Scheduling tasks with different structures and arrival times in cloud manufacturing systems by considering combined logistics

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Abstract

The cloud manufacturing system is a customer-oriented paradigm that benefits from centralized management of all available resources. This paper focuses on the integration of sub-task scheduling and logistics (ISSL) in the cloud manufacturing system with two main contributions: 1) using a combined transportation system which provides the advantage of transporting more than one sub-task by a vehicle at the same time, and 2) tasks can have different structure types including sequential or parallel. To get the model closer to reality, two factors are considered: 1) different task arrival times; and 2) The setup time/cost. The proposed model aims to optimize task completion time, cost, and average quality service concurrently. To solve the proposed model, GAMS software is utilized for small/medium-sized samples while a genetic algorithm is developed for larger-size samples. Three comparative studies are conducted; the findings show that employing combined logistics significantly impacts the cost imposed on cloud systems while the real task arrival time to the cloud platform and setup time/cost have a notable effect on the task completion time and cost, respectively. Eventually, a sensitivity analysis is undertaken to gain insight into the impact of execution time, service cost, and user preferences on the final solution.

Keywords: cloud manufacturing; combined logistics; task structure; task arrival time; scheduling; setup time/cost; genetic algorithm.

1. Introduction

The cloud manufacturing platform is defined as a centralized management system for both integrating and sharing resources such as production services and logistic services. However, task or sub-task scheduling to assign them to provided services is one of the main challenges in this platform. Hence, enterprises are affording to employ approaches for optimal production in this competitive environment [1] which cloud manufacturing systems can provide them. It's worth noting that the cloud manufacturing platform combines logistics by decomposing tasks with different structures into smaller sub-tasks.

In recent years, researchers in cloud manufacturing have increasingly focused on optimization problems. These problems can be divided into three categories: scheduling, project management, and service composition. The main challenge in service composition problems is how to discover and select the suitable service from candidate services and find the optimal service structure [2, 3]. In the scheduling and project management problems unlike service composition, all services can be utilized in parallel. It should be noted that the main difference between scheduling and project management problems is that scheduling problems aim to find the optimal sequence of sub-tasks or tasks assigned to the given service, while in project management, it is not an issue [4].

In the cloud manufacturing platform, most of the submitted tasks have multi-functionality which cannot be performed by a single service. Therefore, in the first step, the received task on this platform decomposed into multiple sub-tasks in different structures. Despite this for simplicity, the models in the literature assume that all tasks follow merely one type of structure. In this regard, Akbaripour et al. [5] formulated four mixed integer programming models for four different types of task structures to allocate sub-tasks of a single task to services in a cloud manufacturing environment. Unlike Akbaripour et al. who considered different task structures, Kerdegari et al. [6] proposed a multi-objective mathematical model by considering different structures of services composition. Furthermore, Xiang et al. [7] presented a model for optimal selection from large-scale composed services by employing the two structures of sequential and parallel. Jin et al. [8] presented a service correlation mapping model by considering the two stated basic composite modes. It is commonly assumed in the studies cited that all tasks possess identical structures, such as adhering to a parallel structure. However, in real situations, it is more likely that the received tasks have diverse structures in a period.

The cloud manufacturing environment as a centralized management system expertly schedules decomposed sub-tasks to complete the overall task. This is achieved through the logistics aspects that guarantee the transportation of sub-tasks to various geographical locations. Despite numerous studies in this field, the application of an efficient transportation system is still one of the fundamental challenges in this platform. In this regard, Zhou et al. [9] addressed the 3D printing service problem in this platform to minimize task completion time by involving logistics. There exist other studies that consider typical logistic aspects and mentioned objective functions in cloud manufacturing systems in their proposed model such as He et al. [10]. To balance the benefits of service demanders and service providers a double action mechanism based on game theory was proposed by Liu et al. [11] according to logistic factors. In other studies, Zhou et al. [12] like Tong and Zhu [13] described the collaborative optimization problem of logistics services and processing services in cloud manufacturing in the form of a mathematical model. In addition, Zhou et al. [14] applied the scheduling problem of collaborative logistic and processing services in cloud manufacturing to minimize the average delivery time. Delaram and Valilai [15] proposed a linear mixed integer programming model to address project management problems to optimize logistics and production costs. To reduce production and transportation costs, Wu et al. [16] integrated cross-supplier orders and third-party logistic scheduling. Unlike other mentioned studies, the main contribution of this study is employing combined transportation in which a group of sub-tasks with the same origin and destination can be transported by one vehicle, simultaneously.

Since the presented enterprises in the cloud manufacturing systems are located in different geographical locations, the transportation time and cost can have a significant effect on the task completion time and cost imposed on the cloud manufacturing as well as the sub-task scheduling. Accordingly, Chen [17] recommended the integration of scheduling and logistics in a unified model. In this regard, in order to improve the utilization rate of dynamic service resources, Yuan et al. [18] proposed the resource scheduling model to reduce time and cost and improve production efficiency by considering logistic aspects. Regarding scheduling problems, Jafarnejad Ghomi et al. [19] and Jafarnejad Ghomi et al. [20] established two studies to present a multi-objective model by considering three criteria including service load balancing, transportation, and queuing theory, the only difference between these two studies is the solution methods.

Two factors affecting scheduling performance in cloud manufacturing are setup time/cost and task arrival time. These factors are rarely used in scheduling problems in cloud manufacturing systems. The setup time/cost can be defined as the time/cost of preparing the given service to handle the sub-task. In this regard, Salmasnia and Kiapasha [21] considered these two factors besides logistics to get their proposed scheduling model closer to reality. Helo et al. [22] dealt with sheet metal manufacturing by introducing a cloud-based model with the aim of setup time. Li et al. [23] developed NSGAII and multiple AOC by involving three objectives of time, cost, and quality and also considered two criteria of logistics and setup. Wang et al. [24], Yang et al. [25], Zhang et al. [26], and Zhang et al. [27] are four other recent studies that considered setup time/cost in their proposed model. There are a few papers that take different task arrival times into account in their presented model which can be mentioned as Zhou et al. [28] provided a mathematical model based on dynamic data-driven simulation for randomly arriving tasks in the cloud manufacturing environment. Ahn and Hur [29] investigated the effect of cost, quality, tardiness, and reliability on customer satisfaction by establishing a mathematical model by considering the available time for each task. [30, 31], and [32] are other similar studies in which different task arrival times are one of the main features of their proposed model. As can be seen, only the project management problems and two of the scheduling problem literature addressed setup and task arrival time parameters in their modeling.

Due to the fact that tasks in cloud manufacturing systems are decomposed into various numbers of sub-tasks and each enterprise offers a variety of services, Liang et al. [33], in contrast to Assari et al. [34], taking into account both the different number of sub-tasks each submitted task as well as the various number of services provided by each enterprise, analyzed the service composition problem. However, many papers like [11] and [14] considered the identical number of sub-tasks and services for each task and enterprise respectively. Several other studies contain a different number of sub-tasks and services for each task and enterprise respectively such as [28], and [29].

Although existing studies have proposed innovative task scheduling methods for cloud manufacturing systems, further investigation is necessary to address remaining shortcomings. To this end, this study proposes a model for the integration of sub-task scheduling and logistics called ISSL in cloud manufacturing. Unlike most of the studies that neglected or simplified transportation among different geographical locations, the proposed model suggests a combined logistics approach to transport multiple sub-tasks by a single vehicle at the same time in case the origin and destination of these sub-tasks are the same. Furthermore, the proposed problem covers the simultaneous scheduling of tasks with different task structures such as sequential, and parallel in the cloud environment. To get close the model to reality, two characteristics, which are seldom noticed in the scheduling problems in this environment, are taken into account as follows: 1) different task arrival times, and 2) setup time/cost when implementing different types of sub-tasks sequentially on a given service. Finally, the proposed model aims to optimize three conflicting objectives of task completion time, the cost imposed on the cloud system, and average service quality, concurrently. Table (1) is provided to give a general view of studies conducted on the optimization problems in cloud manufacturing systems.

The rest of this paper is organized as follows: in **Section 2**, the details of the problem definition are stated. In **Section 3**, the mathematical model is formulated. The implementation of the genetic algorithm is described in **Section 4**. **Section 5** reports the computational experiment results. And eventually, **Section 6** covers the conclusion and recommendation for future work.

Insert Table 1 here

2. The problem definition

The ISSL problem in the cloud manufacturing system can be defined as, how to assign a bunch of sub-tasks to the sequence positions of a provided service by considering combined logistics. As can be seen in Figure (1), users submit tasks at different times to the cloud manufacturing platform. Then, each of which is decomposed to at most U sub-tasks in sequence, or parallel structures. That is to say, the cloud manufacturing platform can concurrently schedule tasks with various structures. The set of the subtasks of a sequential task is denoted by SET while that of a parallel task is represented by PAT. Furthermore, the sub-tasks of task $T_k; k = 1,...,K$ are embedded into set U_k generally. Also, set H_k consists of the type of sub-tasks related to task k , and its u^{th} element is denoted by h_u^k . For example in the cutting process, as given in Table (2), the type of sub-tasks including blanking, notching, trimming, shaving, and punching are coded by 1, 2, 3, 4, and 5, respectively. As can be seen, task 1 is decomposed into three sub-tasks as $T_1 \in \{1,2,3\}$ with types of notching, blanking, and shaving, respectively, therefore, $H_1 \in \{2,1,4\}$, $h_1^1 = 2, h_2^1 = 1,$ and $h_3^1 = 4.$

In order to accomplish the received tasks, each sub-task is assigned to one of the candidate services according to binary matrix $V_{s,u}^{i,k}$ in which element will be 1 if sub-task u of task k can be implemented by service s of enterprise i based on its technical requirements. In the cloud manufacturing system, there are I enterprises that are distributed in different geographical locations each of which provides several services as presented in set S_i . For more clarification, Table (3) gives information related to the services of each enterprise. For example, Enterprise 3 provides services 1, 2, and 3 according to the fourth column of this Table. When identical sub-tasks are sequentially assigned to s^{th} service requires an initial setup process. In contrast, executing two sub-tasks with different types consecutively by a given service needs a separate setup process which imposes an additional time/cost on the cloud system. Furthermore, it is worth mentioning that the transportation between enterprises is undertaken by third-party logistics services with enough vehicles denoted by $V_j; j = 1,...,J.$ As depicted in Figure (2), there are some services in the cloud manufacturing platform that are provided by multiple enterprises as well as different types of logistic services. In the case that the origin and destination locations of several sub-tasks are the same, employing the combined logistics is allowed. It means that several sub-tasks are transported by a single vehicle from one enterprise to another one.

