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ORIGINAL ARTICLE

Task-driven manufacturing cloud service proactive discovery and optimal configuration method

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Abstract Cloud manufacturing (CMfg) is emerging as a promising manufacturing paradigm, which can realize and provide distributed and heterogeneous manufacturing resources as services for all phases of the product lifecycle. A task-driven manufacturing cloud service (MCS) proactive discovery and optimal configuration method is presented in this paper to realize full-scale sharing, on-demand use, and collaborative configuration of manufacturing resources in CMfg. In this research, two kinds of resources, including manufacturing machine and manufacturing cell (MC), are viewed as a breakthrough point of the investigation of multi-granularity resource configuration process. During resource modeling, advanced information and sensor technologies are adopted to construct the information models of resources, which consist of static attributes, real-time manufacturing data, and evaluation information. It makes the traditional production process more transparent, traceable, and on-line controllable. By applying the service proactive discovery mechanism, service providers rapidly respond to task requirements on the basis of real-time status and submit requests to perform tasks proactively. Hence, the responsiveness and initiative of service providers are highly enhanced. Consequently, the efficient discovery of potential services can be achieved. In service configuration process, a scientific evaluation system is established to perform the comprehensive assessment of services. Then, through the evaluation method based on grey relational analysis (GRA), the service optimal configuration is implemented. Finally, the effectiveness of proposed models and methods is validated by a case study.

Keywords Cloud manufacturing · Multi-granularity resources · Proactive discovery · Optimal configuration · Grey relational analysis

1 Introduction

In recent years, rapid development and widespread application of information and sensor technologies have been achieved in manufacturing field, such as Cloud Computing (CC) [1], Internet of Things (IoT) [2], service-oriented technologies (SOT) [3], and so on. These technologies have brought vigorous development opportunities to modern manufacturing industry. Under this background, CMfg as a new computing and service-oriented manufacturing mode is developed from various existing advanced manufacturing modes (e.g., agile manufacturing (AM), application service provider (ASP), and manufacturing grid (MGrid)) and enterprise information technologies [4]. The concept of CMfg was presented by Li et al. [5], and the architecture, characteristics, and core enabling technologies are extensively researched [6–8].

Cloud manufacturing as the manufacturing version of cloud computing [9] extends the philosophy of "everything is a service" by adding new concepts like "manufacturing resource as a service" and "manufacturing capability as a service" [3]. In CMfg, distributed manufacturing resources and capabilities are virtualized and encapsulated into MCSs, which can be managed and operated in an intelligent and unified way to achieve the full sharing and circulation of manufacturing resources and capabilities [10]. The service

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demanders can then search and hire MCSs through the pay-as-you-go mode to execute manufacturing tasks according to their requirements [4].

Due to complexity and diversity of manufacturing resources, resource optimal configuration has become a key issue in CMfg and has been widely studied in both industrial community and academia. Generally, manufacturing resources comprise four different granularities, namely enterprise level, workshop level, cell level, and machine level. In this circumstance, resource search and invocation mainly depend on the granularity of task requirements [11]. For instance, process-level tasks can be executed by machine-level resources while complex tasks, like assembly-level or product-level tasks, need to be performed by invoking cell-level resources or higher. Accordingly, further resource allocation can be implemented. However, existing researches have a vague explanation for resource granularity. The optimization configuration process for multi-granularity resources and further internal resource optimal allocation within coarse-grained ones are few discussed. To achieve the efficient implementation of CMfg, the following questions should be taken into consideration:

1. How to apply IoT technologies to traditional production activities, so that the real-time running data and dynamic capability information of manufacturing resources can be timely sensed and captured.
2. How to establish a scientific information model for two kinds of resources investigated in this research, including manufacturing machines and cells, before these resources can be registered and published to CMfg platform.
3. How to realize efficient service discovery and optimization configuration, especially during the implementation process from cell level to machine level for coarse-grained tasks which require for multi-level decomposition.

To address the above questions, this research adopts and develops three critical technologies. They are IoT, SOT, and GRA. Within IoT, multi-source real-time manufacturing data can be sensed and captured easily by radio frequency identification (RFID) techniques, and intelligent interconnection between different manufacturing resources and objects can also be achieved [12]. SOT (e.g., service-oriented architecture (SOA), Web service, semantic web and ontology) can provide support for intelligently constructing a virtual manufacturing and service environment, which is one of the key enabling technologies to realize access, invoking, deployment, and on-demand use of MCSs [5]. GRA is a multiple criteria decision support approach to establish a ranking and suggest a best choice on a set of alternatives by analyzing relational grade among the discrete data sets [13, 14].

The rest of the paper is organized as follows. "Literature review" section reviews the literatures related to this research. A framework of MCS proactive discovery and optimal configuration method is presented in "Framework of MCS proactive discovery and optimal configuration method" section. Servitization of multi-granularity manufacturing resources is described in "Servitization of multi-granularity manufacturing resources" section. "Service optimization configuration" section elaborates the service optimization configuration method. A case study is simulated in "Case study" section. Conclusions and further work are summarized in "Conclusion and future work" section.

2 Literature review

Three streams of literatures are relevant to this research. They are cloud manufacturing, real-time manufacturing information perception and acquisition, and service selection and composition method.

2.1 Cloud manufacturing

As a new promising manufacturing paradigm, CMfg is reshaping the service-oriented, highly collaborative, knowledge-intensive, and eco-efficient manufacturing industry [15]. Significant efforts have been expended on the investigation of CMfg. To realize the full sharing, free circulation, on-demand use, and optimal allocation of various manufacturing resources and capabilities, Tao et al. investigate the applications of the technologies of IoT and CC in manufacturing firstly, and service system, architecture, and relationship of CC-based and IoT-based CMfg is studied [16]. Intelligent perception and access of various manufacturing resources based on IoT in CMfg has also been achieved [17]. In addition, virtualization is important for resources sharing and dynamic allocation in CMfg. Consequently, an effective resources virtualization mechanism for CMfg is presented. Also, a multi-granularity manufacturing model is designed to manage manufacturing resources based on manufacturing capabilities [8]. Luo et al. present a modeling and description method of multidimensional information for manufacturing capability in CMfg system [18]. Wang et al. propose an information model for manufacturing resources under CMfg environment, which consists of capability information and server information [19]. A new organization and model based on physical manufacturing unit (PMU) layer, working cell layer, and physical equipment layer was proposed by Yao et al. [20]. Zhang et al. present a service encapsulation and virtualization access model for manufacturing machine by combining the IoT and CC in CMfg [21]. A SME (small-sized and medium-sized enterprise)-oriented CMfg service and capability transaction platform for small- and medium-sized enterprises is presented to serve the sharing and coordination of network-based manufacturing resource of SMEs, and to address the key problems (e.g., deficiency of self-innovation and design capability) [22]. A hybrid manufacturing cloud is proposed to allow companies to deploy different cloud modes for their periodic business goals with the self-defined access rules and self-managed mechanism [23].

2.2 Real-time manufacturing information perception and acquisition

The Internet of Things (IoT) is a novel paradigm which is rapidly gaining ground in the scenario of modern wireless telecommunications, and it relies on technologies such as RFID, sensor, etc. [24]. It has been reported that IoT is widely applied in manufacturing field based on its significant advantages by many researchers. A real-time information capturing and integration framework of the Internet of Manufacturing Things (IoMT) is presented by extending the techniques of IoT to manufacturing field [12]. RFID technology has been used in manufacturing industries to form a RFID-enabled ubiquitous environment. Zhang et al. describe a framework of multi-agent-based real-time production and logistics scheduling system for RFID-enabled ubiquitous shopfloor environment [25]. Zhong et al. utilize real-time advanced production planning and scheduling to improve the quality and reliability of plans and schedules to achieve collective intelligence based on the RFID-enabled real-time information for RFID-enabled ubiquitous manufacturing [26]. Based on acquired real-time and multi-source manufacturing data, Zhang et al. propose an optimization method for assigning shopfloor material handling tasks [27]. Moreover, a kind of real-time information-driven intelligent navigation method for assembly station in unpaced lines is also presented [28]. Guo et al. describe the RFID-based intelligent decision support system architecture by integrating RFID technology and cloud technology to handle real-time and remote production capturing, monitoring, and scheduling in a distributed manufacturing environment [29]. Wang introduced IoT and cloud manufacturing to help a conventional assembly modeling system evolve into an advanced system and to deal with complexity and change in their application of modern enterprise [30]. Huang et al. apply the RFID technology into automotive manufacturing and deploy RFID-enabled real-time services in a common platform across members of automotive part and accessory manufacturer alliance [31]. Zhong et al. introduce a big data approach into RFID-enabled logistics production data to mining the invaluable trajectory knowledge [32]. Li et al. conclude and analyze the various date involved in the three main phases of product lifecycle management (PLM) and investigate the potential applications of "Big Data" techniques in PLM [33].

