A state-of-the-Art Literature Review on Service and Task Scheduling in Cloud Manufacturing

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Abstract

Several smart manufacturing concepts have been proposed during the past half-decade, such as cloud manufacturing, industry 4.0 based manufacturing, industrial Internet, and many more. One of their shared objectives is to enhance joint efforts across the enterprise by building up a stage to deliver an appropriate smartness in manufacturing. A total manufacturing framework consists of a given actual manufacturing framework and a stage incorporating a virtual manufacturing framework (planned from actual manufacturing itself). The research on scheduling in cloud manufacturing faces numerous difficulties. So, there is a need to comprehend the current circumstances and recognize future issues and problems related to scheduling in a cloud manufacturing environment. This work covered the spread of the most recent ten years and present state-of-the-art studies on scheduling issues in cloud manufacturing. The operating modal and procedure are elaborated. Also, this domain is classified precisely. Various conclusions are drawn, and future research directions are suggested.

Keywords
Cloud Manufacturing; Task Decomposition and Scheduling; Smart Manufacturing; Scheduling; Industry 4.0; Virtual Manufacturing; Literature Review

1. Introduction

The past few years are driven by new industrial production trends and demands such as globalization, personalization, digitization, collaboration, and integration by newly emerging technologies such as cloud computing, the Internet of Things (IoT), and cyber-physical systems (CPS). It results in a new production paradigm known as cloud manufacturing by big data analytics and artificial intelligence (AI) (Li *et al.* 2010, Zhang *et al.* 2011, Xu 2012). So far, cloud production has attracted a lot of research worldwide (Zhang *et al.* 2013). More than 900 articles have been published in this research area (Adamson *et al.* 2017, Liu *et al.* 2017). The purpose of cloud manufacturing is to provide consumers with on-demand manufacturing services over the Internet. Scheduling is a critical way to reach your cloud manufacturing goals. Scheduling has been for decades like operating system process and threat scheduling (Tanenbaum *et al.* 1987) workshop scheduling (Chaudhry and Khan 2016, Sharma and Jain 2016) and flow shop scheduling (Yenisey and Yagmahan 2014). In addition, it was a research theme in various fields. Scheduling tasks for computing and manufacturing systems such as production environments and computing grids (Rahman et al. 2013) Cloud Computing (Singh and Chana 2016) and Manufacturing Grid (Tao *et al.* 2009).

Scheduling in manufacturing can be characterized as the process of deploying, controlling, and optimizing tasks or workloads (Pinedo and Michael 2016) Scheduling can be defined narrowly or broadly in the context of cloud manufacturing. In a narrow sense, scheduling and allocating resources/services to tasks (or dispatching tasks to resources/services) refers only to processes that monitor, control, optimize the status of resources/services, and execute tasks and satisfy the individual needs of consumers. Scheduling in the broad sense includes the scheduling process in the narrow sense and many other activities such as job processing (especially work decomposition), service search, matching, selection, and configuration (Tao *et al.* 2015, Cheng *et al.* 2017). Scheduling in the broadest sense to date, it has been the hottest research theme in the field of cloud manufacturing and published more than 200 papers on this topic (Liu *et al.* 2016). There are dozens of research papers focusing on scheduling aspects considered in cloud manufacturing. In this case, understanding the current situation and extracting future challenges are urgently needed. Only Zhou, Zhang, and Liu (Zhou *et al.* 2017) discussed some issues related to scheduling in cloud manufacturing. In contrast, the current work presents a more comprehensive literature search and provides a detailed discussion and analysis on service and task scheduling in production.

The following section presents the operation modal of cloud manufacturing. Section three discuss the procedure of scheduling in the cloud manufacturing environment and section four present the classification. Section fifth and seventh present the literature review and conclusion.

2. Operation Model of Cloud Manufacturing

Production scheduling using cloud computing has a lot to do with its operating model. Therefore, its behavioral model is highly important. A complete cloud manufacturing system consists of three types of stakeholders: operator(s), supplier(s), and consumer(s). The functioning of each stakeholder is presented in table 1. It is their cooperation that will maintain the sustainable functioning of manufacturing in cloud systems. Cloud manufacturing is a knowledge-based manufacturing paradigm. Knowledge of (models, rules, standards, protocols, and algorithms) plays an essential role in many processes and activities of the service lifecycle, including service creation (such as awareness, connectivity, virtualization and encapsulation) and service management (such as description cloud deployment). Clustering configuration, search match, and service applications (such as failure tolerance, business process management and task fulfillment) are also necessary.

Table 1: Stakeholders in behavioral model for production scheduling in cloud manufacturing environment.

Stakeholders	Functioning
Operator	Manage and operate the cloud manufacturing platform. It helps consumers to obtain sustainable, reliable, high-quality manufacturing services on-demand, cloud platforms, and provide tools (*e.g.,* virtualization and services) on cloud platform.
Provider	It publishes manufacturing resources (including physical manufacturing resources and manufacturing functions throughout the product life cycle). It provides cloud platform for sharing while receiving dispatched manufacturing operations. Here, all production resources from various vendors are clustered in multiple manufacturing cloud systems (design cloud, manufacturing cloud, logistics cloud).
Consumer	The corporate consumers and individual consumers submit their requirement work (*e.g.,* design work, manufacturing work, test work, simulation work *etc.*) to cloud manufacturing. As a result, the platform receives the execution result of the order.

