac{t_{T_j}^{\max}-t_{T_j}}{t_{T_j}^{\max}-t_{T_j}^{\min}}, & t_{T_j}^{\max}-t_{T_j}^{\min}\neq 0,\\ 1, & t_{T_j}^{\max}-t_{T_j}^{\min}=0,\end{cases} \tag{29}$$

$$Q_j^{\mathrm{c}}=\begin{cases}\dfrac{c_{T_j}^{\max}-c_{T_j}}{c_{T_j}^{\max}-c_{T_j}^{\min}}, & c_{T_j}^{\max}-c_{T_j}^{\min}\neq 0,\\ 1, & c_{T_j}^{\max}-c_{T_j}^{\min}=0,\end{cases} \tag{30}$$

$$Q_j^{\mathrm{rel}}=\begin{cases}\dfrac{\mathrm{rel}_{T_j}-\mathrm{rel}_{T_j}^{\min}}{\mathrm{rel}_{T_j}^{\max}-\mathrm{rel}_{T_j}^{\min}}, & \mathrm{rel}_{T_j}^{\max}-\mathrm{rel}_{T_j}^{\min}\neq 0,\\ 1, & \mathrm{rel}_{T_j}^{\max}-\mathrm{rel}_{T_j}^{\min}=0,\end{cases} \tag{31}$$

$$T_j^{\mathrm{c}}\leq \mathrm{BUD}_j, \tag{32}$$

$$T_j^{\mathrm{rel}}\geq \mathrm{REL}_j, \tag{33}$$

and w_{t}, w_{c}, and w_{rel} are weight coefficients that characterize the contributions of the three different metrics to the overall objective, which are subject to the constraint $w_{\mathrm{t}}+w_{\mathrm{c}}+w_{\mathrm{rel}}=1.0$ (Liu et al., 2019). The objective of scheduling is to maximize Q_j while satisfying constraints (31) and (32). As a result, the resource agents as a composition that together lead to the highest Q_j will be selected to fulfill T_j. After determining the optimal resource composition, the composition management agent offers the subtasks to the corresponding resource agents in the composition (For resource agents who are not chosen, no action is needed). In the current model, only one resource agent is selected for each subtask. In the case where two resource agents are the same, one of them will be selected randomly.

Scheduling composition solution generation is carried out under the management of the PSM-MAS, PMC-MAS, ESM-MAS, and EMC-MAS modules. For example, during the scheduling process, disruptions (e.g., machine failures, tool shortages, and requirement variations) may occur, and are monitored by the PMC-MAS module together with the EMC-MAS module (due to limited space, we do not consider such disturbances in this work). Dynamic events may trigger scheduling adjustment or rescheduling, which is managed by the scheduling management agent.

5.4.4 Task offer acceptance

Because only one resource agent is selected for each task, only that resource agent will be granted the offer. After receiving the task offer from the task agent, the resource agent will choose to accept it, and inform the task agent of the acceptance. In some special cases, one resource agent may be selected to undertake more than one subtask. This will not incur conflicts because different subtasks are executed sequentially.

5.4.5 Schedule execution

After task offer acceptance by resource agents, the scheduling execution process can start.

In the current model, tasks, including PTs and ETs, are scheduled one by one according to the order in which they enter the system. Scheduling of the next task can take place only when the scheduling solution for the current task is found and execution is started. As a result, the above procedure will be repeated until scheduling of all tasks is finished.

In the preceding section, we discussed mainly the PT scheduling process. For ETs, the scheduling process is similar. The only difference is that some subtasks are executed within the enterprise whereas some are executed in the platform (Fig. 7), but the scheduling process and principle are the same.

6 Case study

In the following, we present a simplified case to briefly demonstrate the operational principle of the model and architecture proposed, focusing on the effects of the task arrival probability and logistics. In this case study, there are 30 manufacturing resource providers and three logistics resource providers. All providers are encapsulated into provider agents. Thirty types of resources (i.e., R1–R30) that can perform 30 different types of functions (i.e., F1–F30) are considered. Each type of resource from a provider is encapsulated in a resource agent. Resources considered here are hard manufacturing resources such as machine tools, industrial robots, and a machining center, which can perform functions such as lathing, welding, milling, drilling, cutting, grinding, painting, pick-and-place, assembly, and transfer. Tables 2–7 and Fig. 8 show the common variables and parameters, information about manufacturing resource providers and their resources, logistics providers and logistics services, consumers and their tasks, and the logistics network of the first logistics service provider. Note that in this case study, some aspects of the model proposed in Section 5 are simplified without losing the essence of the model. The simplifications include the following:

1. Provider reputation is not considered in this case study. Reputation, like other QoS metrics such as time, cost, and reliability, provides a criterion for consumers to select providers and resources. Considering provider reputation will make the model more realistic and the scheduling results more comprehensive and accurate. Because the purpose of the current case study is mainly to demonstrate the operation principle of the architecture and model in a more concrete way instead of investigating the effects of reputation on scheduling results in detail, we leave them to our future work.