2.3 Service selection and composition method

In CMfg, services can be searched, invoked, and deployed by service demanders. Selection of single service and service composition is of great importance to provide an ideal solution for specific manufacturing tasks. Wang et al. study the selection strategy of machining equipment in CMfg and propose an optimal selection of machining equipment model [34]. A trust evaluation model oriented to mechanical manufacturing filed based on the framework of CMfg service platform is established by Li et al. to achieve the effective management, convenient use, and reliable transactions of resources and tasks [35]. Service composition and optimal selection (SCOS) is a typical multi-objective combinatorial optimization (MOCO) problem in CMfg. Tao et al. point out that SCOS is one of the key technologies to implement CMfg, and investigate the multi-objective MGrid SCOS problem [36], then propose a new manufacturing grid resource SCOS method, based on the principles of particle swarm optimization (PSO), to minimize implementation time and cost, and maximize the reliability of MGrid resource service composition paths [37]. Tao et al. also investigated the formulation of SCOS in CMfg with multiple objectives and constraints. And a parallel intelligent algorithm was developed [38]. Liu et al. describe a "Multi-Composition for Each Task" (MCET) pattern-based global approach to combine the incompetent composite services into a whole to perform each multi-functionality manufacturing task collaboratively [39]. Xiang et al. introduce a new multi-objective optimization algorithm based on the combination of the idea of Pareto solution and group leader algorithm (GLA) to address the problem of SCOS based on quality of service and energy consumption in CMfg [40]. Huang et al. design a new chaos control optimal algorithm (CCOA) to address the SCOS problem with large-scaled and irregular cloud services in CMfg [41]. Qu et al. propose a generic analytical target cascading optimization system for decentralized supply chain configuration [42]. Lartigau et al. develop an adapted Artificial Bee Colony optimization algorithm based on quality of service with geo-perspective transportation to answer all the challenges identified in CMfg service composition, satisfying computational optimization [43]. Li et al. propose a decision diagram extension method based on original Binary decision diagram for large-scale system [44].

3 Framework of MCS proactive discovery and optimal configuration method

Figure 1 illustrates the framework of MCS proactive discovery and optimal configuration in CMfg which consists of four modules, namely servitization of multi-granularity manufacturing resources, manufacturing task publishing,

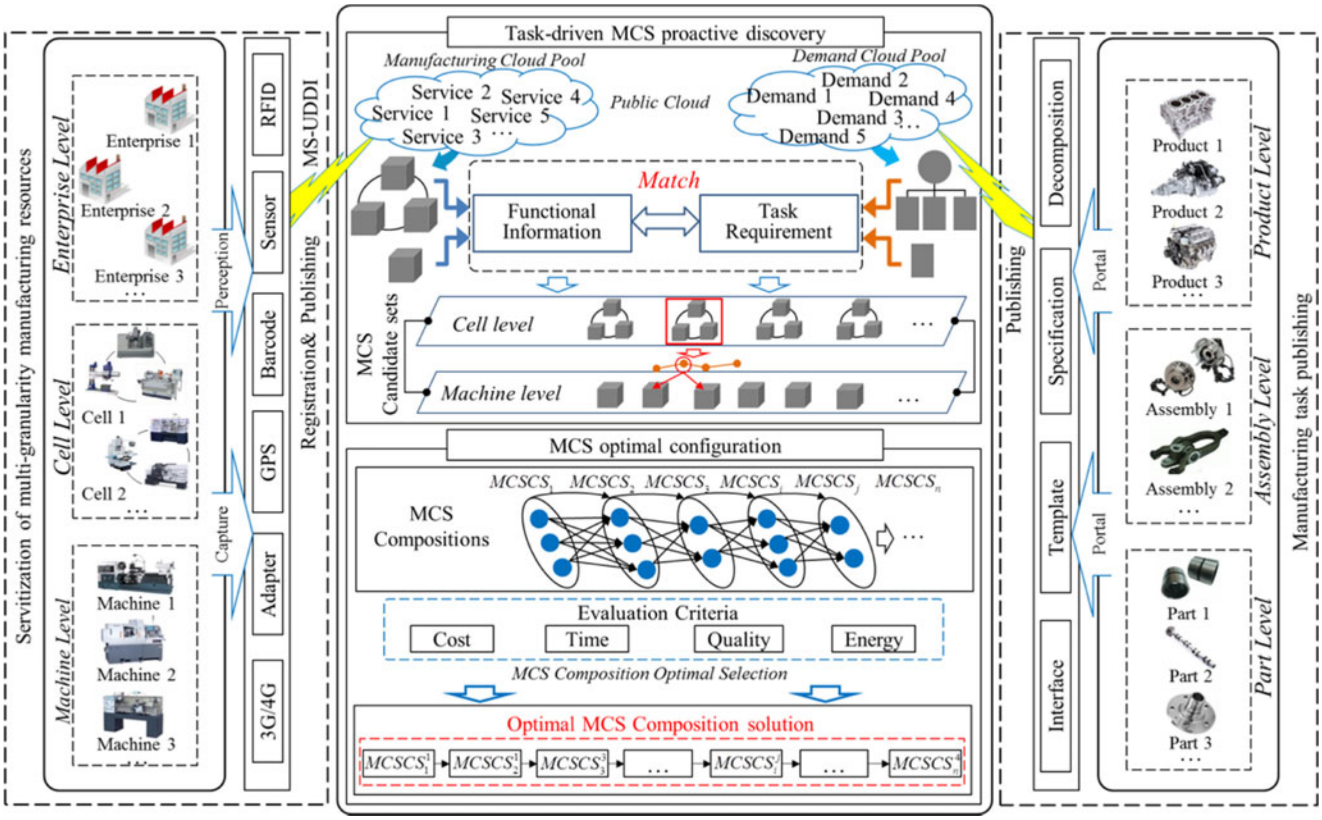

Fig. 1 Framework of MCS proactive discovery and optimal configuration

task-driven MCS proactive discovery, and MCS optimal configuration.

Manufacturing resource full-scale sharing and circulation are the very important objectives in CMfg. It is the prerequisite of achieving on-demand use and collaborative configuration of resources and services, e.g., cluster supply chain configuration (CSCC) [45]. In order to achieve these goals above, the issue of realizing reasonable and scientific description of manufacturing resources needs to be further studied, especially when it comes to complex coarse-granularity ones. In resource modeling, a service provider (the machine or MC) needs to emphasize following points to clarify its manufacturing capability, basic description of service, manufacturing resource information, real-time execution status and production logistics (PL) process [46], typical product information, service implementation process, and evaluation of the service. Based on the resource servitization method and core enabling technologies, resources are virtualized and encapsulated into MCSs, including manufacturing cell cloud service (MCCS) and manufacturing machine cloud service (MMCS), and registered and published to manufacturing cloud pool latterly. Meanwhile, manufacturing tasks are published to the demand cloud pool so that service demanders can find satisfying solutions with low cost and time consumption.

The task-driven MCS proactive discovery mechanism proposes a pattern that service providers make real-time response to task requirements according to their real-time manufacturing status, and submit requests to undertake tasks proactively. This pattern is capable of enhancing providers' responsiveness and initiative. By adopting the proposed intelligent match method between service functional information and task requirements, the MCS candidate sets (MCSCSs) for manufacturing tasks will be formed. Here, tasks with different granularities have different candidate sets, including MCCS candidate sets (MCCSCSs) and MMCS candidate sets (MMCSCSs). In particular, MMCS discovery process in MC (private cloud) will be further investigated. By adopting this service discovery approach, the solution space of service compositions can be greatly reduced. As a result, the efficiency of service configuration is effectively enhanced.

The MCS optimal configuration method is proposed to select an optimal solution from large-scale service compositions (for both MCCSs and MMCSs). Based on the real-time manufacturing status data and evaluation information, this research establishes a systematic evaluation system, which contains criteria like cost, time, quality, and energy consumption. In addition, a comprehensive evaluation approach based on GRA is presented to assess and optimize service compositions. As a consequence, the optimal MCS composition solution is generated for the manufacturing task.