The purpose of the ISSL problem is to optimize three indicators to meet the preferences of cloud platform users including the task completion time, the cost imposed on the cloud system, and the average quality process of the selected services. To this end, optimal values of the decision variables are related to the assignment of sub-tasks to services.

Insert Figure 1 here

Insert Figure 2 here

Insert Table 2 here

Insert Table 3 here

The notations of the following presented model are shown in Table (4).

Insert Table 4 here

3. Formulation of the mathematical model

As mentioned in section 2, this study presents the ISSL problem which is formulated as a mixed integer programming (MIP) model as follows:

The combined logistics indicators are such as unit distance $d_{i,i'}$, logistics time lt_j, and logistics cost lc_j. In this regard, the logistics time and cost of j^{th} vehicle between two enterprises i, and i' are respectively calculated as below:

$$lti_j^{i,i'} = lt_j \times d_{i,i'} \tag{1}$$

$$lco_j^{i,i'} = lc_j \times d_{i,i'} \tag{2}$$

In the proposed model, three objective functions are considered, minimization of the task completion time (T), and cost imposed on the cloud system (C) as well as maximization of the average quality (Q) of services. To this end, in function T, a min-max operator is primarily employed to minimize the maximum task completion times. Notably, the calculation of task completion time is different based on task structure. In the case of task k having a sequential structure, the task completion time is equal to the termination time of its last sub-task. Otherwise, the completion time of a task with a parallel structure equals the maximum termination time of its sub-tasks. The C function refers to four kinds of cost factors: service cost, initial setup cost, setup cost, and logistic cost. Accordingly, the first factor depends on service unit cost c_s^i, and service unit a_u^k. The combined logistics cost is one of the main characteristics of the problem which encompasses the logistics cost of the j^{th} vehicle between two enterprises i, and i'

obtained in Equation (2). Function Q also determines the average quality of the selected services.

$$Min\ T = \max_{k}\{CT^{k}\} \tag{3}$$

$$\begin{aligned}Min\ \mathrm{C} = &\sum_{k=1}^{K}\sum_{u\in U_k}\sum_{i=1}^{I}\sum_{s\in S_i} suc_u^k \times Y_{s,u}^{\,i,k} + \sum_{k=1}^{K}\sum_{u\in U_k}\sum_{i=1}^{I}\sum_{s\in S_i} isuc_u^k \times N_{s,u}^{\,i,k} + \\ &\sum_{k=1}^{K}\sum_{u\in U_k}\sum_{i=1}^{I}\sum_{s\in S_i}\sum_{\rho}(c_s^i \times a_u^k)\times X_{s,\rho,u}^{\,i,k} + \sum_{\substack{i,i'=1\\ i\neq i'}}^{I}\sum_{j=1}^{J}\sum_{\varphi=1}^{\phi} lco_j^{i,i'} \times Z_{\varphi}^{\,i,i',j}\end{aligned} \tag{4}$$

$$Max\ \ Q = \frac{\left(\sum_{k=1}^{K}\sum_{u\in U_k}\sum_{i=1}^{I}\sum_{s\in S_i}\sum_{\rho} qp_s^i \times X_{s,\rho,u}^{\,i,k}\right)}{NU} \tag{5}$$

Constraints(6)-(9) specify the value of main decision variable $X_{s,\rho,u}^{\,i,k}$, where Constraint(6) expresses that only one service is selected to process sub-task u of task k, while Constraint (7) guarantees that at most one sub-task can be scheduled in position ρ of service s. Constraint (8) ensures the execution sequence of sub-tasks on service s. Constraint (9) confines the service selection by parameter $V_{s,u}^{\,i,k}$.

$$\sum_{i=1}^{I}\sum_{s\in S_i}\sum_{\rho} X_{s,\rho,u}^{\,i,k} = 1 \qquad \forall k\ \&u \in U_k \tag{6}$$

$$\sum_{k=1}^{K}\sum_{u\in U_k} X_{s,\rho,u}^{\,i,k} \leq 1 \qquad \forall i,\rho\,\&\,\forall s \in S_i \tag{7}$$

$$\sum_{k=1}^{K}\sum_{u\in U_k} X_{s,\rho+1,u}^{\,i,k} \leq \sum_{k=1}^{K}\sum_{u\in U_k} X_{s,\rho,u}^{\,i,k} \qquad \forall i,\rho\,\&\,\forall s \in S_i \tag{8}$$

$$\sum_{\rho} X_{s,\rho,u}^{\,i,k} \leq V_{s,u}^{\,i,k} \qquad \forall i,k\ \ \&\ s \in S_i\ \ \&\ u \in U_k \tag{9}$$

Constraint (10) ensures the necessity of setup time/cost just in case that h_u^k and $h_{u'}^{k'}$ are different then the corresponding decision variable $Y_{s,u}^{\,i,k}$ becomes 1. In this regard, Constraint (11) computes setup time $Tsut_u^k$ of sub-task u of task k. Besides, Constraint (12) takes the initial setup time/cost into consideration under the condition of sub-task u of task k assigned to the first position of service s of enterprise i . Accordingly, initial setup time $Isut_u^k$ of sub-task u of task k is obtained by Constraint (13).

$$X_{s,\rho+1,u}^{i,k} + X_{s,\rho,u'}^{i,k'} - 1 \le Y_{s,u}^{i,k} \qquad \forall i,\rho,k,k' \,\&\, \forall u,u' \in U_k, h_u^k \ne h_{u'}^{k'} \,\&\, s \in S_i \tag{10}$$

$$Tsut_u^k = \sum_{i=1}^{I} \sum_{s \in S_i} sut_u^k \times Y_{s,u}^{i,k} \qquad \forall k \,\&\, \forall u \in U_k \tag{11}$$

$$X_{s,\rho,u}^{i,k} \le N_{s,u}^{i,k} \qquad \forall i,k \,\&\, \forall s \in S_i \,\&\, \forall u \in U_k \,\&\, \rho = 1 \tag{12}$$

$$Isut_u^k = \sum_{i=1}^{I} \sum_{s \in S_i} isut_u^k \times N_{s,u}^{i,k} \qquad \forall k \,\&\, \forall u \in U_k \tag{13}$$

Service time St_u^k of sub-task u of task k is determined by Constraint (14), that is to say, this time is dependent on the chosen service. With respect to the use of the combined logistics in the presented problem and the importance of model linearization, an intermediate decision variable is defined as $\lambda_{u,\varphi}^{k,i,i',j}$. Thus, Constraints (15)-(23) are embedded in the model due to the integration of scheduling and combined logistics exclusively for the tasks with sequential structure. Constraint (15) as a linearized form of a non-linearized constraint is defined as shipment φ of the j^{th} vehicle transforms sub-task u of task k from enterprises i to i' in the condition of the locations of these enterprises are different. Constrain (16) indicates the interrelationship between decision variables $\lambda_{u,\varphi}^{k,i,i',j}$ and $Z_{\varphi}^{i,i',j}$. Constrain (17) ensures the sequence of shipment usage of vehicle j . Constrains (18) and (19) state that at most one shipment can transport between enterprises i and i', as well as shipment φ, can only shift from one enterprise to another one. Constrain (20) represents that sub-task u of task k cannot use more than one logistic service.

$$St_u^k = \sum_{i=1}^{I} \sum_{s \in S_i} \sum_{\rho} t_{s,u}^{i,k} \times X_{s,\rho,u}^{i,k} \qquad \forall k \,\&\, \forall u \in U_k \tag{14}$$

$$\begin{gathered} X_{s,\rho,u}^{i,k} + X_{s',\rho',u'}^{i',k} - 1 \le \sum_{j=1}^{J} \sum_{\varphi=1}^{\phi} \lambda_{u,\varphi}^{k,i,i',j} \qquad \forall k,u,u' \in SET\ (u' = next\ sub-task) \\ \&\, \forall i,i',s,s' \in S_i \,\&\, i \ne i',\ \forall \rho,\rho' \end{gathered} \tag{15}$$

$$\lambda_{u,\varphi}^{k,i,i',j} \le Z_{\varphi}^{i,i',j} \qquad \forall i,i' \,\&\, i \ne i', \forall k,u \in SET, \forall j,\varphi \tag{16}$$

$$\sum_{\substack{i,i'=1\\ i\neq i'}}^{I}\sum_{k\in SET}\sum_{u\in SET}\lambda_{u,[\varphi+1]}^{k,i,i',j} \leq M \times \sum_{\substack{i,i'=1\\ i\neq i'}}^{I}\sum_{k\in SET}\sum_{u\in SET}\lambda_{u,[\varphi]}^{k,i,i',j} \qquad \forall j,\varphi \tag{17}$$

$$\sum_{\substack{i,i'=1\\ i\neq i'}}^{I} Z_{\varphi}^{i,i',j} \leq 1 \qquad \forall j,\varphi \tag{18}$$

$$\sum_{j=1}^{J}\sum_{\varphi=1}^{\phi} Z_{\varphi}^{i,i',j} \leq 1 \qquad \forall i,i' \& i \neq i' \tag{19}$$

$$\sum_{\substack{i,i'=1\\ i\neq i'}}^{I}\sum_{j=1}^{J}\sum_{\varphi=1}^{\phi}\lambda_{u,\varphi}^{k,i,i',j} \leq 1 \qquad \forall k,u \tag{20}$$

Constraint (21) indicates that the departure time is greater than or equal to the maximum of the termination time of the sub-tasks which have the same departure and arrival points. Constraint (22) guarantees that the departure time of shipment φ of the j^{th} vehicle from enterprise i is computed if and only if transportation from enterprises i to i' is required. Constraint (23) expresses that the departure time of shipment φ of vehicle j from enterprise i'' must exceed the departure time of its previous shipment plus the logistic time from enterprises i to i'.