3. Procedure of Scheduling in Cloud Manufacturing

There are five stages in the entire cloud manufacturing scheduling process: task submission, preliminary task processing, scheduling, results delivery, and service evaluation.

(1) Task Submission: The entire scheduling process begins with the consumer task submission. From a functional requirements perspective, tasks can be divided into design tasks, manufacturing tasks, test tasks, etc., or a combination of them.

(2) Preliminary Task Processing: After the task is submitted to the cloud platform, preliminary processing is required, including the classification, description, analysis and decomposition. After initial processing, the requirements for each task include precise functional needs and non-functional needs. The first refers to the functions (such as parts or products with specific functions) that must be implemented to complete the task. In addition, the realization of this function needs to call and execute the type of service required. The latter generally refers to some standards (such as time, cost, quality) and related restrictions.

(3) Scheduling: After initial order processing, the scheduling management module performs task scheduling with the support of the scheduling support module, the business management module, and the monitoring management

module. The central programming module is responsible for generating optimized processes for the execution of programming and management tasks. The scheduling support module is responsible for managing scheduling indicators, rules, methods, and algorithms and supporting the scheduling management pack (for example, helping the scheduling management pack determine the scheduling method). The role of the service management module is to manage the service-related activities required for scheduling, including service classification, matching, merging, and evaluation. Orders on the factory shop floor provide real-time status information (such as machine availability) of resources and demands required to achieve optimal scheduling. The process of performing is as follows. First, generate optimized schedules and then send tasks to different vendors for execution. During the execution process, the real-time monitoring of the status of resources and tasks needs to be performed. Sometimes it is necessary to control resources from the cloud platform remotely. In the scheduling process, companies that serve different subtasks of the task interact and communicate with each other to ensure the smooth execution of the task.

(4) Delivery: After completing a task, the relevant resources are released, and the result of the execution (such as parts, components or final products) is delivered to consumers through logistics or the Internet.

(5) Service Evaluation: After receiving the execution results, consumers can evaluate the services they have used. Assessment results reflect your overall satisfaction with the products and can also provide an essential reference for subsequent consumers to choose services.

4. Classification of Scheduling in Cloud Manufacturing

Cloud manufacturing is an evolving manufacturing model but differs from previous production models such as agile, networked, and mesh manufacturing in terms of operating model, system size, and technologies. In addition, this technology is integrated (Zhang *et al.* 2011). There are several typical characteristics of scheduling in cloud manufacturing, and they can be broadly divided into modes of operation resource/service requirements and skills and knowledge-related characteristics. Table 2 present the detailed classification and sub-classification of production scheduling environment based on the characteristics of cloud manufacturing systems.

Table 2. Classification of Scheduling in Cloud Manufacturing

Classification Criteria		**Description**
Operation Mode	Production Scheduling involving Stakeholders	This classification is based on operation mode associated with stakeholders such as customers, operators, and suppliers while implementing cloud manufacturing. Moreover, the task performed by operators is stored in cloud manufacturing and the operators are selected by the management accordingly. Hence the engagement of stakeholders is improved in manufacturing. Therefore, it can be called collaborative production scheduling in cloud manufacturing.
	Production Scheduling involving Tasks	In this category, scheduling in cloud manufacturing empowers integration of distributed resources and systematically shares the integrated resources because of coordination and centralized management. It enables several tasks to be handled simultaneously, which leads to many resources/service-to-many task scheduling. Therefore, it is a more significant classification.
Resource/Service and Requirements	Scheduling with Large-scale Resources/Services	Here, a large scale of resources/services are engaged. It requires more efficient planning techniques and algorithms. During the scheduling cycle, vast volumes of data are generated on the usage of resources/services. Collection and use of this information can viably support scheduling efficiency and improve scheduling executions.
	Production Scheduling Concerning Multiple Task Level	This classification involves inter-enterprise, enterprise-level, workshop and cell-level tasks. Different levels of resources can be encapsulated in different granularity of service, with different amounts and types. High-level functions can be broken down into a series of smaller operations into smaller granularity, and each small process is broken down into several smaller operations. Due to the multiple subdivision types of manufacturing resources and manufacturing operations, cloud manufacturing schedules may always be performed at several levels rather than at the lowest or minimum subdivisions.

	Individualized Production Scheduling	Here, the critical issues of cloud manufacturing scheduling meet as per individual consumer needs. Cloud manufacturing performance standards include time, cost and quality (*e.g.,* machining accuracy and pass rate), energy consumption, service evaluation, company reputation, and location). Various consumers have different affinities. Consumer needs can be more personalized for cloud manufacturing through large-scale manufacturing services and configuration possibilities.
	Scheduling with Complexities and Dynamics	It is based on complexities, variety and its dynamic nature. The complexity of scheduling in cloud manufacturing comes from associating a wide zone in exchange for goods and resources. Manufacturing enterprises enrolled in a cloud manufacturing system are shared in broad areas systematically so that it helps logistics to be a necessary consideration for scheduling. In addition, various resources are involved in the process like renewable or non-renewable, quantifiable, or non-quantifiable, organized or unstructured.
Technology and Knowledge	Production Scheduling in Cloud Platform	This is the most generalized category since the cloud service makes it easy to exchange information and change the information of resources. Therefore, the cloud service-based production scheduling enables automated configuration and exchange of resource information to the different task levels.
	Real-time Production Scheduling	Industry 4.0 tools in production scheduling makes a way to get into atomized management of the manufacturing resources. It enables the data extraction and exchanges between different levels of tasks in the real-time. The changes in the information of the manufacturing resources remain transparent through the different levels. Thus, the subtraction of resources in lower levels can be monitored by the higher levels with real-time information.
	Production Scheduling with Collaborative Cloud Computing	This classification is based on infrastructure which contains CPU, storage, servers, and networks. This systematic infrastructure helps in the computing and storage capabilities of the data, which are generated in real-time. The collaboration work of computing with the manufacturing resources results in optimal production scheduling.
	Information-based Production Scheduling	This category is based on information-based manufacturing pattern/system. The information of models, standards, guidelines, calculations, and the algorithm play a significant role in production scheduling. This information plays a vital role because of the complexities, diverse tasks, and tasks level in cloud manufacturing. In addition, it is involved by the individualized requirements and focuses on customer satisfaction.