4 Servitization of multi-granularity manufacturing resources

4.1 Servitization framework of manufacturing resources

Servitization of manufacturing resources is the key technique in CMfg. Distributed and heterogeneous manufacturing resources are virtualized and encapsulated as MCSs. They can be registered and published to CMfg platform to achieve efficient management and extensive application which contributes to the full-scale sharing, dynamic allocation, and on-demand use of MCSs.

As shown in Fig. 2, the proposed manufacturing resources servitization framework consists of three layers, resource layer, perception layer, and service registration and publishing layer. They are described as follows:

The resource layer contains various manufacturing resources that can support manufacturing activities which are involved in the product lifecycles. Here, manufacturing machines and cells that are involved in production process are thoroughly investigated.

Perception layer is responsible for collecting, processing, and managing the related manufacturing information, including static description information derived from inherent attributes of resources and history record, and dynamic sensing manufacturing information based on real-time status data captured by advanced technologies such as RFID, IoT, etc.

Service registration and publishing layer enables the multi-granularity resources to seamlessly access the CMfg platform. The following steps are done in this process:

Step 1 Information model of multi-granularity manufacturing resources: Manufacturing service information models with different granularities will be constructed, including manufacturing machine service model and manufacturing cell service model.

Step 2 Ontology model of manufacturing service: Manufacturing service ontology endowed with semantic information based on ontology and semantic web technology is established.

Step 3 Registration and publishing mechanism of manufacturing service based on the Manufacturing Service Universal Description, Discovery, and Integration (MS-UDDI): The MS-UDDI constructed in registration module, publishing module, and search module is presented to realize manufacturing service registration, publishing, searching, and invoking.

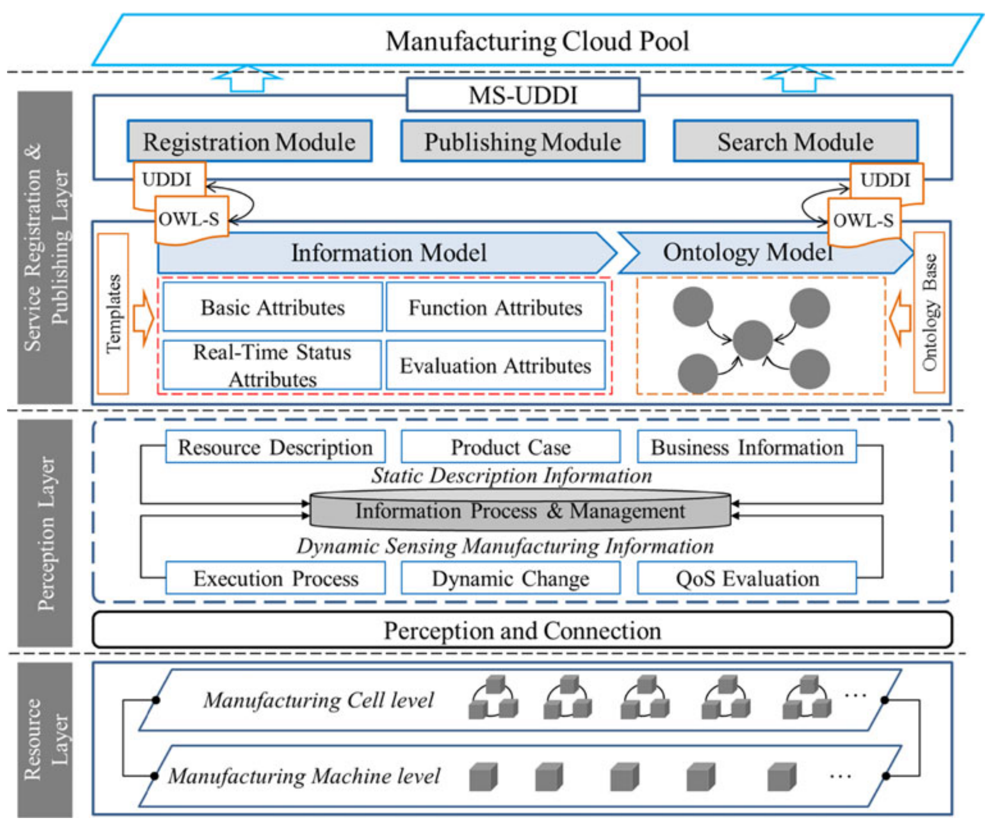

Fig. 2 Servitization framework of manufacturing resources

4.2 Capability model of manufacturing machine

In this section, the capability model of manufacturing machine is investigated at first. Manufacturing machine is the basic execution unit in manufacturing activities and the major element of the complex MC. Thus, a reasonable and detailed machine service model is the foundation of constructing a complex manufacturing cell service information model. The presented model is responsible for describing the manufacturing machine capability explicitly from two aspects: static description information and dynamic sensing manufacturing information based on real-time running data.

As shown in Fig. 3, the manufacturing machine service model consists of four attributes; they are basic attributes, function attributes, real-time status attributes, and evaluation attributes, respectively. The circles marked with numbers represent the subclasses of corresponding attributes. For each circle, the solid line arrow denotes the "Own" relationship and the dotted line arrow denotes the "Belong to" relationship. So manufacturing machine cloud service is defined as:

$$MMCS = (MMBasicAttr, MMFunctionAttr, MMStatusAttr, MMEvaluationAttr).$$

4.2.1 Basic attribute

The basic attribute of machine provides an overview of manufacturing machine, which can reflect the unique identification information of machine in CMfg platform. It facilitates the quick positioning of related MCSs during the stage of service discovery and match. Here, basic attribute primarily includes service ID, service name, work shop, the purchase date, manufacturer, and service life of machine. It is defined as:

$$MMBasicAttr = (MMID, MMName, Workshop, MMPurDate, MMManufacturer, MMLife).$$

4.2.2 Function attribute

The function attribute of machine is the core component of capability model. It provides technical support for searching potential services and completing function match in CMfg by describing capabilities of machines in details. It mainly includes processing part type, processing method, processing characteristic, achievable processing size, processing material, processing precision, and processing roughness. It is defined as:

$$MMFunctionAttr = (MMPartType, MMMethod, MMCharacteristic, MMSize, MMMaterial, MMPrecision, MMRoughness).$$

4.2.3 Real-time status attribute

In CMfg, real-time manufacturing data is accurately captured by attaching heterogeneous sensors and adapters on machines. This makes the whole manufacturing process more transparent, traceable, and controllable. Thus, it provides a sound basis for real-time scheduling and optimal configuration of MCSs, which contains service status, manufacturing task sequence, load status of the machine, and detailed processing information. It is defined as:

$$MMStatusAttr = (MMStatus, MMTaskSequ, MMLoadStatus, MMProcessingInfo).$$

4.2.4 Evaluation attribute

The evaluation attribute of machine is a significant part of capability model and plays an important role in the stage of service optimal selection. It contains the cost of service, pass rate, on-time delivery rate (OTDR), reliability, service times in CMfg platform, maintainability, and customer satisfaction (CS). It is defined as:

$$MMEvaluationAttr = (Cost, PassRate, OTDR, Reliability, STimes, Maintainability, CS).$$

4.3 Information model of manufacturing cell

Based on the capability model of manufacturing machine mentioned above, the MC information model is further researched to build a solid foundation for full-scale sharing and on-demand use of MCCSs. Compared to the manufacturing machine, the MC is capable of undertaking more complex manufacturing tasks, like assembly-level tasks or even product-level tasks. In manufacturing process, complex tasks are completed by invoking, scheduling, and managing the collaborative manufacturing resources in real time. Therefore, MC can display different capabilities at different times in different manufacturing activities. The presented MC information model takes exhaustive consideration of both static and dynamic information of related manufacturing resources in MC.