$$det_{\varphi}^{i,j} \geq TT_{u}^{k} - M \times (1-\lambda_{u,\varphi}^{k,i,i',j}) \quad \forall k,u \in SET \ \& \forall i,i' \& i \neq i' \& \forall j,\varphi \tag{21}$$

$$det_{\varphi}^{i,j} \leq M \times \sum_{i'=1}^{I} Z_{\varphi}^{i,i',j} \quad \forall i \ \& i \neq i' \& \forall j,\varphi \tag{22}$$

$$det_{[\varphi+1]}^{i'',j} + M \times (1-Z_{\varphi+1}^{i'',i''',j}) \geq det_{\varphi}^{i,j} + lti_{j}^{i,i'} - M \times (1-Z_{\varphi}^{i,i',j}) \quad \forall i,i',i'',i''' \ \& i \neq i' \& i''' \neq i'' \ \& \forall j,\varphi \tag{23}$$

With regard to the Constrain (24) the termination time of sub-task u of task k equals the summation of start time Stt_{u}^{k}, initial setup time $Isut_{u}^{k}$, total setup time $Tsut_{u}^{k}$, and service time St_{u}^{k}. With respect to Constraints (25) and (26), the start time of sub-task u of task k with sequential structure is greater than or equal to the sum of departure time $\det_{\varphi}^{i,j}$ and logistic time $lti_{j}^{i,i'}$, as well as the termination time of its previous sub-task. Constraints (27)-(29) emerge in the proposed model for simultaneous scheduling of tasks with different structures as one of the main contributions of this study. Constraint (27), regardless of the task structure that can be sequential or parallel, guarantees that the start time of sub-task u' of task k' in position $\rho+1$ of service s must be greater than or equal to the termination of sub-task u of task k in position ρ of this service. Furthermore, Constraint (28) ensures that the start time of the first sub-tasks of tasks with sequential structure and sub-tasks of tasks with parallel structure is greater than or equal to the task arrival time.

$$TT_u^k = Stt_u^k + Isut_u^k + Tsut_u^k + St_u^k \qquad \forall k, u \in U_k \tag{24}$$

$$Stt_{u'}^k \geq det_{\varphi}^{i,j} + lti_j^{i,i'} - M \times (1 - \lambda_{u,\varphi}^{k,i,i',j}) \quad \forall k, u, u' \in SET \ \& \forall i, i', j, \varphi \ \& i \neq i', u' = next\ sub-task \tag{25}$$

$$TT_u^k \leq Stt_{u'}^k \qquad \forall k, u, u' \in SET \ \& u' = next\ sub-task \tag{26}$$

$$Stt_{u'}^{k'} \geq TT_u^k - M \times (2 - X_{s,\rho,u}^{i,k} - X_{s,[\rho+1],u'}^{i,k'}) \quad \forall k, k', u, u' \in SET \ || PAT \ \& \forall \rho, i \ \& \ \forall s \in S_i \tag{27}$$

$$ar^k \leq Stt_u^k \quad \forall (k, u \in SET \ \& u = first\ sub-task) \,||\, k, u \in PAT \tag{28}$$

As a consequence, the completion time of task k with sequential structure is greater than or equal to the termination time of its last sub-task, while that of with parallel structure is greater than or equal to the termination time of its sub-tasks as stated in Constraint (29). The next three Constraints (30)-(32) are about the cloud user preferences of task completion time, cost, and average quality of services. The defined variable TCT in Constraint (33) is the maximum task completion time which is replaced in objective function T as shown in Equation (34). Eventually, Constraint (35) indicates the admissible intervals of the presented decision variables.

$$CT^k \geq TT_u^k \quad \forall (k, u \in SET \ \& u = last\ sub-task) \,||\, k, u \in PAT \tag{29}$$

$$T \leq T_{\max} \tag{30}$$

$$C \leq C_{\max} \tag{31}$$

$$Q \geq Q_{\min} \tag{32}$$

$$TCT \geq CT^k \quad \forall k \tag{33}$$

$$Min\ T = TCT \tag{34}$$

$$Z_{\varphi}^{i,i',j}, \lambda_{u,\varphi}^{k,i,i',j}, X_{s,\rho,u}^{i,k}, Y_{s,u}^{i,k}, N_{s,u}^{i,k} \in \{0,1\} \quad \&$$
$$CT^{k}, Stt_{u}^{k}, Tsut_{u}^{k}, Isut_{u}^{k}, St_{u}^{k}, TT_{u}^{k}, \det_{\varphi}^{i,j}, TCT \geq 0 \tag{35}$$
$$\forall \rho, i, i' \ \& \ s \in S_{s}^{i} \ \& \ k, u, u' \in U_{k}$$

Since there are contradictions between the objective functions corresponding to task completion time, cost, and average quality, the LP-metric method is considered to construct an objective function. Then the combined objective function (COF) in the proposed model is as follows:

$$COF = w_1\left(\frac{T^{*} - T}{T^{*}}\right) + w_2\left(\frac{C^{*} - C}{C^{*}}\right) + w_3\left(\frac{Q^{*} - Q}{Q^{*}}\right) \tag{36}$$

4. Genetic Algorithm (GA) implementation

For three reasons, a customized version of the Genetic Algorithm (GA) is provided to solve the proposed model: 1) the good performance of the genetic algorithm for tackling a wide range of optimization problems with binary decision variables such as scheduling and assignment problems; 2) GA versatility in its proficiency to address problems with numerous decision variables, making it an ideal approach for solving sub-task scheduling problem in cloud manufacturing systems with multiple tasks, services, and constraints; 3) employing GA in several studies in the literature such as [16], [20], and [21]. Accordingly, the procedure of the proposed GA for specific changes in solution representation, crossover, and mutation operators are described in detail in the following sub-sections.

4.1. Solution representation

The chromosome encoding as intended in Figure (3) as an example is based on Constraints (6)-(9). In this Figure, the chromosome structure represents each service as a row and the non-zero values of each row indicate the sub-tasks processed by each service. It is notable that the empty matrix cells indicate that these service positions have not been occupied by any sub-task. The services are derived from set ES as given in Figure (4a) where the rows are defined as enterprises and the digits represent the services belonging to each enterprise. Likewise, sets $SETN$ and $PATN$ in Figures (4b) and (4c) demonstrate the sub-tasks of tasks with sequential and parallel structures, respectively in which each element identifies the sub-tasks belonging to task k . Accordingly, a new chromosome is generated first by conducting a random selection of services for desired sub-task $u;u=1,..,U$ from the concrete candidate services. Afterward, a random permutation approach is used to determine the sequence of sub-task assignments to service $s;s=1,...,S$. So generally, the proposed chromosome is a $S \times P$ matrix wherein S is the total number of given services and P is the maximum number of positions that are occupied by sub-tasks. Notably, the number of columns on assorted chromosomes is not essentially the same, as the number of allocated sub-tasks to each service is distinctive.

Insert Figure 3 here

Insert Figure 4 here

Even though the mentioned constraints are satisfied, there are three challenges associated with generating a feasible chromosome: 1) failure to follow the sequence of sub-tasks of a task. For instance, in Figure (5), based on the sequence of sub-tasks in Figure (4b), sub-tasks 12 and 10 of task 4 must be replaced with each other; 2) Creating an infinite loop due to the inability to calculate the start time of sub-task u ; 3) Infinite loop caused by combined logistics. As an illustration of this possible fact, Figure (6) presents that based on the given Figure (4a)-(4b) and problem definition, a logistics service ships sub-tasks 2 and 9 of tasks 1 and 4, from enterprise 2 to 3. However, this transportation must be delayed because the termination time of sub-task 2 cannot be attained before the calculation of sub-tasks 1 and 11. As can be seen, there is no start time value for sub-task 11, the reason for this situation is that until transportation from enterprise 2 to 3 is not carried out, the termination time of sub-task 10 and 11, respectively, cannot be obtained. Hence, to solve this issue, using an innovative approach to modifying the chromosome, the positions of those sub-tasks with unknown start times are changed to the sequence positions of their other candidate services randomly. In this case, there are two notable points: 1) in the case the positions of the chosen service are occupied, the sub-task must be preserved in its previous position; 2) in the end, all the sub-tasks must change their positions in the sequence of the service positions.

Insert Figure 5 here

Insert Figure 6 here

4.2. Crossover

In this study, the employed innovated crossover operator is similar to the uniform crossover. In this operation, after choosing two parents through the Roulette Wheel method strategy, a binary matrix called mask is randomly generated as the same size as the parent with the largest number of columns. Then, the identified genes corresponding to elements of the mask by value 1 from the first parent swap to the same services of offspring 1 in the sequence positions of service. The remaining sub-tasks in the second parent are copied in the first empty position of the same services of this parent in offspring 1. In the circumstances that the positions of the selected service are occupied, the sub-task is placed in the sequence positions of the same service that implements it in the first parent. Similarly, this procedure is applied for offspring 2 in which the place of the first and second parents are changed. Ultimately, the sub-tasks of task k with sequential structure in the generated offsprings are arranged in the service positions based on the $SETN$. In this regard, Figure (7) depicts an example of this operator.

Insert Figure 7 here

4.3. Mutation

The major role of the Mutation operator in GA is to exploit the solution space and preserve the population diversity over the next generations. In this study, the mutation operator is inspired by displacement mutation which is adapted to the solution representation. As illustrated in Figure (8), after selecting a parent randomly, the positions of the sub-tasks in each service are randomly changed. Eventually, the messed-up sequence of sub-tasks of $SETN$ in services is improved to the correct form of it.

Insert Figure 8 here

5. Computational experiments

In this section, three sets of numerical experiments are employed encompassing analyzing the proposed model and GA on small to large-sized samples, comparing the performance of the model by using numerous comparative models, and finally presenting sensitivity analysis on five key parameters.

5.1. Numerical examples

Three sets of samples are randomly presented in small, medium, and large-sized to validate and evaluate the effectiveness of the developed GA. The model for three small and one medium-sized samples is coded in CPLEX using GAMS 25.1.2 with a 7200 second time limit. Furthermore, a genetic algorithm is presented to implement the model in larger-sized samples with MATLAB R2018b which is run in a computer with a Core i7, 2.40 GHz CPU of 8 GB RAM. The solved samples by GAMS are also implemented by the proposed GA to confirm the validation of it. The set GA fine-tuned parameters are given in Table (5) while the obtained results by CPLEX and GA methods for nine random samples are represented in Table (6). The outcomes show that the GAMS software can only solve four first samples within the mentioned time limitation while it cannot find a feasible solution for the rest of the samples during the same time. Moreover, the results of GA demonstrate that the solutions of the three small and one medium-sized samples are as same as the outputs of GAMS. Accordingly, Table (6) indicates that the proposed GA has also obtained the appropriate solution for larger-scale samples in a reasonable time. Meanwhile, Figure (9) reveals an unsurprisingly wide variation between the computational times of these two mentioned methods. As can be seen, the computational time of GA is significantly lower than in comparison with the computational time of the exact method for medium and large-sized samples.