5. Literature Review on Service and Task Scheduling in Cloud Manufacturing

Many papers aim to the narrow sense of scheduling, and very few are working on scheduling in cloud manufacturing to handle design tasks and computing resources. Lin and Chong (2017) addressed resource constraint project scheduling for computing resource allocation in cloud manufacturing using a Genetic Algorithm (GA). The authors commented that resolving a new issue is not feasible because of the task precedence and resource constraints, so the distribution of tasks and resources in cloud manufacturing will be NP-hard. GA helps in the quality schedule and optimum allocation of resources according to the performed computational results. In this work, they have assumed there will be multiple task planning problem which requires the resources from the system, i.e., cloud manufacturing platform at the same time. The application provider should do the central management of the demand and allocation of computed resources for processing in the organization, and they should retort to users promptly. This study follows only one project (assumed problem), which has many tasks and resource requirements to be uploaded into the cloud manufacturing platform for scheduling. As they took many numbers of tasks, the resources need to be allocated to the task sequentially. GA was used in cloud manufacturing for optimal scheduling. It initializes the process by integrating all tasks duration and dividing them by the total number of tasks without including the first and the last virtual task. Upper and lower duration are calculated by multiplying average time with certain factors. A benchmark problem is extracted from the Project Scheduling Problem Library (PSPLIB) and compared with the proposed GA. Using this PSPLIB, they selected 20 suitable examples and compared them to assess the quality of GA. Authors claimed that the proposed GA has high performance in computing multiple tasks and allocating resources in cloud manufacturing platforms. They have also mentioned that future work can be done to find the optimal solution for minimum resource utilization when the demand increases.

Laila *et al.* 2011 dealt with collaborative design task scheduling in cloud manufacturing using energy adaptive immune GA (EAIGA). They considered the collaborative design task scheduling problem in cloud manufacturing having distributed production environment. This type of scheduling problem involves relation among design and task units to ensure the simultaneous execution of design activity. To solve the proposed production scheduling problem, they modified the Genetic Algorithm (GA) and named EAIGA. In IGA, the antigen extract and vaccine are selected as per the feature information of the problem. It helps to move the population evolved in the right direction. The population initialization and the genetic evolution are all the same as the standard GA. After selection, crossover and mutation, new populations are vaccinated by antibodies. The authors claimed that the possible detection had improved the algorithm's diversity and parameter adaptation had improved the algorithm's stability. Both strategies consumed less time and increased the solution quality. Without the increase of time complexity based on IGA, EAIGA showed quite good balanced capacity and searching ability for addressing the taken production scheduling problem in cloud manufacturing.

Li et al. (2016) presented the architecture for workflow system on cloud platform having a scheduling algorithm calles Max Percentages (MP). They discussed the requirements for the improvement of productivity and efficiency in a manufacturing enterprise. To develop MP, they implemented a big data environment that gives the foundation of data analytics and the opportunity to determine optimal strategy. Using IoT, they adopted smart sensor technology, a wireless sensor network (WSN) and RFID technologies to gather required user data. Computation and computer storage are done using cloud computing, which helps the industries resolve the problems related to fixed resources throughout data analytics. This MP algorithm collects all the data on heterogeneous resources and workflows to confirm load balance using Suffrage algorithms as a reference to obtain short time and optimal scheduling. The main idea of this algorithm is to find out the resources which get more affected while it is in the service period and any task is allocated on it. The effect on resources is measured by calculating the percentages of completion time for each online task and the total time spent on each resource. MP Algorithm is much practical when there are autonomous tasks that are unbalanced, but many long tasks and short tasks are nearly equal. The paper concluded that the proposed MP algorithm uses the intrinsic relationship of data related to tasks and resources. By computing the percentage of completion time, optimal scheduling is achieved. The authors claim the overall performance of the MP algorithm is best and satisfied when compared with classic Dynamic Critical Path, Max-Min, Min-Min, GA, and Sufferage algorithms

5.1 Static Scheduling in Cloud Manufacturing

It is noticed that the present research is concentrated on the scheduling of tasks and resources in manufacturing. Li *et al.* (2012) had given a structure for resource scheduling in cloud manufacturing using Petri nets. They presented a queue balancing policy to solve the dispatching problem. Lartigau *et al.* (2012) introduced a scheduling system in cloud manufacturing to improve services through order decomposing. Lartigau *et al.* (2015) offered a scheduling outline having definite resource service readiness during cloud manufacturing. Cao *et al.* (2016) presented the scheduling and service choice aspects in cloud manufacturing. They considered a single task service composition problem. Akbaripour *et al.* (2017) recommended a mixed-integer programming model for service selection and scheduling in cloud manufacturing. All composition structures, including sequential, parallel, loop and selective, are incorporated.