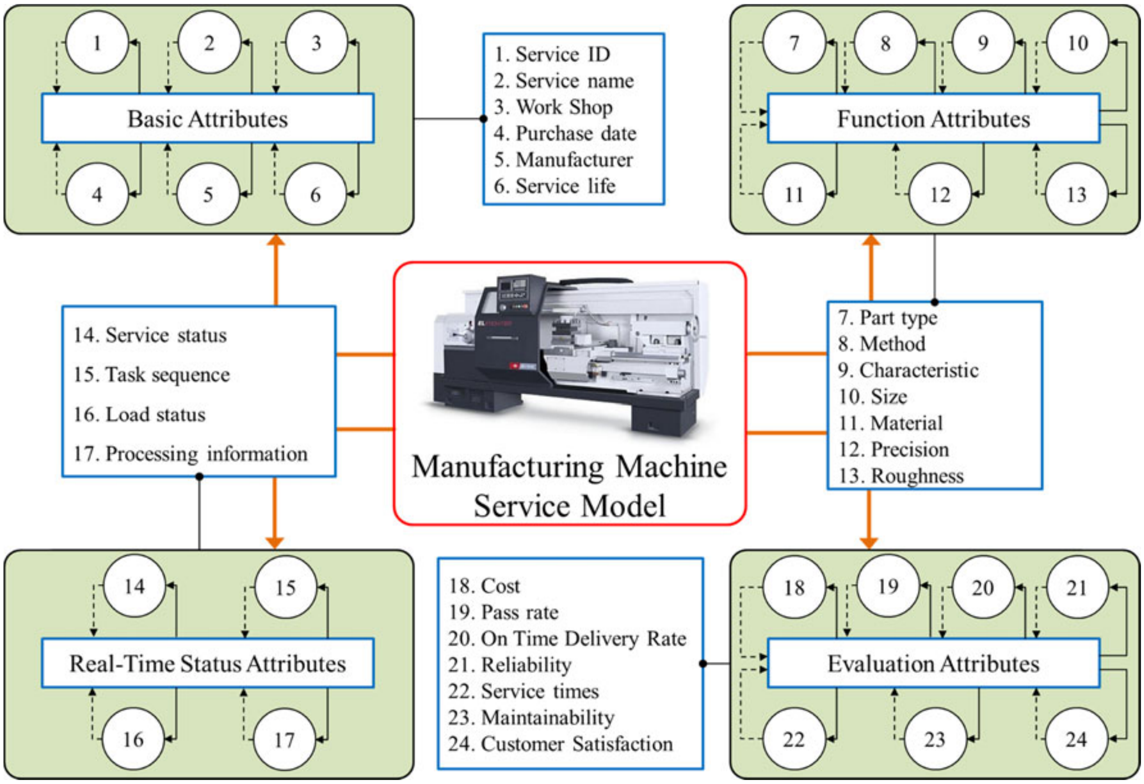

Fig. 3 Manufacturing machine service model

The structure of manufacturing cell service model is shown in Fig. 4, which consists of description information, resource information, status information, and evaluation information. It is defined as:

$$MCCS = (MCDescriptionInfo, MCResourceInfo, MCStatusInfo, MCEvaluationInfo).$$

4.3.1 Description information

The description information is responsible for clarifying the following points: what the MC is, the job can be undertaken, and service implementation process. It is defined as:

$$MCDescriptionInfo = (MCBasicInfo, MCProductInfo, MCBusinessInfo)$$

where *MCBasicInfo* is the identification information of MC in CMfg platform, which is similar to that of manufacturing machines. *MCProductInfo* is the general description of product output from MC, which contains typical product, production record, etc. *MCProductInfo* can reflect the intuitive manufacturing capability of MC. Meanwhile, a product case base is established by taking advantage of product information, which can enhance the efficiency of intelligent match in service discovery stage. *MCBusinessInfo* is used to describe the specific implementation of business. It mainly includes transaction information, transaction record, etc.

4.3.2 Resource information

MC is the integration of heterogeneous manufacturing resources related to manufacturing activities. Manufacturing resources are the main carriers of capability of MC. The resource information can reflect the manufacturing capability by elaborating the resource structure of MC. Here, it is defined as:

$$MCResourceInfo = (MResource, Human, Knowledge, Software)$$

MResource refers to hard resources involved in manufacturing activities, which includes manufacturing machines, tools, varieties of sensors, raw materials, etc. *Human*, *Knowledge*, *Software* are soft resources in MC. *Human* describes the information of personal and organization in MC, such as operators, designers, technicians, and so on. *Knowledge* is the basis of supporting manufacturing activities, including engineering knowledge, specifications, product models, etc. Meanwhile, some intellectual elements such as experience and skills are involved. *Software* plays a vital role throughout the product lifecycle, including design, simulation, process planning, fabrication, and test, such as CAD (computer-aided design), CAPP

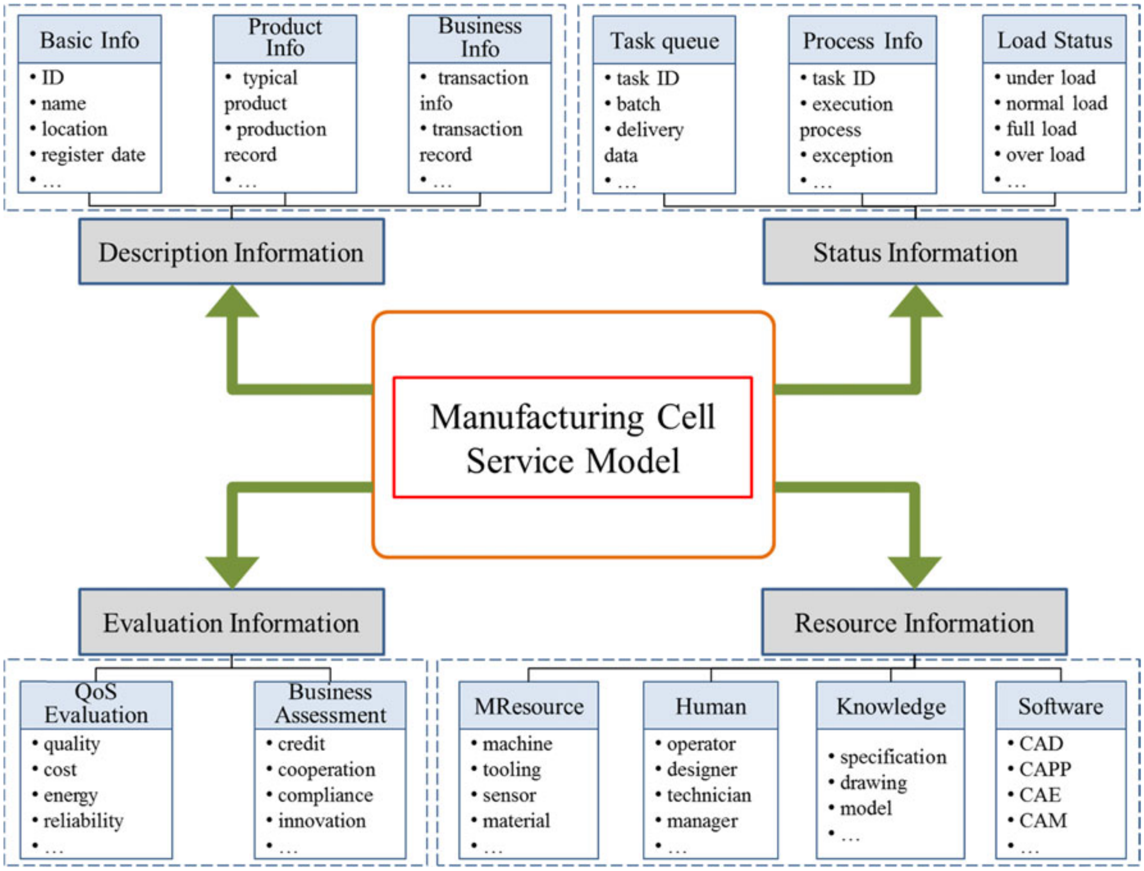

Fig. 4 Manufacturing cell service model

(computer-aided process planning), and CAM (computer-aided manufacturing).

4.3.3 Status information

The status information is capable of sensing the running process and dynamic changes of manufacturing activities in MC, which enables service real-time controlling, scheduling, and exception tracking. Furthermore, real-time updating status information also reflects dynamic manufacturing capability of MC. It is defined as:

$$MCStatusInfo = (MCTaskQueue, MCProcessInfo, MCLoadStatus)$$

MCTaskQueue provides an overview of tasks undertaken by MC, which primarily contains tasks being processed and those waiting to be processed. *MCProcessInfo* is in charge of monitoring and recording current manufacturing process data. It includes current task ID, machining progress, production exceptions and disturbances, etc. *MCLoadStatus* describes load condition of each machine related to manufacturing activities in MC to reflect the capability from a global perspective. For the high load machines, they are the bottleneck of MC to hinder the dynamic capability of undertaking corresponding manufacturing tasks.