2. The time constraint is considered (In the current model, exceeding task due times is allowed, but this will incur a penalty; see Section 5.2 for details), but budget (i.e., cost) and reliability constraints of the required tasks are not taken into account. Considering

Table 2 Common variables and parameters

Parameter	Value	Unit
I_m	30	
I_l	3	
M	30	
F	30	
K_i	[1, 2]	
$z_{i,k}^\mathrm{m}$	[1, 2]	
J	31	
$A_{i,k}^\mathrm{m}$	[5, 10]	
$p_{i,k}^\mathrm{m}$	[15, 25]	
$\alpha_{i,k}^\mathrm{m}$	[0.5, 1.5]	
$\mathrm{rel}_{i,k}^\mathrm{m}$	[0.8, 1.0]	
p_i^l	[0.0001, 0.000 05]	
t_i^l	[0.004, 0.005]	
sc_i^l	[0.8, 1.0]	
p_l	0.5	
n_j	[10, 30]	
β_j	[0.005, 0.01]	
$n_{j,\mathrm{msub}}$	[2, 4]	
$\mathrm{pt}_{j,s}^\mathrm{m}$	[50, 250]	Time step
$\mathrm{wght}_{j,1}$	[200, 1000]	kg
α_d	0.8	
α_0	1.0	
us_0	1.0	
sn_i	1	
d_adj	[125, 500]	km
w_t	0.4	
w_c	0.3	
w_rel	0.3	

budget and reliability constraints can help filter out the scheduling solutions that do not satisfy the constraints and will make the scheduling results more accurate, but for the same reason as not considering reputation, we do not consider them here.

As in the model, the scheduling process undergoes five major phases: task announcement, bid preparation, bid collection and evaluation, task offer acceptance, and schedule execution. In particular, during the task bidding process, an RMA is introduced as an intermediary for matching task agents with resource agents. However, due to the limited number of resource agents, the RMA allows all resource agents to have the chance to bid for subtasks instead of filtering out some of them (i.e., no particular function is assigned to the RMA).

Fig. 9 shows the variations of the average machining time (AMT), average waiting time (AWT), average task completion time (ATCT), and average total task completion time (ATTCT) as functions of p_t with or without consideration of logistics. The results are obtained by averaging over 100 realizations, and for each realization, 200 task arrival time steps are considered (i.e., tasks no longer arrive after 200 time steps, but it takes more than 200 time steps for all the arriving tasks to be completed). It can be observed from Fig. 9 that p_t and logistics have different influences on the different types of time. To be more specific, all of AWT, ATCT, and ATTCT increase monotonically with p_t, while the upward tendency of AMT is not quite apparent. The phenomena above can be analyzed and explained as follows. With the increase of p_t at each time step, more and more tasks enter the system and compete for the limited manufacturing resources. In this case, the overall task queue of each type of resource becomes longer, which makes tasks wait longer time in the queues. From the very slight uptrend of AMT and logistics time (not shown), the great increase in AWT, and the fact that a task's completion time equals the sum of its machining time, logistics time, and waiting time, we can conclude that the increase of ATCT with p_t is caused mainly by the increase in the waiting time. Due to more tasks and resulting resource competition, ATTCT increases with p_t as well. Why does p_t have little effect on AMT? This is because increasing p_t leads to more and more tasks appearing in the system, indicating that the resources are still abundant relative to the number of tasks (even at a high task arrival probability), so that resource quality does not vary greatly for executing the tasks at different p_t (Fig. 10).

Table 3 Information on manufacturing resource providers and their resources

P_i^m	$R_{i,k}^m$	$r_{i,k}^m$	$F_{i,k}^m$	$A_{i,k}^m$	$p_{i,k}^m$	$\alpha_{i,k}^m$	$rel_{i,k}^m$
P_1^m	$R_{1,1}^m$	$r_{1,1}^m(11)$	$f_{1,1,1}^m(11)$	8	0.886	0.636	0.960
	$R_{1,2}^m$	$r_{1,2}^m(6)$	$f_{1,2,1}^m(15)$ $f_{1,2,2}^m(16)$	5	0.990	1.227	0.996
P_2^m	$R_{2,1}^m$	$r_{2,1}^m(4)$	$f_{2,1,1}^m(2)$ $f_{2,1,2}^m(26)$	10	0.879	1.127	0.910
	$R_{2,2}^m$	$r_{2,2}^m(18)$	$f_{2,2,1}^m(17)$	10	1.278	0.611	0.941
P_3^m	$R_{3,1}^m$	$r_{3,1}^m(5)$	$f_{3,1,1}^m(7)$ $f_{3,1,2}^m(14)$	9	1.124	1.353	0.907
P_4^m	$R_{4,1}^m$	$r_{4,1}^m(28)$	$f_{4,1,1}^m(1)$ $f_{4,1,2}^m(4)$	8	1.001	0.700	0.903
P_5^m	$R_{5,1}^m$	$r_{5,1}^m(3)$	$f_{5,1,1}^m(20)$ $f_{5,1,2}^m(22)$	5	1.201	0.576	0.952
P_6^m	$R_{6,1}^m$	$r_{6,1}^m(1)$	$f_{6,1,1}^m(3)$ $f_{6,1,2}^m(28)$	8	0.859	0.753	0.837
	$R_{6,2}^m$	$r_{6,2}^m(11)$	$f_{6,2,1}^m(11)$	7	1.284	0.634	0.919

Due to limited space, only the information for the first six enterprises is shown

Table 4 Information on logistics resources

P_i^l	p_i^l	t_i^l	sc_i^l
P_1^l	0.000 069	0.008 930	0.97
P_2^l	0.000 054	0.009 544	0.90
P_3^l	0.000 080	0.009 914	0.91