Several authors focused on the multitask scheduling scenario. Cheng *et al.* (2014) studied multi-task-oriented scheduling in cloud manufacturing, taking virtual resource correlations into account. They considered entirely matching subtask execution flows and thus require the identical candidate resource sets. They have proposed GA based on actual number matrices encoder to solve the problems related to resource integration, multiple tasks oriented virtual addition of resources by analyzing the existing works and optimum scheduling in the cloud manufacturing environment. First, the virtual resource association model is established within and between tasks. According to the associated model and the characteristics of resource sharing, a formula using the resource time-sharing scheduling strategy is proposed. Then the procedure is simplified for an easy solution. They have divided the tasks into three categories viz different types of tasks, the task of the same type and the tasks of mixed type. The experimental results show that the proposed model and method are feasible and effective in many tasks with sufficient resources and limited resources. In this paper, the association and sharing of resources and the association and sharing model are considered virtual resources for multitask integration and cloud manufacturing scheduling optimization. They considered only cost and time of QoS and reliability and credibility are ignored. They suggested avoiding weak solutions in the algorithm processing process or reduce the solution space by optimizing the solution code to make the algorithm more practical.

Li *et al.* (2017) investigated the subtask (multi-task-oriented) scheduling of distributed robots in cloud manufacturing. They considered multiple tasks were heterogeneous as per subtask type, execution flow, and required robot resources.

Liu *et al.* (2016) presented a scheduling system with multi-task-oriented service composition in cloud manufacturing. It is essential to mention that they have calculated the execution time of task in real-time as per the capability and workload of company resources. This modal was considered in Liu et al. (2017) to find workload-based multitask scheduling on cloud manufacturing. The authors stated that scheduling large workload tasks with priority can result in a good performance, ignoring time constraints. In Liu *et al.* (2018) authors commented that issues related to enterprise cloud manufacturing rarely arouse the attention of researchers. The most common problem mentioned in the existing research is how to connect enterprise resources to the cloud infrastructure. This problem hinders the development and implementation of cloud manufacturing to a large extent because the lack of business research does not reveal the company's requirements for cloud manufacturing (*i.e.,* Cloud Manufacturing Company - CME). Therefore, it does not refer to evaluating the changes that must be made to adopt this new manufacturing paradigm. They performed a preliminary exploration of CME. First, they discussed the CME requirements and discussed some critical issues with CME, including the business information system, business architecture, and business modeling. This research work does a preliminary scan of CME.

Wang *et al.* (2014) dealt with assignment and scheduling of resources in cloud manufacturing. They considered the operations as minimum task entity which can be utilized as service. Jiang *et al.* (2016) addressed cloud-based product disassembly task scheduling. The makespan was minimized through a mathematical modal having ambiguous disassembly process. These contributions are considering static nature of scheduling.

5.2 Dynamic Scheduling in Cloud Manufacturing

Some researchers paid attention to dynamic scheduling in cloud manufacturing. Tai *et al.* (2013) dealt with multi-objective dynamic scheduling in cloud manufacturing. The new schedule generation process can be initiated if there is a service conflict in the schedule under process. Zhou and Zhang (2016) presented a simulation-based real-time task scheduling procedure. It was defined with task layer, resource layer and scheduling layer. Zhang *et al.* (2017) introduced the cloud manufacturing in the injection moulding industry having dynamic nature. The cloud manufacturing platform for injection moulding companies was built to improve the sharing, circulation, and integration of injection moulding resources. Implementing the IoT technology in an existing injection moulding plant allows you to accurately capture real-time manufacturing information of resources and a better view and track the entire moulding process. The virtual processing service for the injection moulding machine (IMM) is encapsulated as a cloud service posted on the platform for on-demand use. Applying the concept of cloud manufacturing to the injection moulding industry can solve the problems faced by most SMEs and make significant contributions. First, the established cloud manufacturing platform can realize the use of large-scale shared, free movement, efficient integration, and optimized IMM configuration. Second, cloud manufacturing is reshaping the new business pattern of the injection moulding industry.

After the task is assigned to the IMM cloud service (IMMCS), scheduling is done first during service execution and is subject to some time constraints derived from real-time production status (such as availability and workload) and change the task queue. One of the main scheduling challenges in the cloud manufacturing system is scheduling and assigning tasks with an unpredictable order flow, making traditional and static programming methods insufficient (Lartigau *et al.* 2012). Therefore, dynamically optimizing multiple tasks from a global perspective should have a more practical meaning. Considering the dynamic changes in order and the internal disturbances in the actual manufacturing process, a dynamic multi-agent scheduling system explained the multi-agent decision-making mechanism. Furthermore, the proposed task-based proactive service discovery method helps to effectively and proactively discover the potential IMMCS of orders. Furthermore, a multi-objective evaluation method based on TOPSIS, aims to find satisfactory customer services from massive IMMCS candidates. Finally, the proposed configuration method was verified by numerical simulation.