4.3.4 Evaluation information

Comprehensive evaluation is a critical part of assessing manufacturing capabilities in CMfg. Evaluation information is a multi-level integration of service metrics of MC, including business-level metrics and service-level metrics. Evaluation indicators defined in this research come into two classes, customer-oriented indicators and objective ones from actual history data. It is defined as:

$$MCEvaluationInfo = (QoSEvaluation, BusinessAssessment)$$

Here, *QoSEvaluation* describes the functional evaluation of service, which mainly includes quality, cost of service, makespan, reliability, etc. *BusinessAssessment* describes the subjective rating of transaction process, including credit of the service provider, cooperation, compliance, innovation, and so on.

4.4 Registration and publishing method of MCSs

4.4.1 Ontology model of MCSs

To improve the quality and efficiency of service discovery and intelligent match, ontology and semantic web technology are widely applied to describe web service in CMfg. Ontology can not only support the explicit definition of relevant domain knowledge and relationship but also have strong reasoning ability. To achieve effective expression of manufacturing information and connotative meanings, the ontology description language OWL-S is adopted as the description carrier of ontology model of services. In this paper, the ontology model of MCSs is constructed by Protégé series [46] developed by Stanford University which is a widely used ontology modeling tool.

4.4.2 Registration and publishing based on MS-UDDI

This part discusses the issue of publishing services to manufacturing cloud pool. MS-UDDI is used to complete the registration and publishing of MCSs.

UDDI specifications provide a feasible approach to register, publish, and discover information about web services. A standard UDDI XML schema defines four core information structures; they are businessEntity, businessService, bindingTemplate, and tModel. The businessEntity is responsible for representing the providers of web services in CMfg platform which may contain one or more businessServices. The businessServices is a descriptive container of specified technical services. The bindingTemplate defines essential information needed for invoking specific web services. The tModel is a list of references contained in the bindingTemplate and used to access information about specifications.

Based on the UDDI technology, the framework of MS-UDDI consists of three sub-modules. They are registration module, publishing module, and search module.

In registration module, based on captured manufacturing information and supported by ontologies and rules, the information model and ontology model of MCSs are established. Meanwhile, the mapping relationship between the data structure of manufacturing services described by OWL-S and that supported by UDDI is formed through the OWL-S/UDDI matchmaker [47]. In publishing module, distributed manufacturing resources are published to CMfg platform, and then manufacturing cloud pool is formed. In search module, services related to manufacturing activities can be searched and inquired by service demanders, which contributes to quick response to task requirements and on-demand use of MCSs.

5 Service optimization configuration

In CMfg, to meet customized requirements of manufacturing tasks, related MCSs should be invoked and selectively integrated into collaborative service compositions. In order to realize the aims of the shortest execution time, lowest cost, cleanest environment, and highest quality (TCEQ), it is necessary to appropriately orchestrate the service compositions. The proposed service optimization configuration process encompasses two stages: task-driven MCS proactive discovery and MCS optimal configuration.

5.1 Task-driven MCS proactive discovery

5.1.1 Service discovery mechanism

The presented task-driven MCS proactive discovery mechanism enables MCSs to quickly respond to task requirements and to apply to undertake tasks actively. By adopting the semantic match method, CMfg platform can perform intelligent match between requirements and services based on the functional information. In consequence, functionally equivalent services are pooled into MCSCSs. If manufacturing tasks are too complex to find the competent services, CMfg platform would implement the top-down decomposition of tasks until the qualified MCSs can be found. In this case, tasks need to be executed collaboratively by multiple services. Here, to avoid increasing extra transportation expense among distributed services, also for the convenience of controlling and tracking manufacturing process efficiently and continuously, tasks will not be further decomposed into more subtle ones by the platform.

This research considers coarse-grained manufacturing tasks be undertaken by one or more MCs. Here, as shown in Fig. 5, a two-phase service discovery process for tasks which need to invoke multiple collaborative MCs is presented, including the MCCS discovery and MMCS discovery.

Phase 1. Manufacturing tasks are published to the demand cloud pool in CMfg platform. Meanwhile, the platform advertises task requirements for services. The MCs make quick response to task requirements and submit requests. Then, tasks are determined whether they are able to be completed by eligible MCCSs. If unable, they will be progressively decomposed into subtle tasks (part-level, assembly-level, or combination of both) until which can be executed by MCs. Generally, there are no sequence constraints among subtle tasks in production process. Through the presented intelligent match method, MCCSCSs are formed.

Phase 2. CMfg platform issues call for proposals for each subtle task to the MCs from their respective candidate sets. Each MC puts forward a proposal in terms of their real-time manufacturing status. By evaluating the combination proposals of all possible service compositions, the optimal composition solution will be generated, and

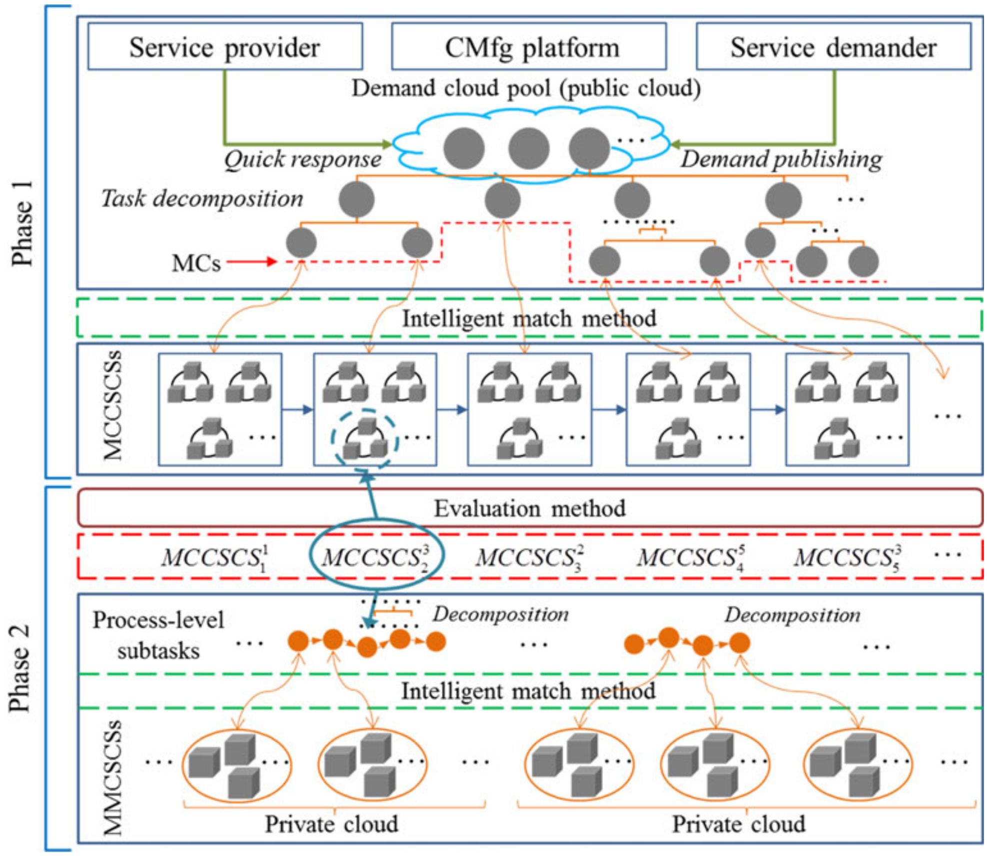

Fig. 5 Task-driven MCS proactive discovery process

MCs will get corresponding subtle tasks. The tasks are further decomposed into several subtasks (process-level) by the selected MCs according to CAPP so that tasks can be assigned to manufacturing machines. These subtasks have to be completed by invoking services in a certain sequence according to the process constraints among themselves. By adopting the intelligent match method based on functional information of services, qualified MMCSs for each subtask will be pooled into MMCSCSs.

Particularly, for tasks which can be completed by single MCCS, the platform evaluates all the proposals submitted by competitive MCs. The optimal proposal will be accepted and corresponding MC will get the task. The MMCSs discovery in public cloud for fine-grained tasks is similar to that described in phase 2.

5.1.2 Intelligent match method

This part is dedicated to describe the intelligent match method between task requirements and services. As shown in Fig. 6, the matching process is presented which includes a product case base and function match module.

The product case base is constructed to achieve quick match between complex tasks and coarse-grained resources (the MCs). Typical products, especially for those with competitive advantages of MCs, are recorded in this case base. The similarity between requirement information and product specifications can be measured by querying the case base. When the similarity exceeds a preset threshold, the MC is considered to be competent for the task.