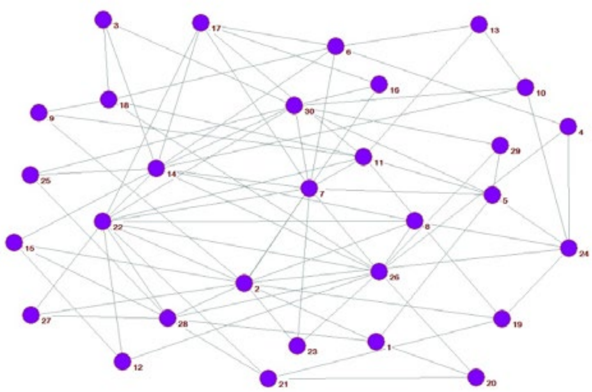

Fig. 8 Logistics network of the first logistics service provider (the numbers besides the solid circles denote enterprises)

Table 5 Information on consumers and tasks

C_j	T_j	Task type	$n_{j,\text{msub}}$	AT_j	DT_j	$h_{j,s}$	PEN_j	$\text{msub}_{j,s}$/ $\text{lsub}_{j,s}$	$\text{pt}^{i,k}_{j,s,\text{m}}$ / $\text{lt}^{i}_{j,s,\text{l}}$	P^{l}_i	$\text{wght}_{j,s}$
C_1	T_1	PT	2	1	42	355	0	$\text{msub}_{1,1}$	5	–	$\text{wght}_{1,1}$(327)
								$\text{lsub}_{1,1}$	3	1	
								$\text{msub}_{1,2}$	5	–	$\text{wght}_{1,2}$(261)
								$\text{lsub}_{1,2}$	2	3	
C_2	T_2	PT	2	2	47	432	0	$\text{msub}_{2,1}$	4	–	$\text{wght}_{2,1}$(634)
								$\text{lsub}_{2,1}$	3	1	
								$\text{msub}_{2,2}$	5	–	$\text{wght}_{2,2}$(507)
								$\text{lsub}_{2,2}$	2	1	
C_3	T_2	PT	2	4	65	616	0	$\text{msub}_{3,1}$	8	–	$\text{wght}_{3,1}$(676)
								$\text{lsub}_{3,1}$	2	3	
								$\text{msub}_{3,2}$	27	–	$\text{wght}_{3,2}$(540)
								$\text{lsub}_{3,2}$	2	2	
C_4	T_4	PT	4	6	53	327	0	$\text{msub}_{4,1}$	3	–	$\text{wght}_{4,1}$(668)
								$\text{lsub}_{4,1}$	3	3	
								$\text{msub}_{4,2}$	15	–	$\text{wght}_{4,2}$(534)
								$\text{lsub}_{4,2}$	4	1	
								$\text{msub}_{4,3}$	4	–	$\text{wght}_{4,3}$(427)
								$\text{lsub}_{4,3}$	3	1	
								$\text{msub}_{4,4}$	6	–	$\text{wght}_{4,4}$(341)
								$\text{lsub}_{4,4}$	3	2	
C_5	T_5	ET	4	7	82	108	0	$\text{msub}_{5,1}$	5	–	$\text{wght}_{5,1}$(887)
								$\text{lsub}_{5,1}$	4	2	
								$\text{msub}_{5,2}$	2	–	$\text{wght}_{5,2}$(709)
								$\text{lsub}_{5,2}$	2	3	
								$\text{msub}_{5,3}$	4	–	$\text{wght}_{5,3}$(567)
								$\text{lsub}_{5,3}$	3	2	
								$\text{msub}_{5,4}$	2	–	$\text{wght}_{5,4}$(453)
								$\text{lsub}_{5,4}$	2	2	
C_6	T_6	ET	3	9	41	385	13.36	$\text{msub}_{6,1}$	7	–	$\text{wght}_{6,1}$(756)
								$\text{lsub}_{6,1}$	2	1	
								$\text{msub}_{6,2}$	8	–	$\text{wght}_{6,2}$ 604)
								$\text{lsub}_{6,2}$	3	2	
								$\text{msub}_{6,3}$	17	–	$\text{wght}_{6,3}$(483)
								$\text{lsub}_{6,3}$	2	1	

Due to limited space, only information for the top six tasks is shown here

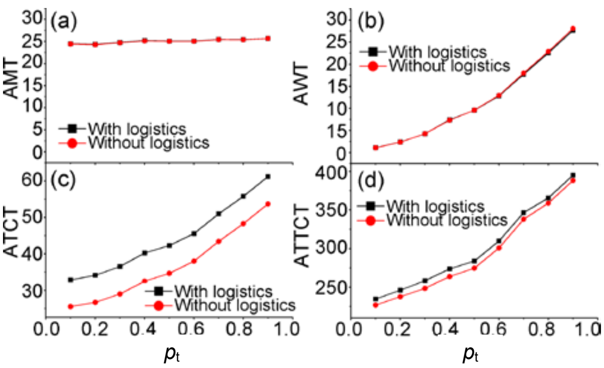

Fig. 9 The average machining time (a), waiting time (b), task completion time (c), and total task completion time (d) vs. the task arrival probability with or without consideration of logistics

On the other hand, it can be observed that the AMT and AWT curves for scenarios with and without logistics almost overlap with each other, indicating that logistics has little effect on them. However, logistics will prolong ATCT and ATTCT. These phenomena are easily understood, because logistics takes time, but it does not cause resource competition. To visually demonstrate the effect of logistics, we show the Gantt chart for p_t=0.5 with and without consideration of logistics in Fig. 11. It can be observed that scheduling without logistics indeed takes less time for all tasks to be completed (refer to Tables 2–7 for details about the scheduling diagrams). We have also developed a software prototype system for the PSMS to

Table 6 Adjacent distance matrix of the logistics network of the first logistics service provider