Zhou *et al.* (2018) addressed a scenario of dynamic scheduling in cloud manufacturing. They considered the dynamic arrival of task, and the scheduling objective was an average execution time of all tasks. Ma *et al.* (2014) proposed cloud agent system. It contains the contract net method to attain the scheduling in cloud manufacturing. Also, some investigators are paying attention to workshop scheduling problems in the perspective of cloud manufacturing. Jian and Wang (2014) presented workshop scheduling in cloud manufacturing for a batch task. In addition, Lu *et al.* (2017) presented hybrid job shop scheduling having mixed flow in assembly and processing task. Zhang *et al.* (2017) proposed a model for flexible job-shop scheduling based on game theory to achieve real-time, data-driven optimized decision-making. Each machine is an active entity that can request task processing and tasks were assigned to optimal machines based on their real-time status.

Jian and Wang (2014) explained that manufacturing batch job scheduling in the cloud has real-time and dynamic features, and there is a need for concurrency and big-data sharing. Still, traditional shop-floor job scheduling models and algorithms cannot be adapted. Initially, to effectively save production time in the shop and reduce costs, they proposed an optimization model. Then an improved collaborative particle swarm optimization algorithm with fast convergence speed and strong ability to avoid local optimization is used to solve the task scheduling problem. Finally, the results of the simulation experiments demonstrate its effectiveness. Task scheduling must consider the execution time and cost of batch production tasks and the production process. Whether it is traditional shop-floor fabrication or cloud fabrication, saving time and reducing costs are two crucial optimization goals. To this end, this paper proposes an optimization model for scheduling batch processing tasks and uses an improved Collaborative Particle Swarm Optimization (ICPSO) algorithm in this model. They compared it with the traditional workshop production scheduling algorithm, and it can reduce the time and cost of production tasks and meet the needs of large-scale production tasks in the manufacturing environment in the cloud. The simulation of the production of cloud manufacturing workshops for the multichannel process was performed through MATLAB. In order to test the performance of ICPSO, it is compared to PSO and CPSO in the simulation. The algorithmic simulation was performed 20 times under each condition, and the average value was taken because of the simulation. In this work, to reduce time and cost, a dual-objective optimization model was established. They claimed that the model and algorithm proposed in this paper are suitable for large-scale task scheduling in cloud manufacturing and can effectively reduce time and cost.

Yuan *et al.* (2017) proposed a multi-objective optimization planning model to improve the reconfigurable pipeline's production efficiency, to minimize the cost of assembly line reconstruction, and achieve production load balancing. In addition, they used this model to reduce delay workload. However, the proposed multi-objective optimization model is very complicated for the traditional mathematical optimization method. Therefore, they presented an effective solution based on remote sorting particle swarm optimization. Finally, a case study is used to illustrate the feasibility and efficiency of the method proposed. Li *et al.* (2016) minimized the makespan for two parallel machine scheduling in cloud manufacturing. Both, the non-pre-emptive and pre-emptive scenarios were considered.

Another area of research includes the effective use of the surplus capacity of manufacturing available in enterprise in a cloud computing-based manufacturing environment. In this direction, Li et al. (2012) investigated collaborative scheduling among several physically disseminated job shops based on dynamical resource capability services. They proposed to use the time tolerance and dynamically adjustment techniques for scheduling in cloud manufacturing. Mourtzis *et al.* (2015) proposed a cloud-based framework consisting of monitoring services and short-term scheduling applications that aims to generate feasible and efficient scheduling. The short-term scheduling application enriches the data obtained by monitoring the service and generates resource-conscious scheduling by considering the machine tool's applicability and its upcoming status and availability. The scheduling application uses the smart search algorithm, which allows developing and evaluating alternative programs using a set of multiple conflicting criteria, including cost, time, and quality. In addition, they used sets of performance indicators for completion time and resource utilization to evaluate the generated schedule. Wang *et al.* (2017) considered idle time to solve job shop scheduling environments to minimize makespan in the cloud manufacturing environment.

Also, some research is conducted on the cloud manufacturing and scheduling of supply chain activities. For example, Xiao *et al.* (2015) addressed distributed supply chain scheduling to customize multiple products, taking into account the delivery phases in supply chain and including cost, delay, production rate and time as scheduling objectives while manufacturing. Similarly, Xiao *et al.* (2016) presented a review of the scheduling and planning aspects evolving with cloud manufacturing with the supply chain.

Liu *et al.* (2019) proposed a multi-agent architecture for PSMS scheduling, consisting of a platform-level multi-agent scheduling system (MAS) and an enterprise-level programming MAS. Procedures, features, and programming requirements are introduced into PSMS. A PSMS programming model based on this architecture is proposed. A case study was conducted to demonstrate the effectiveness of the architecture and the proposed model.

The main contributions of this work are the following. First, the concept of PSMS was proposed by extracting the standard features of cloud manufacturing system, Industry 4.0 and Internet of Industry, and offered a detailed and comprehensive MA-based two-tier architecture for PSMS Programming Analysis of its procedures, characteristics and requirements. Second, a new task modeling method is proposed, which combines manufacturing subtasks and logistics subtasks, considering business subtasks and platform subtasks, respectively. Third, a new logistics modeling method based on the complex network is proposed. The scheduling procedure was managed by modules PSM-MAS and ESM-MAS, which perform tasks on the platform and the company. Different agents generate the scheduling solution based on contract network agreement negotiation, including the consumer, task, provider, and resource agents. The scheduling process for each task includes five main stages of (1) announcement of the task, (2) preparation of the tender, (3) compilation and evaluation of the offer, (4) acceptance of the quoted task, and (5) execution of the schedule. Then, they showed a simplified case, briefly showing the operation principle of the proposed model and architecture, focusing on the effect of task arrival probability and logistics. In this case study, there are 30 manufacturing resource suppliers and three logistics resource suppliers. Providers are encapsulated in provider agents and considered 30 kinds of resources and can perform 30 different functions. Each type of resource from the provider is encapsulated in a resource agent. They considered complex manufacturing resources, such as machine tools, industrial robots, and a machining center, to perform lathe, welding, milling, drilling, cutting, grinding, painting, pick and place, assembly, and transfer.