In contrast, if the similarity is not significant enough or the existing cases in this base cannot match with tasks directly, these tasks will be decomposed into process-level tasks. Semantic match method will be implemented for each subtask one by one. If all the machines involved in manufacturing activities can match accurately with respective subtasks, the corresponding MCCS is viewed as a feasible solution.

Based on semantic match method [48], the semantic matching degree is rated and then defined as four levels. They are *Exact*, *Plug in*, *Subsume*, and *Fail*, respectively.

According to the method above, the semantic match method will be implemented based on the following function attributes of manufacturing machines: processing part type, processing method, processing characteristic, processing size, processing material, processing precision,

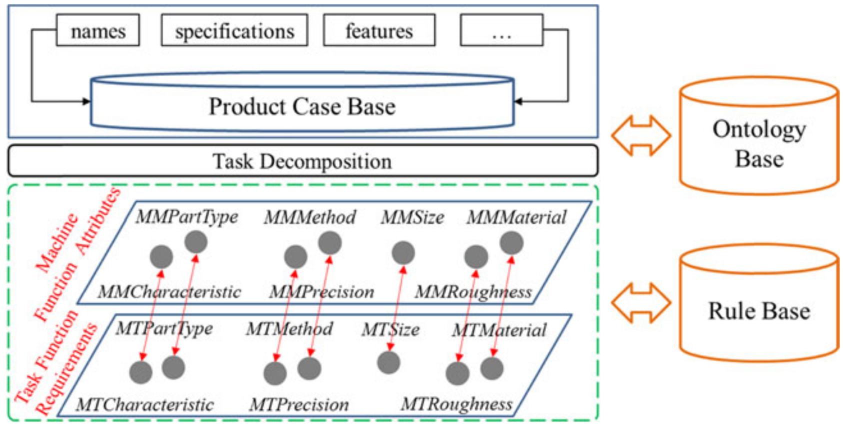

Fig. 6 Intelligent match method

and processing roughness. According to Eq. (1), only if all the matching degrees of corresponding attribute reach *Exact*, the machine can meet the task requirements. Otherwise, it will not be pooled into service candidate set.

$$\begin{aligned}&Match(MMPartType, MTPartType) \wedge Match(MMMethod, MTMethod) \wedge Match(MMSize, MTSize) \wedge \\ &Match(MMMaterial, MTMaterial) \wedge Match(MMCharacteristic, MTCharacteristic) \wedge \\ &Match(MMPrecision, MTPrecision) \wedge Match(MMRoughness, MTRoughness) = Exact\end{aligned} \quad (1)$$

The task-driven MCS proactive discovery mechanism investigated above can facilitate the active discovery of potential services and pool them into candidate sets for specific tasks. As a result, it contributes to reduce the solution space of service compositions to a great extent, which enables to provide a fundamental support for service optimal configuration.

5.2 MCS optimal configuration

This part is responsible for elaborating service optimal configuration process, which includes the configuration process of MCCSs or MMCSs in public cloud, and further optimization composition of machines in MCs (private cloud). Above all, a systematic evaluation system is constructed to achieve comprehensive evaluation of single service or service compositions. Then, by adopting the evaluation method based on GRA, the service optimal configuration is implemented.

5.2.1 Evaluation system

The evaluation system is established by taking full consideration of the particularity, complexity, and difference of different-level manufacturing activities. Thus, the evaluation indicators should be defined in accordance with the specific level of manufacturing activities.

The evaluation system for MCCS aims to evaluate services from an overall perspective, which focuses on all the machines involved in manufacturing activities in the MC. Meanwhile, the defined indicators contain not only quality evaluation criteria of finished tasks but also subjective appraisement of transaction activities from service demanders. Evaluation criteria of MCCS in this research are as follows:

- Cost (C): the cost of MCCS, including machining cost, storage cost, etc.;
- Delivery Time (DT): the date that MCCS promises to deliver tasks according to its real-time status and capacity. It can embody the real-time dynamic capability of MC for different tasks from the perspective of time. The closer it approaches to deadline, the better it is, which means that neither advanced too much nor even delayed can it be;
- Delay Time (dt): the part that Delivery Time exceeds the deadline of task;
- Reliability (R): the execution reliability of MCCS; it changes along with manufacturing activity type and is mainly determined by the global reliability of related machines;
- Credit (Cr): the reputation of MCCS assessed by service demanders (maximum ten points) in CMfg platform;
- Energy (E): the energy consumption (electricity) of MCCS in the whole service process.

Here, the evaluation system used to evaluate MMCSs in MCs (private cloud) focuses on the quality parameters of the finished subtasks. In particular, the evaluation criteria used to assess MMCSs in the public cloud include both objective indicators and subjective ones which are similar to those of MCCSs. Here, they will not be further discussed. The main evaluation criteria of MMCSs in MCs are:

- Cost (C): the execution cost of MMCS;
- Delivery Time (DT): the duration that service (machine) can complete the task;
- Pass Rate (PR): the probability that the machined task meets the functional requirement;
- On-Time Delivery Rate ($OTDR$): the probability that machine can deliver tasks on time referring to the production schedule;
- Reliability (R): the execution reliability of MMCS; it differs from that of MCCS mentioned above. Here, this indicator describes the reliability of single machine;
- Energy (E): the energy consumption of machine.

5.2.2 Evaluation method

Service optimal selection can be implemented by adopting the evaluation method based on GRA, which can be divided into the following steps.

1. Initial evaluation indicator matrix

$$S = \left[s_q^p\right]_{m\times n}$$

Here, s_q^p denotes the value of qth indicator of the pth service, where m is the total number of services in candidate set and n is the total number of defined evaluation indicators.

2. Ideal indicator sequence

The ideal indicator sequence is determined by both task requirement information and the types of evaluation indicators.

Definition 1

$$s_q^+ = \max_{1\le p\le m}\left\{s_q^p\right\} \quad s_q^- = \min_{1\le p\le m}\left\{s_q^p\right\}$$
$$s_q^* = \begin{cases} s_q^+, q\in I^+ \\ s_q^-, q\in I^- \end{cases}, q = 1,2,3\ldots,n \tag{2}$$

where s_q^* is the qth ideal indicator, I^+ is the set of the benefit-oriented indicators, and I^- is the set of cost-oriented ones. Therefore, the ideal indicator sequence is generated as follows:

$$S^* = \left(s_1^*, s_2^*, \cdots, s_n^*\right)$$

3. Normalizing evaluation matrix

Due to different dimensions in the initial evaluation matrix, indicators need to be normalized according to Eq. (3) so that the evaluation results can be more reliable and accurate.

$$\gamma_q^p = \begin{cases} \dfrac{s_q^p - s_q^-}{s_q^+ - s_q^-}, q\in I^+ \\[2ex] \dfrac{s_q^+ - s_q^p}{s_q^+ - s_q^-}, q\in I^- \end{cases}, q = 1,2,3,\ldots,n \tag{3}$$

Thus, the initial evaluation matrix is transformed into $V=[\gamma_q^p]_{m\times n}$.

4. Relational coefficient matrix

According to the grey theory, ξ_q^p represents the grey relational coefficient between the qth indicator of the pth service and the ideal indicator.

Definition 2

$$\gamma_q^+ = \max_{1\le p\le m}\left\{\gamma_q^p\right\} \quad \gamma_q^- = \min_{1\le p\le m}\left\{\gamma_q^p\right\}$$
$$\xi_q^p = \frac{\min\limits_{1\le p\le m}\min\limits_{1\le q\le n}\left|\gamma_q^+ - \gamma_q^p\right| + \eta\max\limits_{1\le p\le m}\max\limits_{1\le q\le n}\left|\gamma_q^+ - \gamma_q^p\right|}{\left|\gamma_q^+ - \gamma_q^p\right| + \eta\max\limits_{1\le p\le m}\max\limits_{1\le q\le n}\left|\gamma_q^+ - \gamma_q^p\right|} \tag{4}$$

where η is distinguishing coefficient, and $\eta=0.5$. Therefore, the obtained relational coefficient matrix is $E=[\xi_q^p]_{m\times n}$.

5. Comprehensive evaluation matrix

The victor $W=(w_1,w_2,w_3\ldots,w_n)^T$ is used to represent the weight of each indicator, which can be determined by the widely used Analytic Hierarchy Process (AHP) [49].

The comprehensive evaluation matrix is obtained as:

$$R[r^p] = EW \tag{5}$$

where r^p is the grey relational degree between pth service and the ideal indicator sequence. The bigger the value of r^p is, the better service behaves.