Insert Table 5 here

Insert Table 6 here

Insert Figure 9 here

5.2. Comparative evaluation of logistics aspects

A comparison of logistics aspects is carried out to check the effect of considering combined logistics on scheduling criteria. Along this sub-section, three studies are conducted including the **first study)** Sample 3 as a general case is called the benchmark which consists of all the model characteristics in particular combined logistics; **second study)** This study takes simple logistics into account; and the **third study)** It is assumed that the logistics time/cost is negligible. In Appendix A, the parameter values of sample 3 are presented in detail.

The results in Table (7) depict the corresponding objective function values of each study in terms of task completion time, cost, average quality, and combined objective function (COF).

The reported values of the mentioned objective functions for the first study are 31.924, 214.368, 12.417, and 0.0717, respectively. In the case of simple logistics being applied instead of combined logistics, the cost function and as a result of that *COF* are changed to 251.048, and 0.0605 in order. Figure (10) is presented to clarify the obtained results. In this figure, as is clear from the solutions presented as decision variables, in combined logistics two sub-tasks are transported by a vehicle which significantly saves cost, while in simple logistics each sub-task is shipped separately by a car. In order to carry several sub-tasks by one vehicle in combined logistics, all the sub-tasks must be completed in the origin enterprise. Therefore, in this example, the vehicle selection and other time terms are such that the task completion times of the two studies are the same. That is to say, their service time, setup time, initial setup time, and logistics time are equal. Consequently, as can be seen in Table (7), by placing the decision variable of the second study in the benchmark, the cost will increment 11.88%. In case the logistics time/cost is omitted in the model, the cost, average quality, and *COF* values respectively become 169.137, 12.833, and 0.0605, whereas, the completion time remains constant. Because the decision variable has changed in such a way that the task completion time remains unchanged. Further on, the outcomes show 22.79%, 1.13%, and 92.46% improvement in the task completion time, cost, and *COF* with the placement of the decision variable of the third study in the first study. It is worth mentioning since the logistics cost in this example is insignificant compared to logistics time, the logistics cost does not have a great impact on the cost function. In general, as illustrated in Figure (11), ignoring logistics aspects has more adverse effects on the scheduling than considering simple logistics. Indeed, the impact of logistics, especially combined logistics, on scheduling in the cloud manufacturing environment is undeniable.

Insert Table 7 here

Insert Figure 10 here

Insert Figure 11 here

5.3. Evaluation of task arrival time and setup parameters on the scheduling process

This sub-section is dedicated to an extensive analysis of other proposed model characteristics such as task arrival time and setup parameters. With respect to these two features, three cases are defined to demonstrate the effectiveness of the proposed model. Three cases are as follows:

The first case) this case as a general one is a benchmark to compare the attained outcomes of other cases.

The second case) it is assumed that all the tasks are available at the beginning of the time horizon.

The third case) setup time/cost is excluded in this case, to investigate the effectiveness of this characteristic on scheduling results.

Similar to the previous sub-section, sample 3 is given to use for comparing the mentioned cases. Table (8) reports the experiment results of the second case. The results of the objective functions in terms of task completion time, cost, average quality, and COF in the second case are 17.598, 254.086, 12.000, and 0.1392, respectively. These consequences depict that despite the sharp task completion time value improvement, the rest of the criteria deteriorated. It is obvious that achieving tasks in zero time leads to the earlier implementation of them and eventually lowers the value of the task completion time. Also, due to the changing of the subtask assignment to the services, the cost function increases while the average quality function decreases. Placing the decision variable of the second case in the model known as benchmark shows that all three objective functions are improved by about 29.47%, 16.06%, and 3.35%, respectively. It is necessary to mention that regarding findings compared to the second case the improvement of COF is significantly well over 100%. As expected, these tangible improvements are because of the less dispersion of the sub-tasks on the services which leads to the better values of objective functions in the proposed model. Actually, the outcomes confirm that the consideration of the different task arrival times effectively leads cloud managers to make correct decisions in scheduling.

Insert Table 8 here

For further peruse of the proposed model, the more challenging comparison is assessed by removing setup parameters from the main model. In this regard, the objective function values of the model undergo the eliminating setup time/cost are presented in Table (9). According to this Table, the values of task completion time, cost, average quality, and COF of the third case are 26.127, 181.298, 12.000, and 0.0407, respectively. As can be seen, better results have been obtained by elimination of the setup time and cost corresponding to objective functions.

However, by placing the decision variable of this case in the benchmark model the objective function values of the task completion time, cost, average quality, and *COF* considerably increase about 74.94%, 17.45%, 3.35%, and 444.49%. The results indicate that in the third case, the sub-tasks regardless of their types are allocated to services which is not the case in practice, and mislead the cloud operators.

Insert Table 9 here

5.4. Sensitivity Analysis on Key Parameters

Parameters have a great impact on the performance and the application results of the scheduling process. Hence, in this sub-section, a sensitivity analysis is conducted to justify the robustness of the proposed model by using key parameters such as $t_{s,u}^{i,k}$, c_s^i, $T_{\max}$, $C_{\max}$, and $Q_{\min}$. To this end, the variations in $t_{s,u}^{i,k}$ and c_s^i for sample 3 are increased by {0%, 5%, 10%, 20%, 40%, and 50%}. Likewise, the user preferences of $T_{\max}$, $C_{\max}$, and $Q_{\min}$ are incremented by {100, 50, 30, and 15}, {1000, 250, 200, and 100}, and {10, 11, 12.6, and 13}, respectively.

The results obtained for objective functions for different values of $t_{s,u}^{i,k}$ and c_s^i can be seen in Table (10) and Figure (12). As the execution time of sub-tasks increments, the task completion time increases while the two other objective functions remain unchanged as illustrated in Figure (12a). The main reason for this is that the increase in the execution time of the tasks in an equal proportion does not lead to a change in the allocation of subtasks to the services, and as a result, the cost and average quality remain unchanged. However, an increment in the unit cost parameters with a fixed ratio leads to an increase in the cost function which is approximately commensurate with c_s^i growth. As can be seen in Figure (12b), in two cases 10% and 50% increase in unit costs, the average quality function fluctuates which with respect to the different selections of candidate services for implementing sub-tasks is reasonable.

Insert Table 10 here

Insert Figure 12 here

Table (11) and Figure (13) show the impact of three user preference factors consisting of $T_{\max}$, $C_{\max}$, and $Q_{\min}$ on the task completion time, cost, and average quality. It can be deduced from Figure (13a) that by reducing $T_{\max}$ from 100 to 50, the optimal decision variable vector remains in the feasible region. As a result, the optimal values of objective functions remain the same as in the previous problem. However, decreasing the parameter $T_{\max}$ to 30 leads to the exit of the optimal point of the previous problem from the feasible region. Consequently, a new optimal decision variable vector is obtained, and corresponding to it, the values of the objective functions change. As expected, the value of the task completion time function becomes less than 30, so its value has reduced from 31.924 to 28.535. Under this condition, it is reasonable that the cost increases and the average quality decreases. Likewise, as can be seen in Figure (13b), when $C_{\max}$ changes from 1000 to 250, the cost function value remains 214.368, because the optimal decision variable vector remains in the shrunk feasible region. On the other hand, when $C_{\max} = 200$, the feasible region affects the optimal decision variable values due to the exit of the previous optimal decision variable vector from the feasible region. So, the optimal value of the cost function reduces while the two other objective functions deteriorate because of the shrinkage of the feasible region. Figure (13c) and the tabulation results of $Q_{\min} = 10$ and $Q_{\min} = 11$ demonstrate that there is no change in the values of the objective functions because the optimal decision variable vector remains in the feasible region. Whereas, the completion time, cost, and average quality become 35.946, 221.703, and 12.833, when $Q_{\min}$ increases to 12.6. Furthermore, it is notable that by quantifying $T_{\max}$, $C_{\max}$, and $Q_{\min}$ with values of 15, 100, and 13, respectively, the search space will be infeasible.

Insert Table 11 here

Insert Figure 13 here

6. Managerial insights

This section provides managerial recommendations based on acquired results to improve the efficiency and performance of real industrial systems as below:

1) Cloud managers are advised to optimize costs by utilizing combined logistics when there is a significant distance among enterprises in the cloud system and high transportation costs. This involves transferring multiple sub-tasks simultaneously, even if it leads to a delay in the transfer process of some sub-tasks.
2) Varying the execution time of sub-tasks with a fixed ratio does not lead to any changes in the assignment of sub-tasks to services. However, an increase in the execution cost of sub-tasks with the fixed ratio changes the scheduling decision variable.
3) In case the cost and time of service setup for performing a different type of sub-task is significant, this aspect should be taken into consideration by assigning the same type of sub-tasks to a service as far as possible.
4) Submitting tasks with different arrival times into the system in a planning period has a significant effect on the sub-task assignment to the services and the completion time of the tasks.

7. Conclusion and recommendation for future works

This paper developed an integrated multi-objective mix integer programming model of sub-task scheduling and logistics. This model aimed to minimize the task completion time and cost imposed on the cloud manufacturing system as well as maximize the average quality of selected services. By departing from the literature, two practical concepts of the combined logistics and scheduling of tasks with sequential and parallel structures in a given problem were taken into account in the modeling. Moreover, two complementary concepts were taken into consideration: 1) tasks are available at diverse arrival times, and 2) the setup of services is a costly and time-consuming procedure. The LP-metric method was utilized to combine the three mentioned conflict objective functions into a single one. Afterward, GAMS software was used to solve the small and one medium-sized samples and since this exact method is not tractable for larger-sized ones, the authors developed and validated a genetic algorithm to solve such problems.