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1		221			264															404								210		
2	221						404	477	188						344	426			321			466	227	388			202	402		
3														406				176												226
4						309																		258		146				
5	264						211				495													155					429	308
6				309			328						193	213			326	375												
7		404			211	328					365			434			430					296	244			178				220
8		477												244								273		357		438				
9		188									250							440												
10													256	277										361						282
11					495		365		250				237				495	435	500			161								
12															355							174				259				
13						193				256	237																			
14			406			213	434	244		277					164		225					398			445	446				365
15		344										355		164														206		
16		426															283													144
17						326	430				495			225		283						213								
18			176			375			440		435															216				
19		321									500										434			371						
20	404																				378					263				
21																			434	378		153						171		
22		466					296	273			161	174		398			213				153					450	260	140		365
23		227					244																			493				
24		388		258	155			357		361									371											
25														445														256		297
26				146			178	438				259		446				216		263		450	493					183	158	
27		202																				260						155		
28	210	402													206						171	140			256	183	155			
29					429																					158				432
30			226		308		220			282				365		144						365			297				432	

Due to limited space, only the first logistics network is presented here

perform scheduling simulations (Fig. 12). Because the focus of this study is on the multi-agent architecture, here only preliminary scheduling results are presented and detailed, in-depth research is left for the future.

7 Conclusions and discussion

Thus far, we have proposed a multi-agent architecture for scheduling in PSMSs. First, the procedure, characteristics, and requirements for scheduling in PSMSs were summarized and analyzed. Then, a multi-agent architecture consisting of platform-level scheduling MAS and enterprise-level scheduling MAS was proposed, and their operation models were presented. Then, a specific multi-agent model for scheduling in a PSMS was proposed according to the proposed architecture. Finally, a case study was conducted to validate the effectiveness of the architecture and model.

Due to the high complexity of scheduling in PSMSs, it is very difficult to propose a model that covers all the characteristics of the issue (see Section 3 for details). Here, we would like to discuss the aspects that can be improved to provide reference for future research. In the current model, the characteristics considered include autonomy and preferences of providers and consumers, wide-area logistics, composite tasks, and collaborative scheduling. In the

Table 7 Shortest geographical distances between enterprises in the logistics network of the first logistics service provider

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	0	221	785	539	264	793	475	623	409	780	511	524	748	580	416	647	563	609	542	404	381	350	448	419	466	393	365	210	551	572
2	221	0	796	646	485	721	404	477	188	749	438	636	675	508	344	426	675	628	321	625	528	462	227	388	613	540	202	357	698	570
3	785	796	0	538	534	551	446	650	616	508	611	651	744	406	570	370	631	176	536	655	744	591	690	689	523	392	730	575	550	226
4	539	646	538	0	413	309	324	584	802	619	630	405	502	522	535	688	635	362	629	409	500	469	568	258	585	146	484	329	304	544
5	264	485	534	413	0	539	211	512	673	516	495	648	732	645	680	452	641	605	526	652	645	507	455	155	605	389	629	474	429	308
6	793	721	551	309	539	0	328	457	680	449	430	713	193	213	377	609	326	375	930	718	692	539	572	567	658	455	738	583	613	548
7	475	404	446	324	211	328	0	569	592	502	365	437	521	434	567	364	430	394	725	441	449	296	244	366	517	178	516	361	336	220
8	623	477	650	584	512	457	569	0	665	521	434	447	650	244	408	752	469	654	728	701	426	273	704	357	669	438	533	413	596	609
9	409	188	616	802	673	680	592	665	0	743	250	585	487	696	532	614	624	440	509	813	564	411	415	576	801	656	390	545	814	758
10	780	749	508	619	516	449	502	521	743	0	493	796	256	277	441	426	502	684	732	943	800	647	746	361	579	680	802	647	714	282
11	511	438	611	630	495	430	365	434	250	493	0	335	237	559	507	657	374	435	500	692	314	161	609	650	557	484	421	301	642	526
12	524	636	651	405	648	713	437	447	585	796	335	0	572	519	355	670	387	475	761	522	327	174	681	663	570	259	434	314	417	539
13	748	675	744	502	732	193	521	650	487	256	237	572	0	406	570	682	519	568	737	911	551	398	765	617	794	648	658	538	806	538
14	580	508	406	522	645	213	434	244	696	277	559	519	406	0	164	508	225	582	829	709	541	398	678	601	445	446	525	370	604	365
15	416	344	570	535	680	377	567	408	532	441	507	355	570	164	0	672	389	605	665	652	377	346	571	732	462	389	361	206	547	529
16	647	426	370	688	452	609	364	752	614	426	657	670	682	508	672	0	283	546	747	805	649	496	608	607	441	542	628	636	576	144
17	563	675	631	635	641	326	430	469	624	502	374	387	519	225	389	283	0	701	800	744	366	213	674	796	609	536	473	353	694	427
18	609	628	176	362	605	375	394	654	440	684	435	475	568	582	605	546	701	0	935	479	570	539	638	620	655	216	554	399	374	402
19	542	321	536	629	526	930	725	728	509	732	500	761	737	829	665	747	800	935	0	812	434	587	548	371	861	775	523	605	933	834
20	404	625	655	409	652	718	441	701	813	943	692	522	911	709	652	805	744	479	812	0	378	531	685	667	702	263	601	446	421	661
21	381	528	744	500	645	692	449	426	564	800	314	327	551	541	377	649	366	570	434	378	0	153	693	758	427	354	326	171	512	518
22	350	462	591	469	507	539	296	273	411	647	161	174	398	398	346	496	213	539	587	531	153	0	540	630	396	323	260	140	481	365
23	448	227	690	568	455	572	244	704	415	746	609	681	765	678	571	608	674	638	548	685	693	540	0	610	761	422	429	584	580	464
24	419	388	689	258	155	567	366	357	576	361	650	663	617	601	732	607	796	620	371	667	758	630	610	0	760	404	590	587	562	463
25	466	613	523	585	605	658	517	669	801	579	557	570	794	445	462	441	609	655	861	702	427	396	761	760	0	439	411	256	597	297
26	393	540	392	146	389	455	178	438	656	680	484	259	648	446	389	542	536	216	775	263	354	323	422	404	439	0	338	183	158	398
27	365	202	730	484	629	738	516	533	390	802	421	434	658	525	361	628	473	554	523	601	326	260	429	590	411	338	0	155	496	625
28	210	357	575	329	474	583	361	413	545	647	301	314	538	370	206	636	353	399	605	446	171	140	584	587	256	183	155	0	341	505
29	551	698	550	304	429	613	336	596	814	714	642	417	806	604	547	576	694	374	933	421	512	481	580	562	597	158	496	341	0	432
30	572	570	226	544	308	548	220	609	758	282	526	539	538	365	529	144	427	402	834	661	518	365	464	463	297	398	625	505	432	0