5.2.3 Problem formulation

In this section, the service optimization configuration process is elaborated based on the evaluation system and method. The service configuration process for the coarse-grained manufacturing tasks undertaken by MCCSs can be divided into the following steps:

1. MCCS optimization configuration: Let $T=\{ST_i; i=1,2,3,\ldots,N_T\}$ denote a coarse-grained task, where N_T is the total number of the decomposed subtle tasks which can be executed by the MCs and ST_i is the ith subtle task of T.

(If N_T=1, the task only needs to invoke single MCCS). All the competent MCCSs are pooled into corresponding candidate sets for each subtle task. Here, let $MCCSCS_i=\{MC_i^j;j=1,2,3,\ldots,M_i\}$ represent the candidate set available for ST_i, where M_i is the total number of MCs and MC_i^j is the jth service in the set. In this case, there are $\prod_{i=1}^{N_T} M_i$ possible compositions theoretically. To avoid extremely large solution space, services in each candidate sets can be evaluated in advance by adopting the proposed evaluation method. Then, services are sequenced in descending order in terms of respective grey relational degrees. Top X_i services in queue are selected for ST_i, and consequently, there are $\prod_{i=1}^{N_T} X_i$ compositions. The evaluation criteria of each service composition can be calculated as shown in Table 1. By adopting the evaluation method again, the optimal MCCS composition solution is generated.

2. MMCS optimization configuration: From the optimal MCCS composition solution, it is assumed that $ST_{[i,j]}=\{ST_{[i,j]}^k;k=1,2,3,\ldots,M_{ST}\}$ is assigned to MC_i^j, where M_{ST} is the total number of decomposed subtle tasks (process-level) which can be undertaken by the machines in MC and $ST_{[i,j]}^k$ is the kth subtask. The candidate set for $ST_{[i,j]}^k$ is defined as $MMCSCS_k=\{MM_k^l;l=1,2,3,\ldots,N_k\}$, where N_k is the total number of machines in the candidate set and MM_k^l is the lth machine; Here, service configuration process is divided into two cases.

   Case 1 $ST_{[i,j]}$ without batch: In this case, service optimizing configuration process is similar to that described above. The evaluation criteria of each MMCS composition can be calculated as shown in Table 1. According to the generated optimal MMCS composition solution, let $ST_{[i,j]}^{[k,l]}$ represent the process-level task undertaken by MM_k^l.

   Case 2 $ST_{[i,j]}$ with batch L_i: At first, services in candidate set for each process-level task (e.g., $ST_{[i,j]}^k$) are sequenced in descending order in terms of respective relational degrees. Then, starting with the optimal service, the ordered services take turns to undertake tasks according to respective capacity until the batch tasks are entirely assigned.

Definition 3 Let CA^l denote the capacity of MM_k^l, which can be calculated by Eq. (6):

$$CA^l = (d - T_l)/ET_l \tag{6}$$

where d is the deadline of the batch tasks, T_l is the arranged start time of production, and ET_l is the execution duration for single task.

Table 1 Calculation method for evaluation criteria of service composition

Service composition	Evaluation criteria	Function
MCCS composition	C	$C = \sum_{i=1}^{N_T} C(MC_i)$
	DT	$DT = DT(MC_{N_T})$
	dt	$dt = \max\{DT(MC_{N_T}) - dt_{N_T}\}$
	R	$R = \prod_{i=1}^{N_T} R(MC_i)$
	C_r	$C_r = \sum_{i=1}^{N_T} C_r(MC_i)/N_T$
	E	$E = \sum_{i=1}^{N_T} E(MC_i)$
MMCS composition (e.g., for $ST_{[i,j]}$)	C	$C_{[i,j]} = \sum_{k=1}^{M_{ST}} C_{[i,j]}(MM_k)$
	DT	$DT_{[i,j]} = \sum_{k=1}^{M_{ST}} DT_{[i,j]}(MM_k)$
	PR	$PR_{[i,j]} = \prod_{k=1}^{M_{ST}} PR_{[i,j]}(MM_k)$
	$OTDR$	$OTDR_{[i,j]} = \prod_{k=1}^{M_{ST}} OTDR_{[i,j]}(MM_k)$
	R	$R_{[i,j]} = \prod_{k=1}^{M_{ST}} R_{[i,j]}(MM_k)$
	E	$E_{[i,j]} = \sum_{k=1}^{M_{ST}} E_{[i,j]}(MM_k)$

$DT(MC_{N_T})$ the final *Delivery Time* of MCCS composition, dt_{N_T} the deadline of the initial manufacturing task

The service configuration process for the fine-grained tasks which can be undertaken by MMCSs in public cloud is similar to step 2 described above.

6 Case study

6.1 Case description

This section presents an application of proposed service optimization configuration method by taking a typical complex manufacturing task published to CMfg platform. The detailed structure of task is shown in Fig. 7.

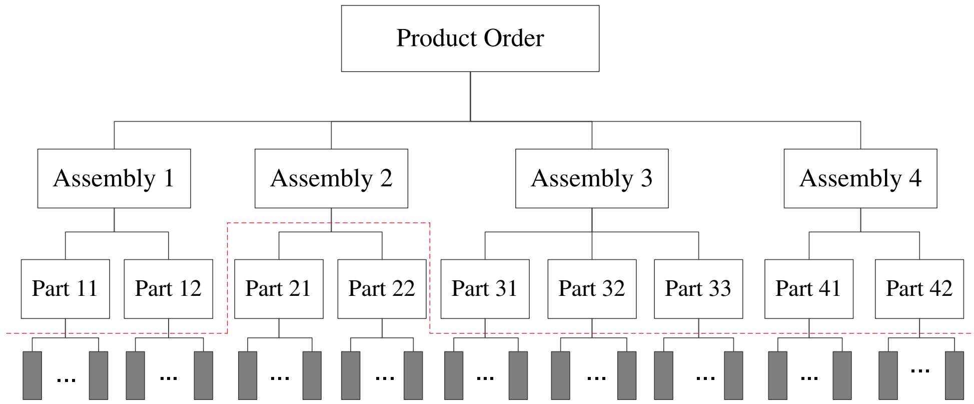

Fig. 7 The structure of manufacturing task

According to the service discovery mechanism illustrated in “Service discovery mechanism” section, the decomposed subtle tasks close above the red dotted line (e.g., Assembly 2, Part 31) can be undertaken by qualified MCCSs. It should be noted that the deadline of each subtle task is determined by the production schedule, which is listed in Table 2. The grey rectangles below the red dotted line denote the decomposed subtle tasks (process-level) which can be assigned to machines in MCs.

6.2 Optimization process

6.2.1 Phase 1: MCCS optimal configuration

Let $T=\{ST_i; i=1,2,3,\ldots,8\}$ represent the coarse-grained task, which is decomposed into eight subtle tasks undertaken by MCs as depicted in Fig. 7. Accordingly, eight MCCSs candidate sets are formed. For instance, there are seven candidate services in the set for Assembly 2 (ST_3), which can be represented as $MCCSCS_3=\{MC_3^1, MC_3^2, MC_3^3, MC_3^4, MC_3^5, MC_3^6, MC_3^7\}$. The evaluation indicator parameters of each candidate service are shown in Table 3.