Ahn and Hur (2021) solved the real-time multi-purpose task scheduling problem to minimize the delay, cost, quality, and reliability penalties in cloud manufacturing. The problem is formulated in binary integer programming. The multi-objective-based GA was designed to solve models with a focus on generating viable solutions. Their experiments showed that the schedule is close to the optimal schedule for small problems based on the proposed approach. The authors also confirmed that the proposed method establishes effective scheduling in a real-time manner for larger problems that are more realistic.

Yu *et al.* (2021) presented the work based on the digital twin technology and combined with production line scheduling problems. The author proposes a new intelligent programming platform to solve the above store programming problem. At the same time, based on big data analysis technology, the dynamic multi-source interference in the production process of the workshop is predicted and diagnosed, and the corresponding interference strategy is formulated in advance through the cloud programming platform. Finally, the simulation experiment of the intelligent dispatching cloud platform model was carried out, and some enterprises in the smart manufacturing workshop were taken as examples to verify the superiority of the dispatching cloud platform.

The author added that with the help of big-data analysis, the product's digital twin could also reveal unknown issues by comparing the actual response of the product and predicting the specific scenario of the product response. Hidden hazards or malfunctions, the maintenance plan is simulated and optimized in the virtual world for actual maintenance. Similarly, the resources and the capabilities, tools, and algorithms required for the daily operations and phase of MRO are used as services. Big data analytics is responsible for analyzing all the data required for smart manufacturing. The digital twin makes up for the lack of big-data simulation and synchronizing to visualize physical processes. Therefore, the integration of digital twins, big data, and services is significant to smart manufacturing. The schedule programming platform has two schedule programming process paths. The workshop tuning of the cloud policy is a complete process, starting from the user's order request, through the decomposition of the order, to the generation of the initial programming plan, to the adjustment of the initial goal in case of interference, and finally, until the order is delivered after the sale end of service.

6. Conclusions

Cloud manufacturing research is in the pipeline for ten years, and scheduling is crucial in attaining customer satisfaction towards services. This paper aims to explore the current research of the scheduling in cloud manufacturing to the scheduling of computing resources and design, scheduling of manufacturing resources and assignments, multi-assignment scheduling settings, dynamic scheduling issues, workshop schedule, and surplus capacities utilization of resources available as well as the supply chain scheduling. In addition, the scheduling classification based on characteristics of the scheduling environment and phases involved in scheduling during cloud manufacturing is presented. Finally, based on the literature review following conclusions can be drawn.

- Implementing manufacturing in the cloud is an evolutionary process since it is a highly complex socio-technical economic system.
- Cloud manufacturing-based scheduling makes it possible to consider customer demand and satisfaction to deliver the product and services on time.
- The multi-agent-based scheduling algorithms are essential to explore since it delivers proposing results in the cloud manufacturing environment.
- The integration of digital twins, big data, and services is significant to smart manufacturing under a cloud computing framework.
- Job shop production system is the most critical environment to be considered while forming the scheduling centric cloud manufacturing framework.
- Data and status of resources (like machine, equipment, and software), from different factories need to upload on the cloud computing platform so that the Computer Aided Process Planning (CAPP), Product Data Management (PDM), Manufacturing Execution Systems (MES) and Product Lifecycle Management (PLM) can be integrated.
- The Enterprise Resource Planning (ERP) system must receive the task details from cloud and transmit the information to the MES. Later, the MES is responsible for monitoring and gathering information about orders and equipment (such as robots, machines, tools, and machining centres) on the factory shop floor. Therefore, it is necessary to implement multiple sensors on equipment to collect equipment operational status data.
- The machine monitoring application can be implemented under model Infrastructure as a Service (IaaS), but the scheduling application is to be implemented as Software as a Service (SaaS).

References

Li, B. H., Zhang, L., Wang, S. L., Tao, F., Cao, J. W., Jiang, X. D., Song, X., and Chai, X. D., Cloud Manufacturing: A New Service-Oriented Networked Manufacturing Model, *Comp Integ Manuf Syst 16 (1): 1–7*, 2010.

Zhang, L., Luo, Y. L., Fan, W. H., Tao, F., and Ren, L., Analyses of Cloud Manufacturing and Related Advanced Manufacturing Models, *Computer Integrated Manuf. Systems 17 (3): 458–468*, 2011.

Xu.X., From Cloud Computing to Cloud Manufacturing, *Robotics and Comp Integ Manuf 28 (1): 75–86,* 2012.

Zhang, L., Ou, H., Luo, Y., and Tao, F., Current Status of Research and Applications of Cloud Manufacturing, *New Mat. Ind. 8: 63–68*, 2013.

Adamson, G., Wang, L., Holm, M., and Moore, P., Cloud Manufacturing – A Critical Review of Recent Development and Future Trends, *International Journal of Computer Integrated Manufacturing 30 (4–5): 347–380*, 2017.

Liu, Y., and Xu, X., Industry 4.0 and Cloud Manufacturing: A Comparative Analysis, *Journal of Manufacturing Science and Engineering, Transactions of the ASME 139 (3): 034701*, 2017.