In order to investigate the proposed model characteristics and effectiveness of the developed GA, two sets of studies were carried out: 1) Two comparative studies were conducted to demonstrate the effectiveness of the combined logistics. To this end, the proposed model was compared with two similar models, one without considering logistics service and the other with simple logistics. The tabulated results confirmed the undeniable impact of the combined logistics on the scheduling process. 2) Three models were compared to assess the importance of taking the different task arrival times and setup parameters into account. The obtained results showed the inevitable effects of these two features to prevent misleading the cloud manager. After that, a series of sensitivity analyses were conducted to evaluate the robustness of the proposed model. The computational results of increasing the execution time and the unit cost illustrated that the task completion time and cost functions at least increment as much as the growth of the mentioned parameters, respectively, while, the rest of the objective functions remained almost constant. In addition, the user preferences were also examined to determine their effectiveness on the scheduling process. The outcomes revealed that each of these parameters plays an important role in improving the corresponding objective function. Hence, in general, the findings demonstrated the applicability and efficacy of the proposed model for solving the ISSL problem.

Two directions for extending the suggested model as future research are: (1) taking both different task arrival times and service availability, and (2) taking equity among customers into consideration.

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Appendix:

The parameter values of sample 3 including service information, geographical distances between enterprises, information of tasks with sequential and parallel structures, and other parameters of this sample are presented in Tables A (12) to (15).

Insert Table A.12 here

Insert Table A.13 here

Insert Table A.14 here

Insert Table A.15 here

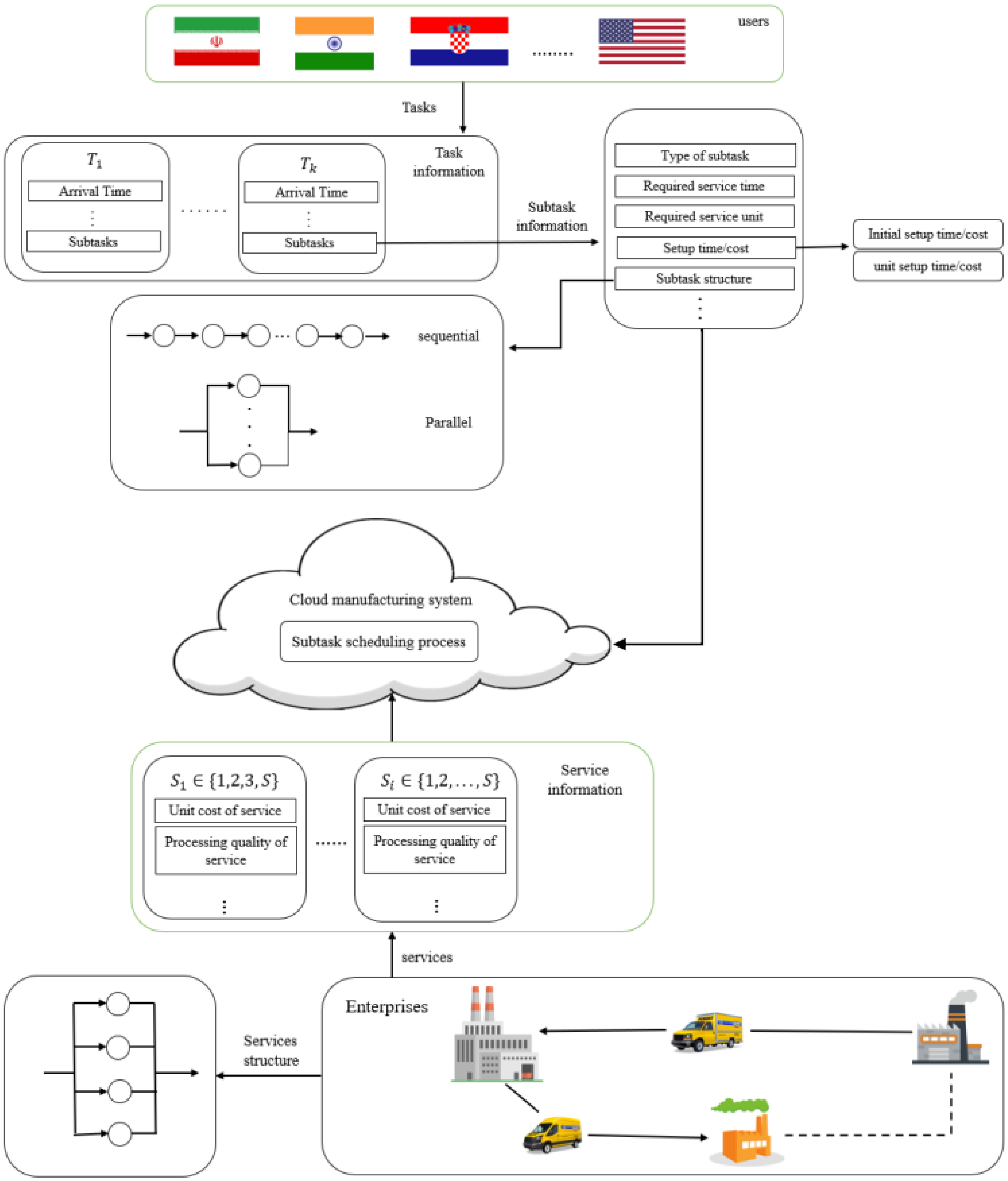


Figure 1- Scheduling process framework in cloud manufacturing

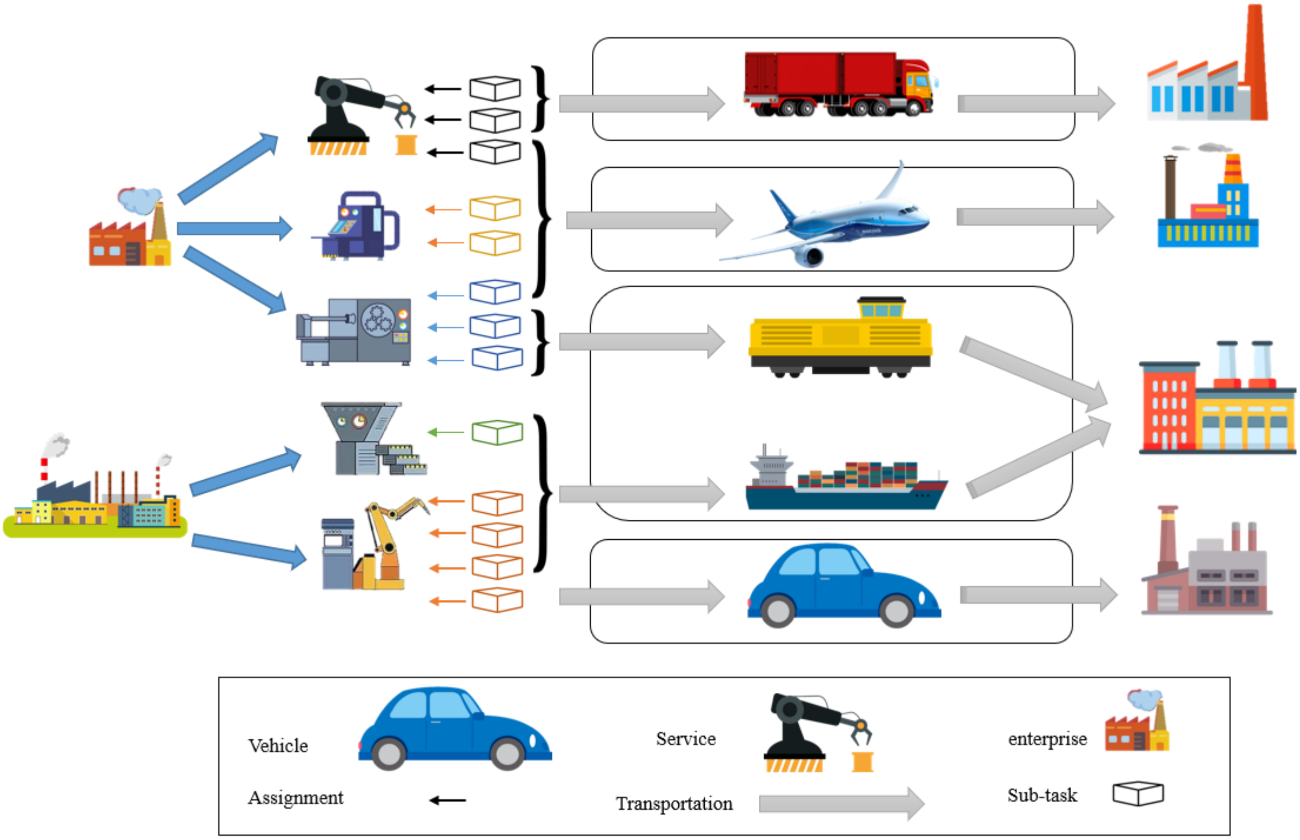


Figure 2- The Logistics diagram of the ISSLS problem

	$\rho = 1$	$\rho = 2$	$\rho = 3$	$\rho = 4$
$s = 1$	1			
$s = 2$				
$s = 3$	9	2		
$s = 4$				
$s = 5$	8	11		
$s = 6$	4	6	7	5
$s = 7$	3	10	12	

Figure 3- chromosome encoding

$i=1$	1	2	
$i=2$	3	4	
$i=3$	5	6	7

(a)

$k=1$	1	2	3	
$k=4$	9	10	11	12

(b)

$k=2$	4	5	
$k=3$	6	7	8

(c)

Figure 4- a) set of services belongs to enterprises; b) set of sub-tasks belongs to tasks with sequential structures; c) set of sub-tasks belongs to tasks with parallel structures

	$\rho=1$	$\rho=2$	$\rho=3$
$s=1$	1	7	5
$s=2$	3		
$s=3$	9	2	
$s=4$			
$s=5$	8	11	
$s=6$	4	6	
$s=7$	12	10	

	$\rho=1$	$\rho=2$	$\rho=3$
$s=1$	1	7	5
$s=2$	3		
$s=3$	9	2	
$s=4$			
$s=5$	8	11	
$s=6$	4	6	
$s=7$	10	12	

