Research on modeling of cloud manufacturing resources selection

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Abstract. Cloud Manufacturing (CMfg) combines computing resources of the Internet and manufacturing resources of the enterprise into a large data resource pool to realize the configuration of manufacturing resources and manufacturing tasks. In order to solve the hugeness and complexity of the resource pool in CMfg, simplify the process links and save manufacturing resources, shorten the production time of enterprises and improve the production efficiency of enterprises, a model for the optimal selection of cloud manufacturing resources is proposed, which was based on production cost, production time, processing quality and other evaluation factors.

1. Introduction
With the rapid development of Internet technology, the manufacturing industry has undergone amazing changes, and the goals pursued by the manufacturing industry have gradually changed, from the previous large-scale production, low-cost production, high-efficiency production to the current high-tech innovative production and networked manufacturing and its service model. CMfg, as a new manufacturing model, embodies the perfect combination of manufacturing and the Internet in the information age. It breaks the limitation of spatial location, can collect manufacturing resources distributed in different locations through the server, and provides users in different locations with more convenient and timely services than traditional networked manufacturing. It absorbs the advanced achievements of manufacturing models such as grid manufacturing and application service providers, and draws on the development of cloud computing. In 2010, the concept of CMfg [1, 2] was officially pointed out, which promotes the intellectualization and networking of manufacturing models. However, the influx of manufacturing resources and inefficient matching capabilities make it difficult for traditional methods to meet market demands. The huge resource pool and resource dispersion and heterogeneity are three prominent features of cloud manufacturing platform manufacturing resources. One of the keys to complete the manufacturing task of an enterprise is the allocation of cloud manufacturing resources, which will directly affect the quality of manufacturing services and the efficient operation of service processes. Therefore, the traditional method cannot reasonably configure the resources in the cloud manufacturing platform, and it is difficult to optimize the resources. It is important to optimize the cloud manufacturing resources.

2. Related work
Many scholars have conducted corresponding research on cloud manufacturing resources. Many researchers have established mathematical models based on different evaluation schemes based on their respective research directions, and use some intelligent algorithms such as genetic algorithm
(GA), particle swarm optimization (PSO), and ant colony algorithm (ACO) to achieve resource intelligence optimization. Based on previous research on service-oriented manufacturing such as manufacturing grid [3-4], a new model was proposed, which fully considered the characteristics of cloud manufacturing, and then an efficient OACR intelligent algorithm was designed in the cloud manufacturing resource configuration [5]. Based on the gray-scale evaluation method (GRA), the optimized resource allocation of on-demand services was realized, and which was applied to the optimization of simulation task configuration schemes, providing the best solution for high quality and high production [6]. Furthermore, a new group leader algorithm (GLA) [7] was put forward to effectively solve the multi-objective SCOS problem when facing a key problem in cloud manufacturing system service composition and optimal selection (SCOS). The complex problem of the best service composition in the cloud platform to respond to the user's request was solved by introducing the sensitive optimization approach (EOA) [8]. The problem of cloud service combination optimal selection (CSCOS) in CMfg was studied [9], and the categories of cloud services and their QoS indicators was established. And based on the genetic algorithm, a new chaos control optimization algorithm was designed to search for more effective solutions. The crossover and mutation operation rules [10] was designed for real matrix, a genetic algorithm based on real matrix coding was proposed to solve the problem of resource association and sharing in multitask-oriented virtual resource integration and optimal scheduling in cloud manufacturing. A relevant perceptual QoS computing model was established for manufacturing business aggregation in cloud manufacturing [11]. And an improved discrete bee algorithm based on Pareto optimal concept is proposed to enhance the ability of escaping from local optimal and improve the efficiency of resource allocation. There are uncertainties and dynamics in cloud manufacturing platform, and it leads to the conflict of manufacturing service requirements among multiple projects. In order to solve this problem, a minimum model of global objective and task partial objective change with the shortest duration is proposed [12], and a method based on serial scheduling generation scheme (SSGsS) and ant colony optimization algorithm is used to solve this model. A global optimization model was proposed to quantify manufacturing resources and capabilities to allocate manufacturing resources and capabilities [13], so as to support cloud manufacturing to effectively deal with the management and allocation of large-scale and distributed manufacturing resources. In order to deal with the optimal selection of processing equipment in cloud manufacturing and introduce the optimal selection strategy for the processing equipment in cloud manufacturing to find the most reasonable resource scheduling solution, the priority method was used to transform the multi-objective problem into a single objective problem, and a modified particle swarm optimization algorithm (IPSO) [14] was proposed, which provides theoretical support for the development of cloud manufacturing. In addition, a mathematical model [15] was built with cost, time, quality and risk indicators in 2015, and a swap-shuffled leap-frog algorithm (SSFLA) model with good robustness and convergence was used to implement resource optimization configuration.