Tanenbaum, S., and Woodhull, A. S., Operating Systems: Design and Implementation, *Vol. 2. Englewood Cliffs, NJ: Prentice-Hall*, 1987.

Chaudhry, A and Khan, A. A., A Research Survey: Review of Flexible Job Shop Scheduling Techniques, *International Transactions in Operational Research 23 (3): 551–591*, 2016.

Sharma, P., and Jain, A., A Review on Job Shop Scheduling with Setup times, *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture 230 (3)*: 517–533, 2016.

Yenisey, M. M., and Yagmahan, B., Multi-Objective Permutation Flow Shop Scheduling Problem: Literature Review, Classification and Current Trends, *Omega 45: 119–135*, 2014.

Rahman, M., Hassan, R., Ranjan, R., and Buyya, R., Adaptive Workflow Scheduling for Dynamic Grid and Cloud Computing Environment, *Concurrency and Computation: Practice and Experience 25 (13): 1816–1842*, 2013.

Singh, S., and Chana, I., A Survey on Resource Scheduling in Cloud Computing: Issues and Challenges, *Journal of Grid Computing 14 (2): 217–264*, 2016.

Tao, F., Hu, Y., Zhao, D., and Zhou, Z., An Approach to Manufacturing Grid Resource Service Scheduling Based on Trust-QoS, *International Journal of Computer Integrated Manufacturing 22 (2): 100–111*, 2009.

Pinedo., and Michael, L., Scheduling: Theory, Algorithms, and Systems, *New York: Springer*, 2016.

Tao, F., Zhang, L., Liu, Y., Cheng, Y., Wang, L., and Xu, X., Manufacturing Service Management in Cloud Manufacturing: Overview and Future Research Directions, *Journal of Manufacturing Science and Engineering* 137 (4): 040912, 2015.

Cheng, Y., Tao, F., Zhao, D., and Zhang, L., Modeling of Manufacturing Service Supply–Demand Matching Hypernetwork in Service-oriented Manufacturing Systems, *Robotics and Computer-Integrated Manufacturing* 45: 59–72, 2017.

Liu, Y., Xu, X., Zhang, L., and Tao, F., An Extensible Model for Multitask-oriented Service Composition and Scheduling in Cloud Manufacturing, *J of Comp and Info Science in Eng 16 (4): 041009*, 2016.

Zhou, L., Zhang, L., and Liu, Y., Survey on Scheduling Problems in Cloud Manufacturing, *Computer Integrated Manufacturing Systems 23 (6): 1147–1166*, 2017.

Lin, Y. K., and Chong, C, S., Fast GA-based Project Scheduling for Computing Resources Allocation in a Cloud Manufacturing System, *Journal of Intelligent Manufacturing 28 (5): 1189–1201*, 2017.

Laili, Y., Zhang, L., and Tao, F., Energy Adaptive Immune Genetic Algorithm for Collaborative Design Task Scheduling in Cloud Manufacturing System, *Paper Presented at the IEEE International Conference on Industrial Engineering and Engineering Management, Singapore, Singapore December 6–9*, 2011.

Li, X., Song, J., and Huang, B., A Scientific Workflow Management System Architecture and Its Scheduling Based on Cloud Service Platform for Manufacturing Big Data Analytics, *International Journal of Advanced Manufacturing Technology 84 (1–): 119–31*, 2016.

Li, J. S., Wang, A.M., Tang, C.T., and Lu, Z. B., Distributed Coordination Scheduling Technology Based on Dynamic Manufacturing Ability Service, *Computer Integrated Manufacturing Systems 18 (7): 1563–1574*, 2012.

Lartigau, L., Nie, L., Xu, X., Zhan, D., and Mou, T., Scheduling Methodology for Production Services in Cloud Manufacturing, *Paper Presented at the 2012 Inter. Joint Conf. on Service Sciences, Service Innovation in Emerging Economy: Cross-Disciplinary and Cross-Cultural Perspective, Shanghai, China, May 24–26*, 2012.

Lartigau, L., Xu, X., and Zhan, D., Artificial Bee Colony Optimized Scheduling Framework Based on Resource Service Availability in Cloud Manufacturing, *Paper Presented at the International Conference on Service Science, Wuxi, China, May 22–23*, 2015.

Cao, Y., Wang, S., Kang, L., and Gao, Y., A TQCS-based Service Selection and Scheduling Strategy in Cloud Manufacturing, *International Journal of Advanced Manufacturing Technology 82 (1–4)*: 235–251, 2016.

Akbaripour, H., Houshmand, H., Woensel, T., and Mutlu, N., Cloud Manufacturing Service Selection Optimization and Scheduling with Transportation Considerations: Mixed-integer Programming Models, *International Journal of Advanced Manufacturing Technology 95 (1–4): 43–70. DOI:10.1007/s00170-017-1167-3*

Cheng, Z., Zhan, D., Zhao, X., and Wan, H., Multitask Oriented Virtual Resource Integration and Optimal Scheduling in Cloud Manufacturing, *Journal of Applied Mathematics 2014 (2014): 1–9. DOI:10.1155/2014/369350*

Li, W., Zhu, C., Yang, L. T., Shu, L., Ngai, E. C. H., and Ma, Y., Subtask Scheduling for Distributed Robots in Cloud Manufacturing, *IEEE Systems Journal 11 (2): 941–950*, 2017.