Figure 5- Example of failure to follow the sequence of sub-tasks of a task

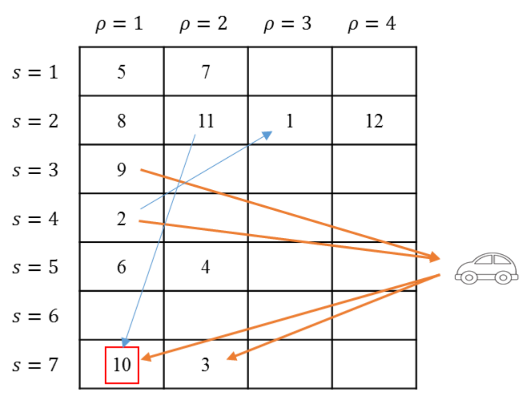


Figure 6- Example of Infinite loop caused by combined logistics

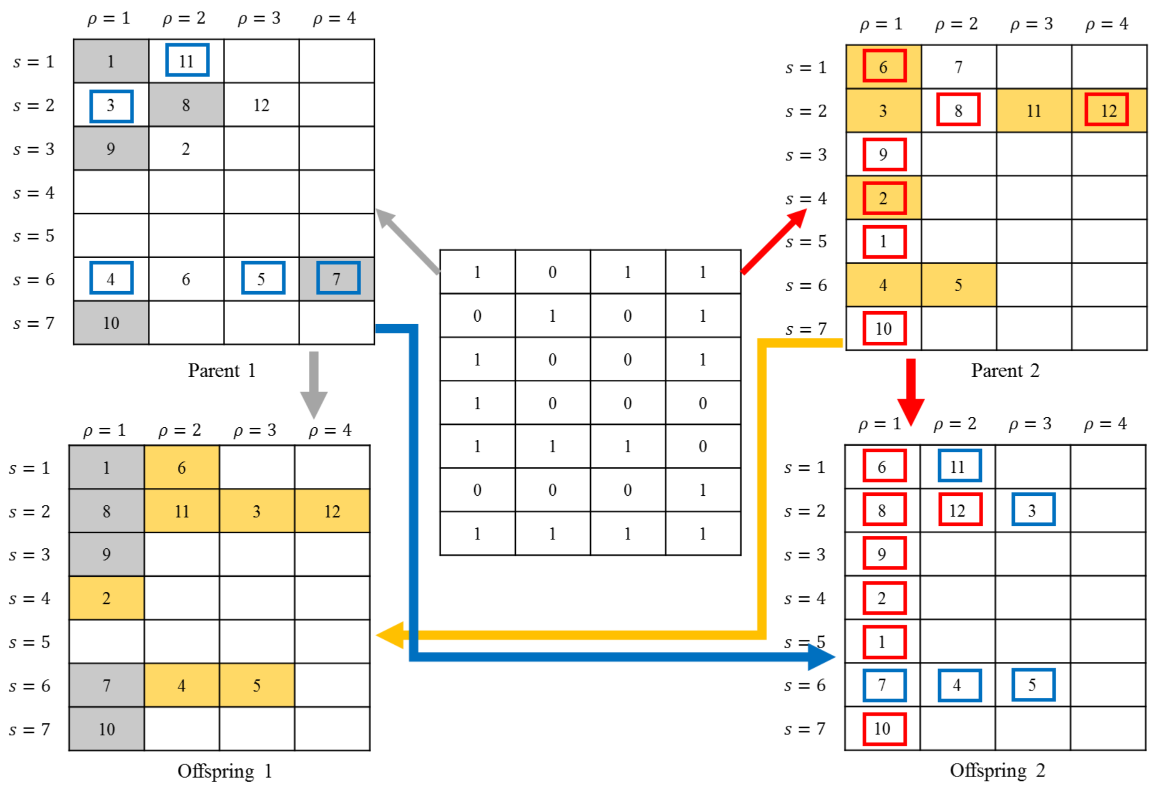


Figure 7- The example of the crossover operation

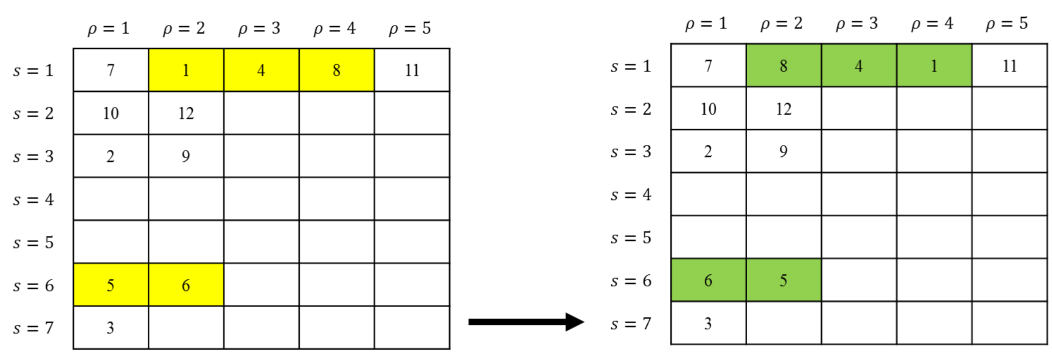


Figure 8- A typical case of Mutation operation

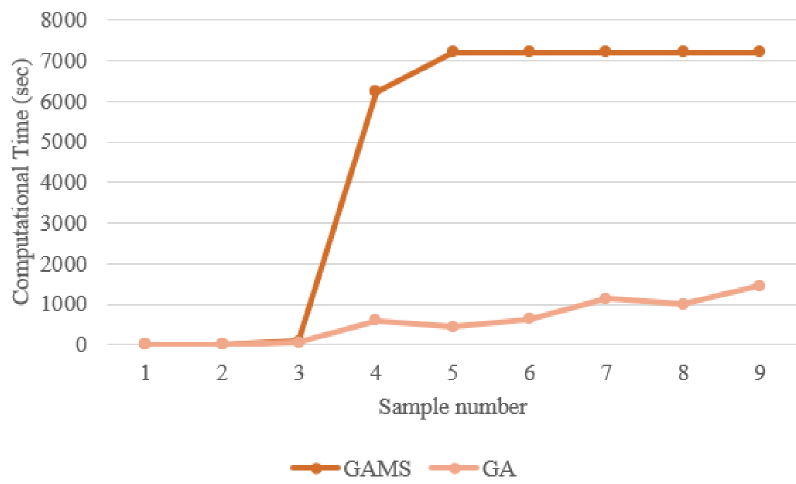


Figure 9- Computational time of GAMS and GA

	$\rho = 1$	$\rho = 2$	$\rho = 3$	$\rho = 4$
$s = 1$				
$s = 2$				
$s = 3$	2	9		
$s = 4$				
$s = 5$	1	11	8	
$s = 6$	4	6	7	5
$s = 7$	3	10	12	

third study

	$\rho = 1$	$\rho = 2$	$\rho = 3$	$\rho = 4$
$s = 1$	1			
$s = 2$				
$s = 3$	9	2		
$s = 4$				
$s = 5$	8	11		
$s = 6$	4	6	7	5
$s = 7$	3	10	12	

first study

	$\rho = 1$	$\rho = 2$	$\rho = 3$	$\rho = 4$
$s = 1$	1			
$s = 2$	3			
$s = 3$	9	2		
$s = 4$				
$s = 5$	8	11		
$s = 6$	4	6	7	5
$s = 7$	10	12		

second study

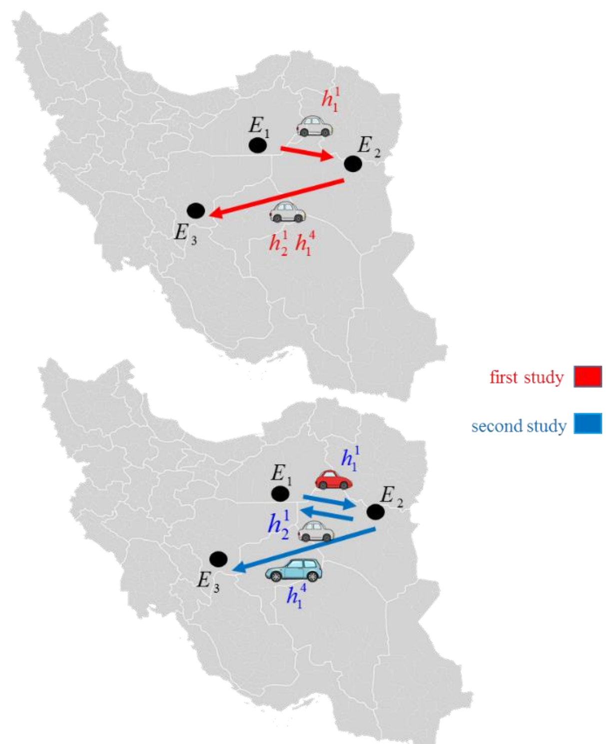


Figure 10- shipment for three comparative studies of the logistics aspect

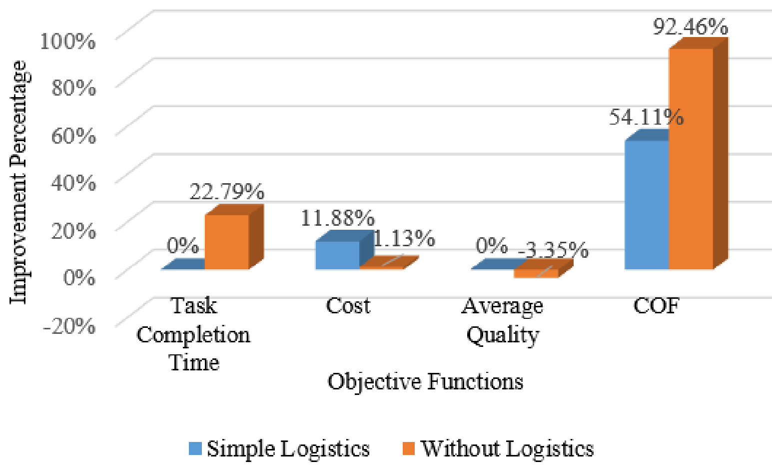
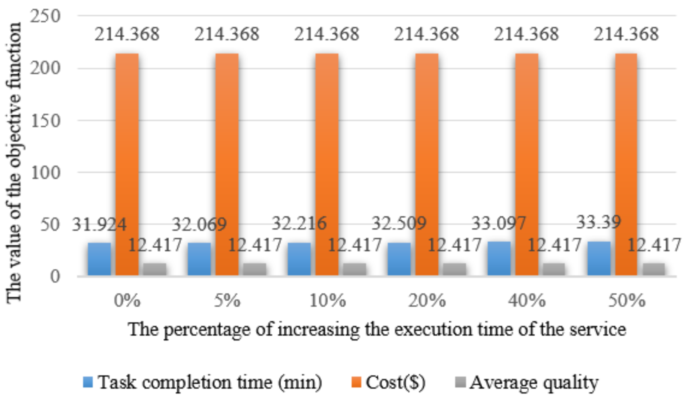
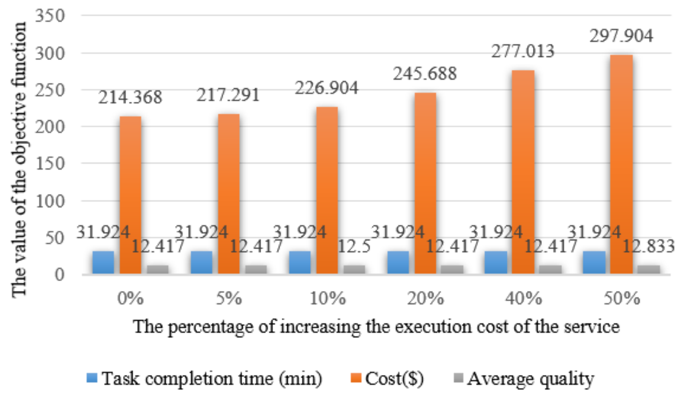