Based on the existing research results, this study not only takes the production cost, production time and processing quality as evaluation indexes, but also introduces other evaluation indexes such as personnel requirements, material grade technical information, etc. to construct the model of cloud manufacturing resource selection.

3. Mathematical model of cloud manufacturing resource selection

In order to achieve cloud manufacturing resource selection, a multi-objective optimization model needs to be established. Because the traditional resource selection only considers the preference of narrowly manufactured resources. It is one-sided. The selection of cloud manufacturing resources requires a comprehensive consideration of generalized manufacturing resources. Therefore, the selection of cloud manufacturing resources is not only related to production cost, production time, processing quality, but also related to raw material supply, related personnel factors, software factors and other technical information factors. Facing this kind of problem, we can solve it with multi-objective optimization mathematical model. Therefore, a mathematical model was established for the resource optimization selection process in the cloud environment. Different resource selection
schemes will bring different economic benefits to the enterprise, mainly involving production cost, production time, processing quality and other evaluation indicators.

It is assumed here that the processing procedure and other selection categories of manufacturing resources have been determined, called Processing Task (PT), which is recorded as:

$$PT = \{PT_1, PT_2, \cdots, PT_m\}$$

(1)

For each processing task $PT_i$, there are $n_i$ manufacturing resources that can be used to complete the processing task, which are recorded as:

$$MR = \{MR_1, MR_2, \cdots, MR_n\}$$

(2)

The value of $n_i$ is not fixed, but variable, that is to say, the number of manufacturing resources corresponding to each processing task that can complete the task is not fixed, but can be different. According to the production needs of different enterprises, the production cost, production time, processing quality and other evaluation indicators caused by the manufacturing resources that can complete each processing task are different. In order to meet the production needs and design requirements of the enterprise, it is necessary to match the appropriate manufacturing resources for each processing task, and finally select the optimal processing plan. In addition, design variables are required as shown in equation (3).

$$x_{ij} = \begin{cases} 1 & \text{Task } i \text{ selects the corresponding } j \text{th resource} \\ 0 & \text{otherwise} \end{cases}$$

(3)

When the $i$-th processing task selects the $j$-th resource in the corresponding manufacturing resource, the value of the $x_{ij}$ is 1, otherwise it is recorded as 0, and the overall formula is expressed as:

$$x_{ij} = \begin{cases} 1 & \text{Task } i \text{ selects the corresponding } j \text{th resource} \\ 0 & \text{otherwise} \end{cases}$$

(3)

However, when the design variables are specifically used, for example, the manufacturing resources and the detailed classification need to be reflected, the design variables need to be adjusted in time, so the design variables can also be expressed as:

$$x_{ik} = \begin{cases} 1 & \text{Task } i \text{ selects the } k \text{th resource in the } j \text{th resource class} \\ 0 & \text{otherwise} \end{cases}$$

Before designing the multi-objective function, it is necessary to design the function model separately for the influencing factors such as production cost, production time, processing quality and other evaluation indicators.