Liu, Y., Xu, X., Zhang, L., Wang, L., and Zhong, R. Y., Workload-based Multi-task Scheduling in Cloud Manufacturing, *Robotics and Computer-Integrated Manufacturing 45: 3–20*, 2017.

Liu, Y., Wang, L., Wang, X. V., and Xu, X., Scheduling in cloud manufacturing: state-of-the art and research challenges, *ISSN: 0020-7543 (Print) 1366-588X (Online)*, 2018.

Wang, Z., Zhang, J., and Si, J., Application of Particle Swarm Optimization with Stochastic Inertia Weight Strategy to Resources Scheduling and Assignment Problem in Cloud Manufacturing Environment, *Paper Presented at the 33rd Chinese Control Conference, Nanjing, China, July 28–30*, 2014.

Jiang, H., Yi, J., Chen, S., and Zhu, X., A Multi-objective Algorithm for Task Scheduling and Resource Allocation in Cloud-Based Disassembly, *Journal of Manufacturing Systems 41: 239–255*, 2016.

Tai, L., Hu, R., Zhao, H., and Chen, C., Multi-objective Dynamic Scheduling of Manufacturing Resource to Cloud Manufacturing Services, *China Mechanical Engineering 24 (12): 1616–1622*, 2013.

Zhou, L., and Zhang, L., A Dynamic Task Scheduling Method Based on Simulation in Cloud Manufacturing, *Communications in Computer and Information Science 645: 20–24*, 2016.

Zhang, Y., Xi, D., Yang, H., Tao, F., and Wang, Z., Cloud Manufacturing Based Service Encapsulation and Optimal Configuration Method for Injection Molding Machine, *Journal of Intelligent Manufacturing. doi:10.1007/s10845-017-1322-6*, 2017.

Zhou, L., Zhang, L., Sarker, B. R., Laili, Y., and Ren, L., An Event-triggered Dynamic Scheduling Method for Randomly Arriving Tasks in Cloud Manufacturing, *International Journal of Computer Integrated Manufacturing 31 (3): 318–333*, 2018.

Ma, J., Luo, G., Lu, D., and Guo, Y., Research on Manufacturing Resource Cloud Integration Meta Modeling and Cloud-agent Service Scheduling, *China Mechanical Engineering 7: 917–923, 930*, 2014.

Jian, F and Wang, Y., Batch Task Scheduling-oriented Optimization Modelling and Simulation in Cloud Manufacturing, *International Journal of Simulation Modelling 13 (1): 93–101*, 2014.

Lu, J., Hu, Q., Dong, Q., and Tang, H., Cloud Manufacturing-oriented Mixed-model Hybrid Shop-scheduling Problem, *China Mechanical Engineering 28 (2): 191–198, 205*, 2017.

Jian, F., and Wang, Y., Batch Task Scheduling-oriented Optimization Modelling and Simulation in Cloud Manufacturing, *International Journal of Simulation Modelling 13 (1): 93–101*, 2014.

Yuan, M., Deng, K., Chaovalitwongse, W. A., and Cheng, S., Multi-objective Optimal Scheduling of Reconfigurable Assembly Line for Cloud Manufacturing, *Optimization Methods and Software 32 (3): 581–593*, 2017.

Li, K., Zhang, H. J., Cheng, B. Y., and Pardalos, P. M., Uniform Parallel Machine Scheduling Problems with Fixed Machine Cost, *Optimization Letters 12 (1): 73–86. doi:10.1007/s11590-016-1096-3*, 2016.

Mourtzis., Vlachou, E., Doukas, M., Kanakis, N., Xanthopoulos, N., and Koutoupes, A., Cloud-based Adaptive Shop-floor Scheduling Considering Machine Tool Availability, *Paper Presented at the ASME International Mechanical Engineering Congress and Exposition, Houston, TX, November 13–19*, 2015.

Wang, Z., Zhang, J. H., and Qi, Y. Q., Job Shop Scheduling Method with Idle Time in Cloud Manufacturing, *Control and Decision 32 (5): 811–816*, 2017.

Xiao, Y. Y., Li, B. H., Zhuang, C. H., Chai, X. D., and Lin, T. Y., Distributed Supply Chain Scheduling Oriented to Multi-Variety Customization", *Computer Integrated Manufacturing Systems 21 (3): 800–812*, 2015.

Xiao, Y., Li, B., Hou, B., Shi, G., Lin, T., and Yang, C., Planning and Scheduling Technology Review of Supply Chain Management in Smant Manufacturing Cloud, *Computer Integrated Manufacturing Systems 22 (7): 1619–1635*, 2016.

Liu, Y., Zhang, X., Zhang, L., Tao, F., and Wang, L., A multi-agent architecture for scheduling in platform-based smart manufacturing systems, *Frontiers of Information Technology & Electronic Engineering, www.springerlink.com, ISSN 2095-9184 (print); ISSN 2095-9230 (online)*, 2019.

Ahn, G., and Hur, S., Multi-objective Real-Time Scheduling of Tasks in Cloud Manufacturing with Genetic Algorithm, *Hindawi-Mathematical Problems in Engineering, Volume 2021, DOI: 10.1155/2021/1305849*

Yu, H., Han, S., Yang, D., Wang, Z., and Feng, W., Job Shop Scheduling Based on Digital Twin Technology: A Survey and an Intelligent Platform, *Hindawi-Complexity, Volume 2021, DOI: 10.1155/2021/8823273*, 2021.

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