Due to limited space, only the first logistics network is presented here

future, to be more realistic, real-time dynamic events such as machine failures, tool shortages, and requirement variations should be considered. The scheduling of multiple tasks as a whole should be further studied. Multi-granularity as an important characteristic of scheduling in PSMSs should be taken into account as well. The characteristics of multi-granularity in the current model can be reflected by the fact that different resource agents can bid for tasks at different levels in collaboration with each other. Moreover, in the current model, the assumptions can be relaxed to allow more flexible scheduling (e.g., resources of the same type from an enterprise are allowed to bid for more than one subtask by being partitioned into different parts). In the future, work along this line will continue.

Compliance with ethics guidelines

Yong-kui LIU, Xue-song ZHANG, Lin ZHANG, Fei TAO, and Li-hui WANG declare that they have no conflict of interest.

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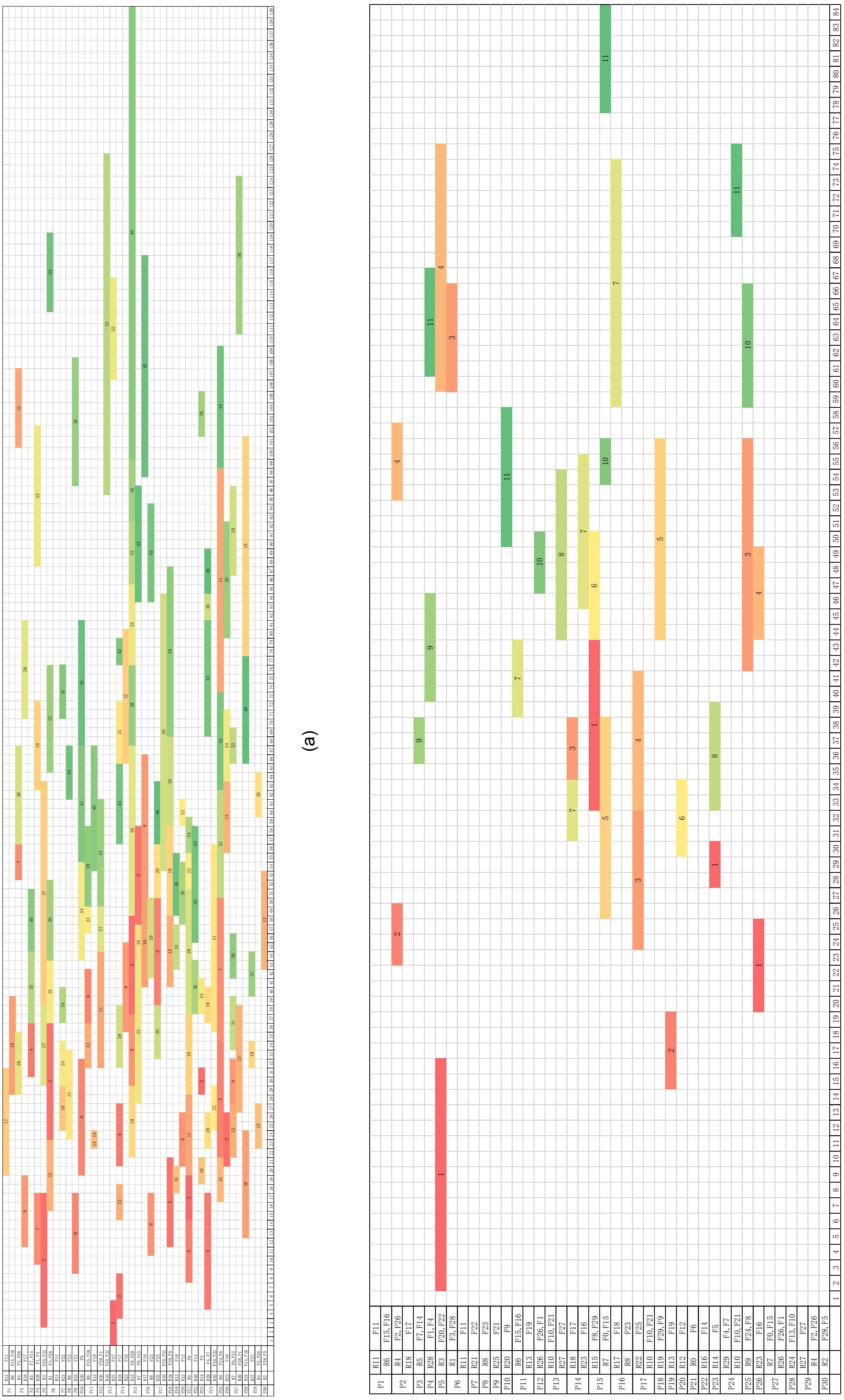
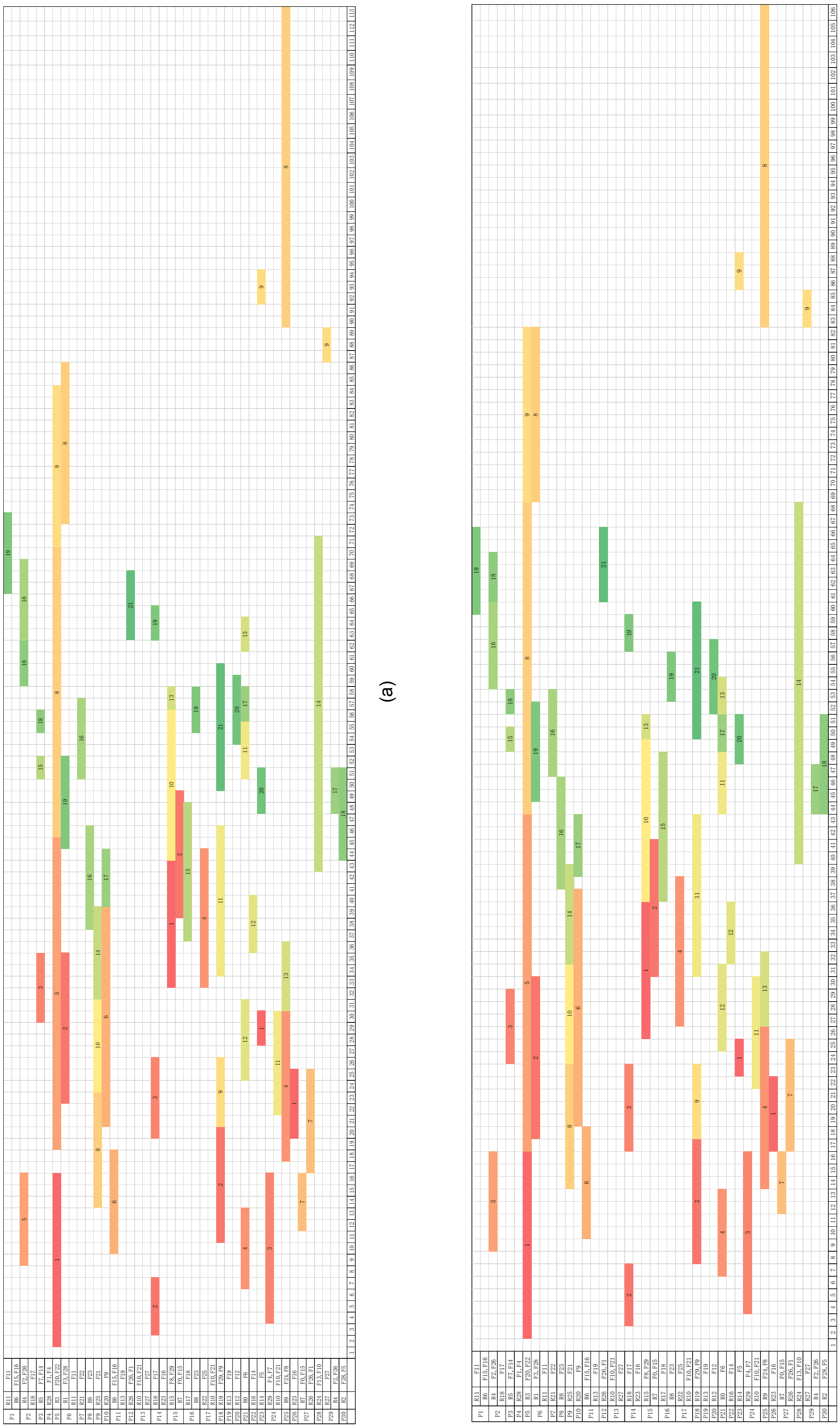


(a)

(b)

Fig. 10 Gantt chart for p_t=0.9 (a) and p_t=0.2 (b) with consideration of logistics



(a)

(b)

Fig. 11 Gantt chart for p_t=0.5 with (a) and without (b) consideration of logistics