3.1. Production cost objective function

$$f_i(x) = C1 + C2 + \cdots + Cn = \sum_{i=1}^{m} \sum_{j=1}^{t} \sum_{k=1}^{n} C_{ijk} x_{ijk} + \sum_{i=1}^{m} \sum_{k=1}^{n} C_{iak} x_{iak} + \sum_{i=1}^{m} \sum_{l=1}^{n} C_{ilk} x_{ilk}$$

(4)

Where, $C_{ijk}$ represents the cost when the equipment resource numbered $k$ in the $j$-th class equipment resource can be used to process the $i$-th machining task. $C_{iak}$, $C_{iak}$, $C_{iak}$, $C_{iak}$, $C_{iak}$ indicates the cost of materials, personnel, software, technical information resources, and resources named $N$ that can be used to process the $i$-th machining task. Where $i=1,\ldots,m$ represents the number of machining tasks, $j=1,\ldots,t$ represents the number of device resource categories (machine tools, tools, fixtures, gauges, etc.), $k=1,\ldots( l_1, l_2, l_3, l_4, \cdots, l_n )$ represents the resource number. $l_1, l_2, l_3, l_4, \cdots, l_n$ respectively represents the specific resource number in the equipment resource (for example, the number of machine tools), the number of material resources, the number of personnel, the number of software resources, and the number of technical information resources, etc. The number of resources named $N$. 
3.2. Production time objective function

\[
f_i(x) = T_1 + T_2 + \cdots + T_n = \sum_{i=1}^{n} \sum_{j=1}^{l_i} \sum_{k=1}^{n} \frac{T_{ik}^{\text{basic}}}{x_{jk}} + \sum_{i=1}^{n} \sum_{j=1}^{l_i} \sum_{k=1}^{n} \frac{T_{ik}^{\text{aux}}}{x_{jk}} + \sum_{i=1}^{n} \sum_{j=1}^{l_i} \sum_{k=1}^{n} \frac{T_{ik}^{\text{serve}}}{x_{jk}} \]

(5)

Where, \( T_{ik}^{\text{basic}} \), \( T_{ik}^{\text{aux}} \), \( T_{ik}^{\text{serve}} \) respectively represents the basic time, auxiliary time, and service time when the device resource numbered \( k \) in the \( j \)-th class equipment resource can be used to process the \( i \)-th processing task. The purpose of adopting \( \frac{T_{ik}^{\text{basic}}}{x_{jk}} \) where the value of \( k \) in the first three formulas is related to the value of \( j \) represents the resource number.

3.3. Processing quality objective function

\[
f_j(x) = Q_1 + Q_2 + \cdots + Q_n = \sum_{i=1}^{n} \sum_{j=1}^{l_i} \sum_{k=1}^{n} Q_{ik}^{\text{basic}} x_{jk} + \sum_{i=1}^{n} \sum_{j=1}^{l_i} \sum_{k=1}^{n} Q_{ik}^{\text{aux}} x_{jk} + \cdots + \sum_{i=1}^{n} \sum_{j=1}^{l_i} \sum_{k=1}^{n} Q_{ik}^{\text{serve}} x_{jk} \]

(6)

Where, \( Q_{ik}^{\text{basic}} \) indicates the processing quality accuracy of the device resource numbered \( k \) in the \( j \)-th equipment resource when processing the \( i \)-th processing task. \( Q_{ik}^{\text{aux}} \) indicates the accuracy of the material resource numbered \( k \) when processing the \( i \)-th machining task. \( Q_{ik}^{\text{serve}} \) represents the precision of the resource named \( N \) with number \( k \) when processing the \( i \)-th machining task.

3.4. Other evaluation index functions

\[
f_k(x) = M_1 + M_2 + \cdots + M_n = \sum_{i=1}^{n} \sum_{j=1}^{l_i} \sum_{p=1}^{n_1} \left( M_{ip} - C_{ik}^{\text{same}} \right) x_{jk} \]

(7)

Where, \( i \) is the number of machining tasks, \( k \) is the material resource numbered \( k \), \( p=1, 2, \ldots, n_1 \) is the number of evaluation indicators in the material resource (with merchant credit, material grade, etc.). \( M_{ip} \) indicates the \( p \)-th evaluation index value when the material resource with no. \( k \) can be used to process the \( i \)-th processing task. The purpose of adopting \( \sum_{i=1}^{n} \sum_{j=1}^{l_i} \sum_{p=1}^{n_1} \left( M_{ip} - C_{ik}^{\text{same}} \right) x_{jk} \) is to ensure that the material resources selected under such evaluation indicators are the same as the material resources selected before, so as to prevent the high evaluation indicators and low cost are not the same material resources.