These candidate services are assessed by adopting the evaluation method based on GRA illustrated in “Evaluation method” section, which will be described as follows:

1. According to Eq. (2), the ideal indicator sequence is:

$$S^* = (550, 35, 0, 85, 9.2, 39)$$

2. According to Eq. (3), normalized evaluation matrix can be derived.

$$V = \begin{bmatrix} 0.5 & 0 & 0 & 0 & 0.307692 & 0.625 \\ 0 & 0.875 & 1 & 0.8 & 0.692308 & 0.5 \\ 0.625 & 0.125 & 0.333333 & 0 & 0.384615 & 1 \\ 1 & 0.375 & 1 & 0.4 & 0.153846 & 0.5 \\ 0.8125 & 0.625 & 1 & 1 & 1 & 0.625 \\ 0.25 & 0.5 & 1 & 0.5 & 0 & 0.875 \\ 0.1875 & 0.875 & 1 & 0.8 & 0.461538 & 0 \end{bmatrix}$$

3. Relational coefficient matrix is arrived by adopting Eq. (4).

$$E = \begin{bmatrix} 0.5 & 0.636364 & 0.333333 & 0.333333 & 0.419355 & 0.571429 \\ 0.333333 & 0.538462 & 1 & 0.714286 & 0.619048 & 0.5 \\ 0.571429 & 0.777778 & 0.428571 & 0.333333 & 0.448276 & 1 \\ 1 & 1.4 & 1 & 0.454545 & 0.371429 & 0.5 \\ 0.727273 & 0.777778 & 1 & 1 & 1 & 0.571429 \\ 0.4 & 1 & 1 & 0.5 & 0.333333 & 0.8 \\ 0.380952 & 0.538462 & 1 & 0.714286 & 0.481481 & 0.333333 \end{bmatrix}$$

Table 2 The production schedule of manufacturing task

Manufacturing task level			Deadline
Product order			40
	Assembly 1		37
		Part 11	36
		Part 12	35
	Assembly 2		35
		Part 21	–
		Part 22	–
	Assembly 3		38
		Part 31	35
		Part 32	37
		Part 33	36
	Assembly 4		37
		Part 41	26
		Part 42	35

Table 3 The evaluation indicator parameters of candidate services (for Assembly 2)

Candidate services	Evaluation criteria					
	C	DT	dt	R	C_r	E
MC_3^1	590	38	3	75	8.3	42
MC_3^2	630	31	0	83	8.8	43
MC_3^3	580	37	2	75	8.4	39
MC_3^4	550	35	0	79	8.1	43
MC_3^5	565	33	0	85	9.2	42
MC_3^6	610	34	0	80	7.9	40
MC_3^7	615	31	0	83	8.5	47

4. According to Eq. (5), the grey relational degree of each candidate service is derived.

Here, the weights for each evaluation indicator determined by AHP method are denoted as $W=(0.186, 0.195, 0.205, 0.147, 0.138, 0.129)^T$. Then, the comprehensive evaluation matrix is obtained as:

$$R = EW = [0.466, 0.627, 0.586, 0.847, 0.851, 0.697, 0.595]$$

In the same way, evaluating other seven candidate services based on the above method, the corresponding comprehensive evaluation matrixes will be achieved. Here, top X_i services (X_i=3) are selected in each descending queue in terms of respective relational degrees, and the evaluation indicator parameters of all candidate services are shown in Table 4.

As shown in Table 4, total 3^8 service compositions can be generated. By calculating the relational degrees of all possible compositions, the highest one is obtained as 0.7184, and the corresponding optimal MCCS composition solution for T is $\{MC_1^3, MC_2^1, MC_3^5, MC_4^5, MC_5^6, MC_6^6, MC_7^7, MC_8^9\}$.

Table 4 The evaluation indicator parameters of candidate services (for T)

Candidate services	Evaluation criteria					
	C	DT	dt	R	C_r	E
MC_1^3	185	36	0	0.95	9.3	19.6
MC_1^6	180	36	0	0.89	7.9	14
MC_1^2	190	35	0	0.85	8.8	16
MC_2^1	295	35	0	0.91	9.1	23.2
MC_2^4	250	32	0	0.88	7.8	21.6
MC_2^3	275	34	0	0.89	8.2	26
MC_3^5	565	33	0	0.85	9.2	42
MC_3^4	550	35	0	0.79	8.1	43
MC_3^6	610	34	0	0.80	7.9	40
MC_4^5	185	32	0	0.92	8.7	32
MC_4^7	245	35	0	0.88	8.8	34
MC_4^8	189	33	0	0.89	9	36
MC_5^6	395	37	0	0.94	8.9	27.6
MC_5^2	410	37	0	0.88	7.3	26
MC_5^3	400	35	0	0.82	9	28
MC_6^6	395	36	0	0.95	8.9	39.5
MC_6^9	375	35	0	0.84	8.8	35
MC_6^4	360	33	0	0.88	8.5	36.5
MC_7^2	320	26	0	0.83	8.8	44
MC_7^7	275	25	0	0.90	7.9	48.5
MC_7^6	335	26	0	0.88	7.5	45
MC_8^9	330	34	0	0.85	7.9	26
MC_8^4	360	35	0	0.85	8.1	30
MC_8^7	365	32	0	0.87	8.4	32

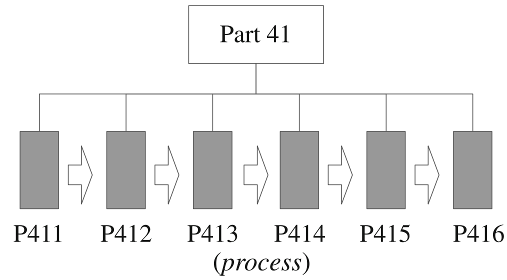

Fig. 8 The process flow of PT41

6.2.2 Phase 2: MMCS optimal configuration

According to the optimal service composition solution generated in above simulation, all eight subtle tasks are assigned to corresponding MCCSs. For example, PT41is undertaken by MC_7^7 and then decomposed into six process-level tasks in a certain sequence based on the CAPP as depicted in Fig. 8. Meanwhile, the scheduled deadline of each subtask can be seen in Table 5. Related manufacturing machines are pooled into corresponding candidate sets for each subtask. Top X_k services (X_k=3) in each queue are selected to constitute compositions as shown in Table 6.

By calculating the relational degrees of all service compositions, the highest one is achieved as 0.6559. Accordingly, the optimal MMCS composition solution for PT41 (ST_7) is $\{MM_1^6, MM_2^5, MM_3^7, MM_4^7, MM_5^5, MM_6^7\}$.

In particular, services optimization selection for coarse-grained task which only needs to invoke single MCCS is similar to that (e.g., Assembly 2) described in "Phase 1: MCCS optimal configuration" section. Besides, for fine-

Table 5 The production schedule of PT41

Process					
P411	P412	P413	P414	P415	P416
4	5	3	4	4	5

Table 6 The evaluation indicator parameters of candidate services (for PT41)

Candidate services	Evaluation criteria					
	C	*DT*	*PR*	*OTDR*	*R*	*E*
MM_1^6	26	4	0.93	0.95	0.94	6
MM_1^1	27	4	0.95	0.85	0.92	4.5
MM_1^7	25	4	0.89	0.90	0.90	5.5
MM_2^5	38	5	0.89	0.91	0.92	7.2
MM_2^4	40	5	0.95	0.89	0.89	7
MM_2^6	36	4	0.93	0.88	0.87	7
MM_3^7	28	3	0.92	0.92	0.93	5
MM_3^4	30	3	0.95	0.88	0.89	4.5
MM_3^8	29	3	0.93	0.87	0.88	4
MM_4^6	34	4	0.96	0.90	0.86	6
MM_4^7	33	4	0.93	0.91	0.93	6.5
MM_4^8	35	4	0.87	0.93	0.84	6.5
MM_5^5	36	4	0.93	0.92	0.90	8.5
MM_5^2	36	4	0.93	0.91	0.91	9
MM_5^7	33	4	0.88	0.90	0.80	9
MM_6^2	48	4	0.95	0.92	0.90	7
MM_6^4	45	5	0.87	0.81	0.90	7.5
MM_6^7	46	5	0.88	0.90	0.83	7.5

grained task (e.g., part-level or even process-level) which can be executed by MMCSs in public cloud, the services optimization process can refer to "Phase 2: MMCS optimal configuration" section.

7 Conclusion and future work

In CMfg, reasonable and systematic manufacturing resource modeling, and accurate and efficient service discovery, along with service optimization configuration, are the key techniques for developing CMfg.

In this paper, the framework of MCS proactive discovery and optimal configuration method is presented to realize the on-demand use and optimization allocation of resources. By applying IoT technologies to traditional manufacturing resources, real-time manufacturing information can be sensed and captured, which makes production activities more dynamically visible, traceable, and controllable. The information models for two kinds of common manufacturing resources (including machines and cells) are constructed, which lay a sound foundation for distributed resource seamless access to manufacturing cloud pool. The proposed task-driven MCS discovery approach enables services to make quick response for task requirements proactively, and then service candidate sets for manufacturing tasks with different granularities are formed. A scientific multi-objective evaluation system is established to achieve comprehensive assessment of MCSs through the evaluation method based on GRA and to realize the service optimization configuration eventually. The presented models and methods will provide support for MCS transparent, high-quality configuration and highly efficient production, which facilitates the implementation of CMfg.

Further research works will focus on the real-time manufacturing information processing mechanism between bottom-level manufacturing machines and up-level cells. In addition, the batch volume of manufacturing tasks should be taken into account in the optimal selection of service compositions.

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