Figure 11- Improvement percentage of the proposed model



(a)



(b)

Figure 12- a) the results of increasing the execution time of the service; b) the results of increasing the execution cost of the service

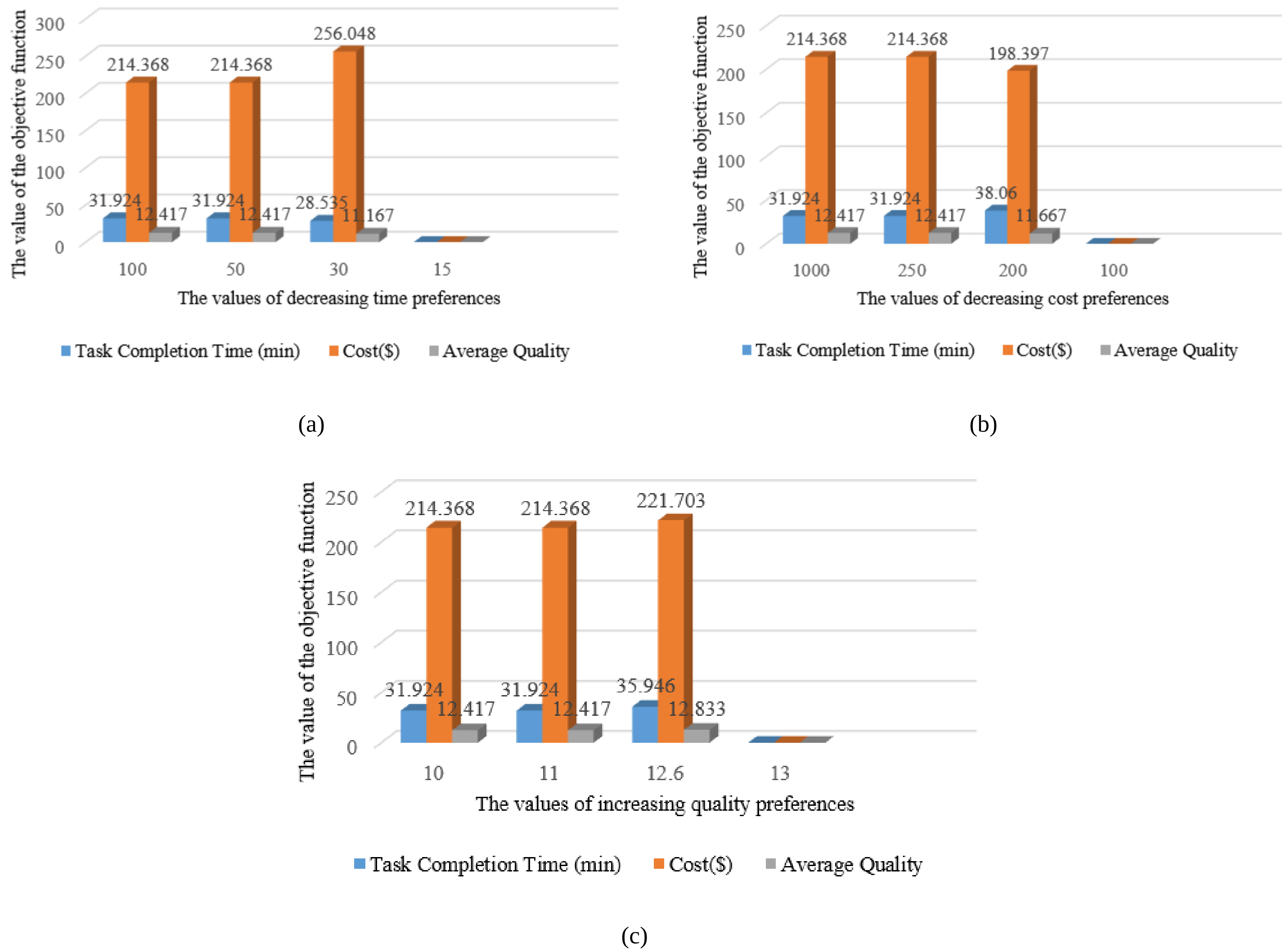


Figure 13- a) the results of decreasing time preferences; b) the results of decreasing the cost preferences; c) he results of increasing the quality preferences;

Table 1- Contribution of optimized-based studies in cloud manufacturing system

Field	Author(s)	Number of sub-tasks		Number of services of each enterprise		Composition Structure		Setup time/cost	Task availability	Logistics time/cost	
		identical	different	identical	different	sequential	parallel			combined	simple
Scheduling	Zhou et al. (2020)	✓		✓		✓					✓
	Vahedi-Nouri et al. (2020)		✓				✓				
	Li et al., (2019)		✓			✓	✓				✓
	Yuan et al., (2021)		✓			✓					✓
	Wu et al. (2022)		✓		✓	✓				✓	
	Zhou et al. (2018b)	✓		✓		✓			✓		✓
	Salmasnia and Kiapasha(2023)	✓		✓		✓		✓	✓		✓
	Jafarnejad Ghomi et al. (2019a)	✓			✓	✓					✓
	Jafarnejad Ghomi et al. (2019b)	✓			✓	✓					✓
Project Management	Helo et al. (2019)					✓		✓			
	Tong and Zhu (2022a)		✓			✓			✓		✓
	Tong and Zhu (2022b)		✓			✓					✓
	Zhang et al. (2023)		✓			✓		✓			✓
	Yang et al. (2020)		✓		✓	✓	✓	✓			✓
	Zhou et al. (2019)		✓		✓	✓			✓		✓
	Zhou et al. (2021)		✓			✓					✓
	Zhang et al. (2021)		✓		✓	✓		✓			✓
	Ahn and Hur (2021)		✓			✓	✓		✓		
	Liu et al. (2018)	✓			✓	✓			✓		✓
	Wang et al. (2022)	✓				✓		✓			✓
	Zhou et al. (2018a)		✓			✓					✓
	Liu et al. (2019)		✓		✓	✓	✓				✓
	He et al. (2019)	✓		✓		✓					✓
	Delaram and Valilai (2018)		✓	✓		✓					✓
	Akbaripour et al. (2018)					✓	✓				✓
Service Composition	Assari et al. (2018)										✓
	Liang et al. (2021)				✓	✓	✓				✓
	Kerdegari et al. (2018)					✓	✓				✓
	Keramatnezhad et al. (2020)										
	Fazeli et al. (2019)			✓		✓					✓

	Xiang et al. (2016)			✓	✓			
	Jin et al. (2017)			✓	✓			
Scheduling	**This study**	✓	✓	✓	✓	✓	✓	✓

Table 2- The tasks structures and sub-task types

Tasks	Sequential (SET)				Type (H_k)			
	$u=1$	$u=2$	$u=3$	$u=4$	h_1^k	h_2^k	h_3^k	h_4^k
T_1	✓	✓	✓		2	1	4	
T_4	✓	✓	✓	✓	1	4	2	4
	Parallel (PAT)				Type (H_k)			
	$u=1$	$u=2$	$u=3$	$u=4$	h_1^k	h_2^k	h_3^k	h_4^k
T_2	✓	✓			3	5		
T_3	✓	✓	✓		3	5	2	
T_5	✓	✓	✓		5	3	1	

Table 3- services of each enterprise

s	S_1	S_2	S_3	...	S_I
1	✓	✓	✓		✓
2	✓	✓	✓		✓
3	✓		✓		✓
⋮					
S	✓				✓

Table 4- the symbols and notations

Symbols	**Description**
Indices	
i,i',i''	Indices of enterprises $i,i',i''=1,2,...,I$ `
s,s'	Indices of service of each enterprise $s,s'\in S_i$
k,k'	Indices of tasks $k,k'=1,2,...,K$
u,u'	Indices of the order of sub-tasks of each task $u,u'\in U_k$
j	index of the vehicles $j=1,2,...,J$
φ	index of the shipments of each vehicle $\varphi=1,2,...,\phi$
ρ,ρ'	Indices of positions of each service $\rho,\rho'=1,2,...$
Sets	
U_k	Set of the order of sub-tasks of task k
H_k	Set of sub-task types of task k
S_i	Set of services of enterprise i
SET	Set of the tasks with sequential structures
PAT	Set of the tasks with parallel structure
Parameters	
T_k	Task k
h_u^k	The type of u^{th} sub-task from k^{th} task
E_i	Enterprise i