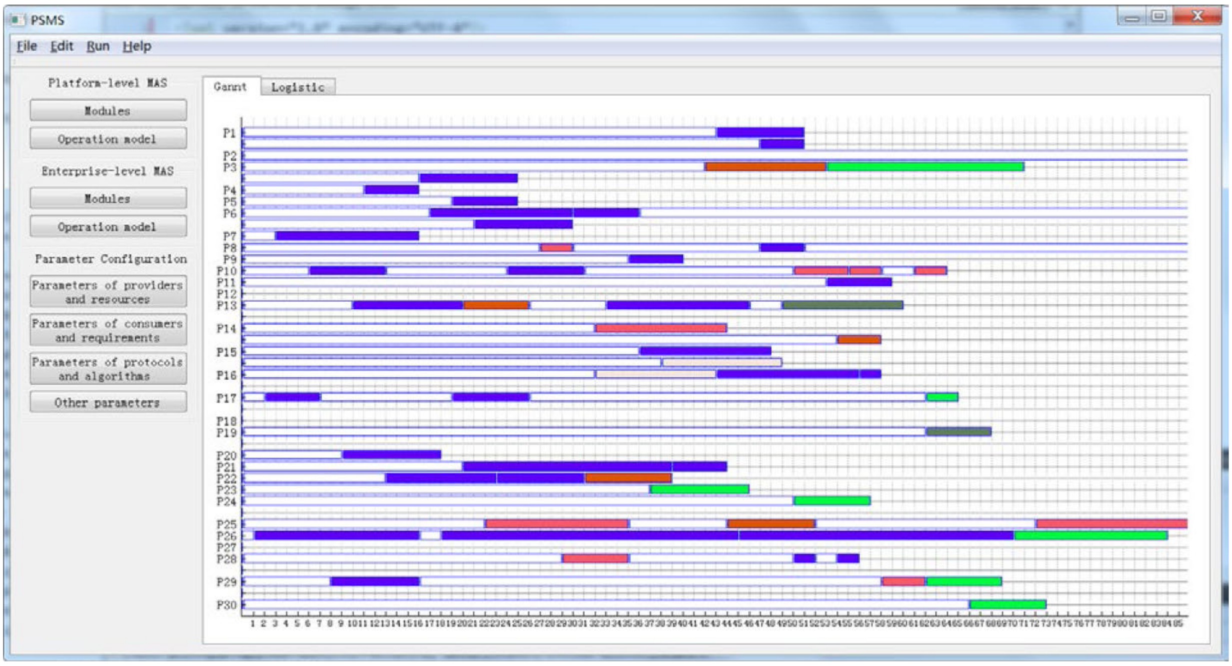


Fig. 12 User interface of the developed software prototype system for multi-agent scheduling in a platform-based smart manufacturing system (PSMS)

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Appendix: Notations

Table A1 Notations used in the paper

Parameter	Meaning	Parameter	Meaning
$A_{i,k}^{\mathrm{m}}$	Quantity of $R_{i,k}^{\mathrm{m}}$	$f_{i,k,g}^{\mathrm{m}}$	g^{th} type of functions of $R_{i,k}^{\mathrm{m}}$
AT_j	Arrival time of T_j	$h_{j,s}$	Number of parts/blanks to be produced for $\mathrm{msub}_{j,s}$
BUD_j	Budget of T_j	I_{l}	Number of logistics service providers
C	Set of consumers	I_{m}	Number of manufacturing service providers
C_j	j^{th} consumer	J	Number of consumers/tasks
CA_j	Agent of C_j	K_i	Number of types of manufacturing resources P_i^{m} offers
$\mathrm{Cons}_j^{\mathrm{QoS}}$	QoS constraint of T_j	$\mathrm{Loc}_i^{\mathrm{m}}$	Location of P_i^{m}
$\mathrm{Cons}_j^{\mathrm{time}}$	Time constraint of T_j	$\mathrm{Loc}_j^{\mathrm{c}}$	Location of C_j
$\mathrm{Cons}_j^{\mathrm{cost}}$	Cost constraint of T_j	$\mathrm{lc}_{j,s,\mathrm{l}}^{i}$	Logistics cost between the two providers that undertake $\mathrm{msub}_{j,s}$ and $\mathrm{msub}_{j,s+1}$
$\mathrm{Cons}_j^{\mathrm{rel}}$	Reliability constraint of T_j	$\mathrm{lc}_{j,n_{j,\mathrm{msub}},\mathrm{l}}^{i}$	Cost for R_i^{l} to deliver parts/blanks of $\mathrm{msub}_{j,n_{j,\mathrm{msub}}}$ to C_j
c_{T_j}	Total cost for completing T_j	lss_j	Logistics subtask set of T_j
Cost_j	Cost of using services in the obtained composition solution to fulfill T_j	$\mathrm{lsub}_{j,s}$	s^{th} logistics subtask of T_j
DT_j	Due time of T_j	$\mathrm{lsub}_{j,n_{j,\mathrm{msub}}}$	$(n_{j,\mathrm{msub}})^{\mathrm{th}}$ logistics subtask of T_j (i.e., delivering parts/blanks to C_j)
d_{adj}	Geographical distance between any two adjacent providers	$\mathrm{lt}_{j,s,\mathrm{l}}^{i}$	Logistics time for R_i^{l} to undertake $\mathrm{lsub}_{j,s}$
$d_{s,s+1}^{\min}$	Shortest geographical distance between providers that undertake $\mathrm{msub}_{j,s}$ and $\mathrm{msub}_{j,s+1}$	$\mathrm{lt}_{n_{j,\mathrm{msub}},c_j,\mathrm{l}}$	Time required for fulfilling $\mathrm{lsub}_{j,n_{j,\mathrm{msub}}}$ using R_i^{l}
$d_{n_{j,\mathrm{msub}},c_j}^{\min}$	Shortest geographical distance between the provider undertaking $\mathrm{msub}_{j,n_{j,\mathrm{msub}}}$ and C_j	M	Number of types of manufacturing resources in a PSMS
ET	Enterprise task	$\mathrm{mc}_{j,s,\mathrm{m}}^{i,k}$	Machining cost for $R_{i,k}^{\mathrm{m}}$ to complete $\mathrm{msub}_{j,s}$
F	Number of types of functions of all resources in a PSMS	mss_j	Machining subtask set of T_j
F_i	Number of types of functions of all resources P_i^{m} offers	$\mathrm{msub}_{j,s}$	s^{th} manufacturing subtask of T_j
$F_{i,k}^{\mathrm{m}}$	Function set of $R_{i,k}^{\mathrm{m}}$	$\mathrm{mswl}_{j,s}$	Workload of $\mathrm{msub}_{j,s}$