\[
f_s(x) = E_1 + E_2 + \cdots + E_n = \sum_{i=1}^{n} \sum_{j=1}^{l_i} \sum_{p=1}^{n_2} \left( E_{ip} - C_{ik}^{\text{same}} \right) x_{jk} \]

(8)

Where, \( i \) is the number of machining tasks, \( p=1, 2, 3, 4, \ldots, n_2 \) represents the number of evaluation indicators of human resources (including popularity, achievement works, personnel level, education background, etc.). \( E_{ip} \) indicates the \( p \)-th evaluation index value when the human resource numbered \( k \) can be used to process the \( i \)-th processing task.

\[
f_s(x) = F_1 + F_2 + \cdots + F_n = \sum_{i=1}^{n} \sum_{j=1}^{l_i} \sum_{p=1}^{n_3} \left( F_{ip} - C_{ik}^{\text{same}} \right) x_{jk} \]

(9)

Where, \( i \) is the number of machining tasks, \( p=1, 2, 3, 4, \ldots, n_3 \) represents the number of technical information resource evaluation indicators (information reliability, etc.). The evaluation index in the technical information resource is the information reliability is recorded as \( r_{ik} \), which indicates the
evaluation index value of the technical information resource with the number of $k$ when processing the $i$-th processing task.

$$f_i(x) = S_1 + S_2 + \cdots + S_n = \sum_{i=1}^{m} \sum_{k=1}^{n} (\sum_{p=1}^{p} S_{ikp} - C_{ik}) x_{ik}$$  \hspace{1cm} (10)$$

Where, $i$ is the number of machining tasks, $p = 1, 2, \ldots, n$, $n$ represents the number of evaluation indicators of software resources (software stability and analysis capabilities, etc.). $S_{ikp}$ represents the $p$-th evaluation index value when the software resource numbered $k$ can be used to process the $i$-th machining task.

In other evaluation index objective functions, there may be other resources besides material resources, human resources, technical information resources and software resources. Here, you can add corresponding other resource evaluation functions according to the actual situation, as shown in the equation (11):

$$f_i(x) = \sum_{i=1}^{m} \sum_{k=1}^{n} (\sum_{p=1}^{p} N_{ikp} - C_{ik}) x_{ik}$$ \hspace{1cm} (11)$$

Where, $i$ is the number of machining tasks, $p = 1, 2, \ldots, n$, $n$ represents the number of evaluation indicators for the resource named $N$. $N_{ikp}$ indicates the value of the $p$-th evaluation index when the resource named $N$ with no. $k$ can be used to process the $i$-th processing task.

To sum up, the total objective function of processing scheme optimization in cloud manufacturing environment is as follows:

$$F(x) = W_1 f_1(x) + W_2 f_2(x) + W_3 f_3(x) + W_4 f_4(x) + \cdots + W_n [\pm f_n(x)] + \cdots + W_n [\pm f_n(x)]$$  \hspace{1cm} (12)$$

Where, $i=1\ldots n$, the positive and negative values of $[\pm f_n(x)]$ depend on the specific meaning of $n$. If it is a maximizing problem, the value is negative; if it is a minimization problem, the value is positive. $W_i$ is the weight of each objective function.

4. Conclusions and prospects
The complexity and hugeness of cloud manufacturing resources make the choice of manufacturing resources more diversified when enterprises process and produce parts products. In order to save production costs, rationally utilize idle manufacturing resources, and improve production efficiency, enterprises have to find more suitable manufacturing resources. These manufacturing resources are brought together, which is a processing plan. This paper analyzes the characteristic attributes of manufacturing resources, screens out the evaluation indexes of cloud manufacturing resources, and establishes the mathematical model of selecting scheme under cloud environment, which mainly includes four kinds of objective functions: production cost, production time, processing quality and other evaluation indicators.

When cloud manufacturing resources are preferred, this paper does not consider the current state of use of certain manufacturing resources, that is, whether the currently selected manufacturing resources are available. The next step of the study will consider this problem, improve the cloud manufacturing resources optimization method and improve the present evaluation indicators to make it more effective to provide reliable theoretical basis and methodological reference for the modeling and optimization of cloud manufacturing resources.

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