$d_{i,i'}$	The geographical distance between two enterprises i,i'
$V_{s,u}^{i,k}$	1 if s^{th} service of enterprise i is able to perform the u^{th} sub-task of the task k , otherwise 0
M	A very large positive number
N_s	Total number of sub-tasks
w_T	Time preference weight
w_C	Cost preference weight
w_Q	Quality preference weight
$C_{\max}$	The maximum acceptable total cost imposed on the cloud system
$T_{\max}$	Maximum acceptable task completion time
$Q_{\min}$	Minimum acceptable total quality
Time parameters	
ar^k	The arrival time of k^{th} task to the cloud manufacturing platform
$t_{s,u}^{i,k}$	The execution time of the u^{th} sub-task of task k by s^{th} service of enterprise i
sut_u^k	Setup time for implementing the u^{th} sub-task of task k
$isut_u^k$	Initial setup time for implementing the u^{th} sub-task of task k
lt_j	Logistics time of j^{th} vehicle of the distance unit
$lti_j^{i,i'}$	Logistics time of j^{th} vehicle, when two sequential sub-tasks are executed in two different enterprises i,i'
Cost parameters	
a_u^k	The service unit for executing the u^{th} sub-task of task k
c_s^i	The unit cost of the s^{th} service of enterprise i
suc_u^k	Setup cost imposed on the system for implementing the u^{th} sub-task of task k
$isuc_u^k$	Initial setup cost imposed on the system for implementing the u^{th} sub-task of task k
lc_j	Logistics cost of j^{th} vehicle of the distance unit
$lco_j^{i,i'}$	Logistics cost of j^{th} vehicle, when two sequential sub-tasks are executed in two different enterprises i,i'
Quality parameters	
qp_s^i	Processing quality of s^{th} service of enterprise i
Decision variables	
binary	
$X_{s,\rho,u}^{i,k}$	1 if u^{th} sub-task of the k^{th} task is executed in the position ρ of the s^{th} service of enterprise i . Otherwise, 0
$Y_{s,u}^{i,k}$	1 if for implementing the u^{th} sub-task of task k on the s^{th} service of enterprise i a setup process is required. Otherwise, 0
$N_{s,u}^{i,k}$	1 if the s^{th} service of enterprise i executes a sub-task in its first position. Otherwise, 0
$\lambda_{u,\varphi}^{k,i,i',j}$	1 if two sequential sub-tasks of the k^{th} task are transformed between two different enterprises i,i' by the φ^{th} shipment of vehicle j . Otherwise, 0
$Z_{\varphi}^{i,i',j}$	1 if a transformation occurs between two different enterprises i,i' by the φ^{th} shipment of vehicle j . Otherwise, 0
Continuous	
CT^k	Completion time of task k
St_u^k	Service time of the u^{th} sub-task of task k
Stt_u^k	The start time of the u^{th} sub-task of task k
TT_u^k	Termination time of the u^{th} sub-task of task k
$det_{\varphi}^{i,j}$	The departure time of the φ^{th} shipment of vehicle j from enterprise i

$Tsut_u^k$	Total setup time of the u^{th} sub-task of task k
$Isut_u^k$	Total initial setup time of the u^{th} sub-task of task k

Table 5- GA set parameters

Parameters / Sample size	Population size	Maximum Iteration	Crossover percentage	Mutation percentage
Small	60	40	0.5	0.5
Medium	200	100	0.9	0.1
Large	200	100	0.9	0.1

Table 6- The results of numerical examples

Sample size	Sample number	No. of tasks with sequential structure	No. of tasks with parallel structure	No. of sub-tasks	No. of enterprises	No. of services	GAMS		GA	
							Best solution	Computational time (min)	Best solution	Computational time (min)
small	1	1	1	6	2	5	0.0439	0.812	0.0439	9.346
	2	1	2	8	3	5	0.0673	1.515	0.0673	9.481
	3	2	2	12	3	7	0.0717	85.468	0.0717	52.116
medium	4	2	3	15	4	9	0.1353	6220.562	0.1353	596.135
	5	4	4	22	5	14	-	-	0.1057	440.528
	6	4	5	25	6	16	-	-	0.1072	623.192
large	7	6	4	30	7	20	-	-	0.1438	1131.560
	8	6	5	35	8	24	-	-	0.0659	999.218
	9	6	6	40	9	27	-	-	0.07061	1453.598

Table 7- The comparison results of studies with different types of logistics aspects

		Simple logistics			Without logistics		
	Benchmark sample	Second study	Expected results based on the second study	Improvement percentage	Third study	Expected results based on the third study	Improvement percentage
Task Completion Time(min)	31.924	31.924	31.924	0%	31.924	39.202	22.79%
Cost ($)	214.368	251.048	239.849	11.88%	169.137	216.797	1.13%
Average quality	12.417	12.417	12.417	0%	12.833	12.833	-3.35%
COF	0.0717	0.0605	0.1105	54.11%	0.0605	0.1380	92.46%

Table 8- The comparison results of the first case and the second case

	Task completion time (min)	Cost ($)	Average quality	*COF*
Benchmark case	31.924	214.368	12.417	0.0717
Second case	17.598	254.086	12.000	0.1392
Expected results based on the second case	41.333	248.800	12.000	0.2350
Improvement percentage	29.47%	16.06%	3.35%	227.75%

Table 9- The comparison results of the first case and the third case

	Task completion time (min)	Cost ($)	Average quality	*COF*
Benchmark case	31.924	214.368	12.417	0.0717
Third case	26.127	181.298	12.000	0.0407
Expected results based on the third case	55.850	251.780	12.000	0.3904
Improvement percentage	74.94%	17.45%	3.35%	444.49%

Table 10- The results of increasing $t_{s,u}^{i,k}$ and c_s^i

parameter	Objective function	0%	5%	10%	20%	40%	50%
$t_{s,u}^{i,k}$	Task completion time (min)	31.924	32.069	32.216	32.509	33.097	33.390
	Cost ($)	214.368	214.368	214.368	214.368	214.368	214.368
	Average quality	12.417	12.417	12.417	12.417	12.417	12.417
c_s^i	Task completion time (min)	31.924	31.924	31.924	31.924	31.924	31.924
	Cost ($)	214.368	217.291	226.904	245.688	277.013	297.904
	Average quality	12.417	12.417	12.500	12.417	12.417	12.833

Table 11– The results of variation in $T_{\max}$, $C_{\max}$, and $Q_{\min}$

Parameters	**Value**	**Task Completion Time (min)**	**Cost ($)**	**Average Quality**
$T_{\max}$	100	31.924	214.368	12.417
	50	31.924	214.368	12.417
	30	28.535	256.048	11.167
	15	infeasible	infeasible	infeasible
$C_{\max}$	1000	31.924	214.368	12.417
	250	31.924	214.368	12.417
	200	38.060	198.397	11.667
	100	infeasible	infeasible	infeasible
$Q_{\min}$	10	31.924	214.368	12.417
	11	31.924	214.368	12.417
	12.6	35.946	221.703	12.833

13	infeasible	infeasible	infeasible

Table A-12– service information of sample 3

Enterprises	**services**	**service unit cost ($)**	**Processing Quality**
E_1	$s = 1$	8.831	6.000
	$s = 2$	10.457	7.000
E_2	$s = 1$	6.965	18.000
	$s = 2$	7.073	9.000
E_3	$s = 1$	4.625	11.000
	$s = 2$	6.941	16.000
	$s = 3$	7.799	7.000

Table A.13 – Geographical distances between enterprises (m) of sample 3

Enterprises	E_1	E_2	E_3
E_1	0	1.087	1.169
E_2	1.162	0	1.498
E_3	1.189	2.399	0

Table A.14- Task information of sample 3

Task structure	**Task**	**Arrival time**	**Sub-task**	**Setup time (m)**	**Setup cost ($)**	**Initial setup time (m)**	**Initial setup cost ($)**	**Candidate service**	**Service time(h)**	**Quantity of unit service for each Sub-task**
Sequential	T_1	9.408	h_1^1	5.102	3.000	6.031	1.769	$S_1 \in \{s = 1\}$	0.465	1.000
								$S_1 \in \{s = 2\}$	1.489	1.000
								$S_3 \in \{s = 1\}$	1.212	1.000
			h_2^1	9.492	20.000	2.806	2.353	$S_2 \in \{s = 1\}$	1.289	2.000
								$S_2 \in \{s = 2\}$	1.153	2.000
			h_3^1	5.364	5.000	4.169	4.908	$S_1 \in \{s = 2\}$	0.413	1.000
								$S_3 \in \{s = 3\}$	0.725	1.000
	T_4	10.508	h_1^4	1.565	4.000	4.088	7.259	$S_2 \in \{s = 1\}$	0.450	1.000
								$S_2 \in \{s = 2\}$	0.673	1.000
			h_2^4	1.066	5.000	3.997	8.612	$S_1 \in \{s = 2\}$	0.689	3.000
								$S_3 \in \{s = 3\}$	0.256	3.000
			h_3^4	5.414	13.000	3.148	6.514	$S_1 \in \{s = 1\}$	1.498	3.000
								$S_1 \in \{s = 2\}$	0.414	3.000
								$S_3 \in \{s = 1\}$	0.289	3.000

			h_4^4	6.719	15.000	8.587	9.784	$S_1 \in \{s=2\}$	0.438	1.000
								$S_3 \in \{s=3\}$	0.875	1.000
Parallel	T_2	24.171	h_1^2	11.044	14.000	3.208	2.682	$S_1 \in \{s=1\}$	0.626	3.000
								$S_3 \in \{s=1\}$	1.195	3.000
								$S_3 \in \{s=2\}$	1.188	3.000
			h_2^2	2.315	16.000	2.219	7.234	$S_1 \in \{s=1\}$	0.615	3.000
								$S_3 \in \{s=2\}$	0.473	3.000
	T_3	24.853	h_1^3	9.090	19.000	8.491	7.867	$S_1 \in \{s=1\}$	0.530	2.000
								$S_3 \in \{s=1\}$	0.605	2.000
								$S_3 \in \{s=2\}$	0.293	2.000
			h_2^3	1.610	5.000	4.381	2.393	$S_1 \in \{s=1\}$	0.687	2.000
								$S_3 \in \{s=2\}$	0.981	2.000
			h_3^3	7.339	6.000	2.077	4.504	$S_1 \in \{s=1\}$	1.320	1.000
								$S_1 \in \{s=2\}$	0.794	1.000
								$S_3 \in \{s=1\}$	0.378	1.000

Table A.15 – Rest of parameter values of sample 3

Parameters	**Value**	**Unit**	**Type**
$lt_{i,i'}$	UI*[3, 6]	min	Integer
$lc_{i,i'}$	U*[12, 20]	$	Decimal
$V_{s,u}^{i,k}$	UI[0, 1]		Integer
$T_{\max}$	100		Integer
$C_{\max}$	1000		Integer
$Q_{\min}$	10		Integer
M	100000		Integer
w_T	0.3		Decimal
w_C	0.3		Decimal
w_Q	0.4		Decimal

It represents the generation of a random number from a discrete uniform distribution in the interval from a to b.	UI[a, b]*
It represents the generation of a random number from a continuous uniform distribution in the interval from a to b.	U[a, b]*

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