To be continued

Table A1

Parameter	Meaning	Parameter	Meaning
$\mathrm{mu}_{j,s}$	Functional type required for performing $\mathrm{msub}_{j,s}$	REL_j	Overall reliability constraint of T_j
mwl_j	Machining workload of T_j	r_i	i^{th} type of manufacturing resources in a PSMS
$\mathrm{msub}_{j,n_{j,\mathrm{msub}}}$	$(n_{j,\mathrm{msub}})^{\text{th}}$ manufacturing subtask of T_j	$\mathrm{Rep}_j^{\mathrm{c}}$	Preference of C_j toward providers' reputation
$n_{j,\mathrm{msub}}$	Number of manufacturing/logistics subtasks in T_j	$\mathrm{Rep}_i^{\mathrm{l}}$	Reputation of P_i^{l}
$N_{\max}$	Upper bound for the number of subtasks	$\mathrm{Rep}_i^{\mathrm{m}}$	Reputation of P_i^{m}
$N_{\min}$	Lower bound for the number of subtasks	sn_0	Number of subtasks executed in the platform for an ET
P^{l}	Set of logistics service providers	$\mathrm{sc}_i^{\mathrm{l}}$	Safety coefficient of R_i^{l}
P_i^{l}	i^{th} logistics service provider	$\mathrm{sc}_{j,s}^{i,l}$	Safety coefficient for R_i^{l} to process $\mathrm{lsub}_{j,s}$
P^{m}	Set of manufacturing service providers	Stru_j	Subtask structure of T_j
P_i^{m}	i^{th} manufacturing service provider	t_i^{l}	Time of R_i^{l} for unit distance
$\mathrm{PA}_i^{\mathrm{l}}$	Agent of P_i^{l}	t_{T_j}	Total time to complete T_j
$\mathrm{PA}_i^{\mathrm{m}}$	Agent of P_i^{m}	T	Task set in a PSMS
PEN_j	Penalty for delaying completing T_j	T_j	j^{th} task
PT	Platform task	TA_j	Agent of T_j
p_1	Probability for tasks to be submitted to the platform	us_0	Unit manufacturing resource
p_{t}	Task arrival probability	$u_{j,s}$	Unit amount of matched service for $\mathrm{msub}_{j,s}$
$p_{i,k}^{\mathrm{m}}$	Price of $R_{i,k}^{\mathrm{m}}$ for us_0 and unit time	$\mathrm{wght}_{j,s}$	Weight of the parts/blanks of $\mathrm{msub}_{j,s}$
$\mathrm{pt}_{j,s}^{\mathrm{m}}$	Time required for completing a part/blank in $\mathrm{msub}_{j,s}$ using unit amount of matched service with α_0	$\mathrm{wght}_{j,n_{j,\mathrm{msub}}}$	Weight of the parts/blanks of $\mathrm{msub}_{j,n_{j,\mathrm{msub}}}$
$\mathrm{pt}_{j,s,\mathrm{m}}^{i,k}$	Time required for $R_{i,k}^{\mathrm{m}}$ to complete $\mathrm{msub}_{j,s}$	$\mathrm{wt}_{j,s,\mathrm{m}}^{i,k}$	Waiting time for $R_{i,k}^{\mathrm{m}}$ to process $\mathrm{msub}_{j,s}$
p_i^{l}	Price of R_i^{l} for the unit weight and unit distance	$\mathrm{wt}_{j,s,\mathrm{l}}^{i}$	Waiting time for R_i^{l} to process $\mathrm{lsub}_{j,s}$
r	Set of all types of manufacturing resources in a PSMS	$\mathrm{wt}_{j,n_{j,\mathrm{msub}},\mathrm{l}}^{i}$	Waiting time for R_i^{l} to complete $\mathrm{lsub}_{j,n_{j,\mathrm{msub}}}$
$r_{i,k}^{\mathrm{m}}$	Type of $R_{i,k}^{\mathrm{m}}$	x_{ikjs}	1 if $R_{i,k}^{m}$ is chosen for handling $\mathrm{msub}_{j,s}$; 0 otherwise
$\mathrm{rel}_{i,k}^{\mathrm{m}}$	Reliability of $R_{i,k}^{\mathrm{m}}$	y_{ijs}	1 if R_i^{l} is chosen for handling $\mathrm{lsub}_{j,s}$; 0 otherwise
$\mathrm{rel}_{j,s}^{i,k}$	Pass rate for $R_{i,k}^{\mathrm{m}}$ to process $\mathrm{msub}_{j,s}$	$z_{ijn_{j,\mathrm{msub}}}$	1 if R_i^{l} is chosen for handling $\mathrm{lsub}_{j,n_{j,\mathrm{msub}}}$; 0 otherwise
rel_{T_j}	Overall reliability of fulfilling T_j	$z_{i,k}^{\mathrm{m}}$	Number of types of functions of $R_{i,k}^{\mathrm{m}}$
R_i^{l}	Set of logistics resource offered by P_i^{l}	α_0	Benchmark efficiency coefficient of manufacturing resources
R_i^{m}	Set of manufacturing resources offered by P_i^{m}	α_{d}	Discounting factor for weight between adjacent subtasks
$\mathrm{RA}_i^{\mathrm{l}}$	Agent of R_i^{l}	$\alpha_{i,k}^{\mathrm{m}}$	Efficiency coefficient of $R_{i,k}^{\mathrm{m}}$
$R_{i,k}^{\mathrm{m}}$	k^{th} type of manufacturing resources P_i^{m} offers	β_j	Coefficient for calculating PEN_j
$\mathrm{RA}_{i,k}^{\mathrm{m}}$	Agent of $R_{i,k}^{\mathrm{m}}$		