Hindawi
Complexity
Volume 2020, Article ID 5619758, 13 pages
https://doi.org/10.1155/2020/5619758

Research Article

Optimized Configuration of Manufacturing Resources for Middle and Lower Batch Customization Enterprises in Cloud Manufacturing Environment

Yinyun Yu and Wei Xu

School of Management, Shenyang University of Technology, No. 111, Shenliao West Road, Economic & Technological Development Zone, Shenyang 110870, China

Correspondence should be addressed to Wei Xu; 369252882@qq.com

Received 19 May 2019; Revised 24 August 2019; Accepted 13 September 2019; Published 9 January 2020

Academic Editor: Chongyang Liu

The optimal configuration of manufacturing resources in the cloud manufacturing environment has always been the focus of research on various advanced manufacturing systems. Aiming at the problem of manufacturing resources optimization configuration for middle and lower batch customization enterprises in cloud manufacturing environment, this paper gives a bi-level programming model for manufacturing resources optimization configuration in cloud manufacturing environment which fully considers customer satisfaction and enterprise customization economic benefits. The method firstly identifies the relationship between customer demands and customer satisfaction through questionnaires and quantifies the Kano model effectively. Then, it uses Quality Function Deployment (QFD) to transform customer demand characteristics into engineering characteristics and integrates the qualitative and quantitative results of the Kano model. Next, the method establishes enterprise economic benefits function according to the factors of order quantity and input cost. Furthermore, a comprehensive nonlinear bi-level programming model is established based on cost, time, and quality constraints. The model is solved by intelligent algorithm. Finally, the validity and feasibility of the model are verified by model simulation of actual orders of an enterprise. This method effectively realizes the optimal configuration of manufacturing resources in the cloud manufacturing environment, while maximizing the interests of both suppliers and demanders.

1. Introduction

In today's economic globalization, the market has gradually transformed from a seller's market to a buyer's market which has prompted more and more companies to start from traditional stock-based production to order-based production, in order to better meet the demand for products and services. The order-based production model requires companies to provide customers with the best possible products and services in the shortest possible time, while reducing the production costs of the company as much as possible [1]. The "cloud manufacturing" production model provides a new development model for the development of the manufacturing industry. In the cloud manufacturing environment, enterprises with insufficient resources can save the cost of purchasing and maintaining large-scale equipment by renting manufacturing equipment, and so on. At the same time, resource idle enterprises can use the method of renting manufacturing equipment to create profits for the enterprise [2]. Manufacturing resources optimization configuration as a core component of cloud manufacturing which is the key link to reduce the cost of resource use and improve the efficiency of resource utilization [3].

How to scientifically and efficiently realize the optimal configuration of production and processing resources, improve the utilization efficiency of production and processing resources, and provide customers with better production and processing services, which become an important issue for the cloud manufacturing model to explore and research [4]. Therefore, this paper presents a bi-level planning manufacturing resource optimization configuration model based on customer satisfaction and economic benefits. The next structure of this paper is as follows: Section 2 introduces the current state of research on manufacturing resource optimization configuration; Section 3 introduces problem description of the paper; Section 4 details the manufacturing resources optimization configuration model proposed in this paper; Section 5 simulates the model with an instance; Section 6 and Section 7 make a brief discussion and conclusion, respectively.

2. Literature Review

If enterprises want to gain a favorable position in the current fierce market competition, they must establish alliance-based networked off-site collaborative manufacturing alliances with other enterprises to form a virtual enterprise and carry out effective manufacturing resources optimization configuration [5]. Due to different manufacturing tasks and different manufacturing capabilities, there are two types of manufacturing resources optimization configuration in the cloud manufacturing environment: optimized configuration of manufacturing resources within the enterprise in cloud manufacturing environment and optimized configuration of manufacturing resources between enterprises in cloud manufacturing environment.

Akbaripour et al. proposed a new mixed integer programming (MIP) model to solve the process of service selection optimization and scheduling (SSOS) under the condition of cost and quality over time which the model is applied to the motorcycle manufacturing task in the cloud manufacturing environment [6]. Wu et al. studied tolerance design, a key technology for developing quality and reducing cost in cloud manufacturing environment, and used two-level game theory to optimize the problem. The supplier level and the demander level are regarded as the two sides of the game. Through this game, both the supplier and the customer can eventually achieve a balance and realize the effective allocation of resources [7]. Zheng et al. proposed an integrated resource service selection method based on designer preference and fuzzy quality of service (FQoS) in cloud manufacturing environment; then particle swarm optimization (PSO) was used to select the optimal service composition; and finally, a numerical example was given to verify the effectiveness and scientificity of the proposed method [8]. Based on the custom technology and order preference method, Zhang et al. establishes a comprehensive objective function which considers the minimum standard cost, the highest priority, the highest reliability, the lowest energy consumption, and the maximum customer satisfaction to facilitate the demand in the cloud manufacturing environment [9]. Cao et al. uses fuzzy decision theory to convert TQCS values into relative dominance, taking into account the factors affecting time, quality, cost, and service (TQCS), and then, by combining the weighted coefficients, the four relative dominances are combined into one overall optimization goal, and the service selection and scheduling model is established [10]. Zhang proposed a new energy adaptive immune genetic algorithm (EAIGA) in order to realize low-cost and high-efficiency mechanical design task scheduling in cloud manufacturing environment. This algorithm can not only improve the search diversity based on immune strategy but also adaptively adjust the probability of crossover and mutation which can effectively achieve a good balance between resource search diversification and intensification [11].

In the existing research on the manufacturing resources optimization configuration in the cloud manufacturing environment, most of the research only considers the unilateral influence factors and constraints in the resource optimization configuration which does not consider the satisfaction of the customized parties. Moreover, there are many research results on the optimal allocation of resources within enterprises, and there are few models considering the collaborative optimal allocation of manufacturing resources among enterprises, which cannot effectively solve the problem of idle and redundant resources in the whole industry. Based on this, this paper proposes a method to manufacturing resources optimization configuration in cloud manufacturing environment, which aims at customer satisfaction and enterprise customization economic benefits.

3. Problem Description

In the cloud manufacturing environment, due to the complexity of the customized product manufacturing process, a manufacturing company often cannot complete the manufacturing orders independently which requires multiple manufacturing companies to work together to complete. When the manufacturing company receives the customer's customized product processing order, it first organizes the process experts to analyze the production process of the customized product according to the customer order details and customer needs and uses the appropriate method to decompose the total production and processing tasks into a single production task; then, according to the production and processing capabilities of the enterprise, it is clarified which sub-tasks can be completed independently by the enterprise and which sub-tasks need to be completed together with other companies by coordinating production. In a cloud manufacturing environment, there are often multiple manufacturing companies that can accomplish collaborative manufacturing sub-tasks. Enterprises should build a collaborative enterprise selection optimization model based on factors such as time, quality, and cost of customer orders, which select the most suitable collaborative manufacturing enterprises among the many candidate collaborative manufacturing enterprises to obtain maximum customer satisfaction and the company's maximum economic benefits [12]. The process of optimizing configuration of manufacturing resources for middle and lower batch customization enterprises in cloud manufacturing environment is shown in Figure 1.

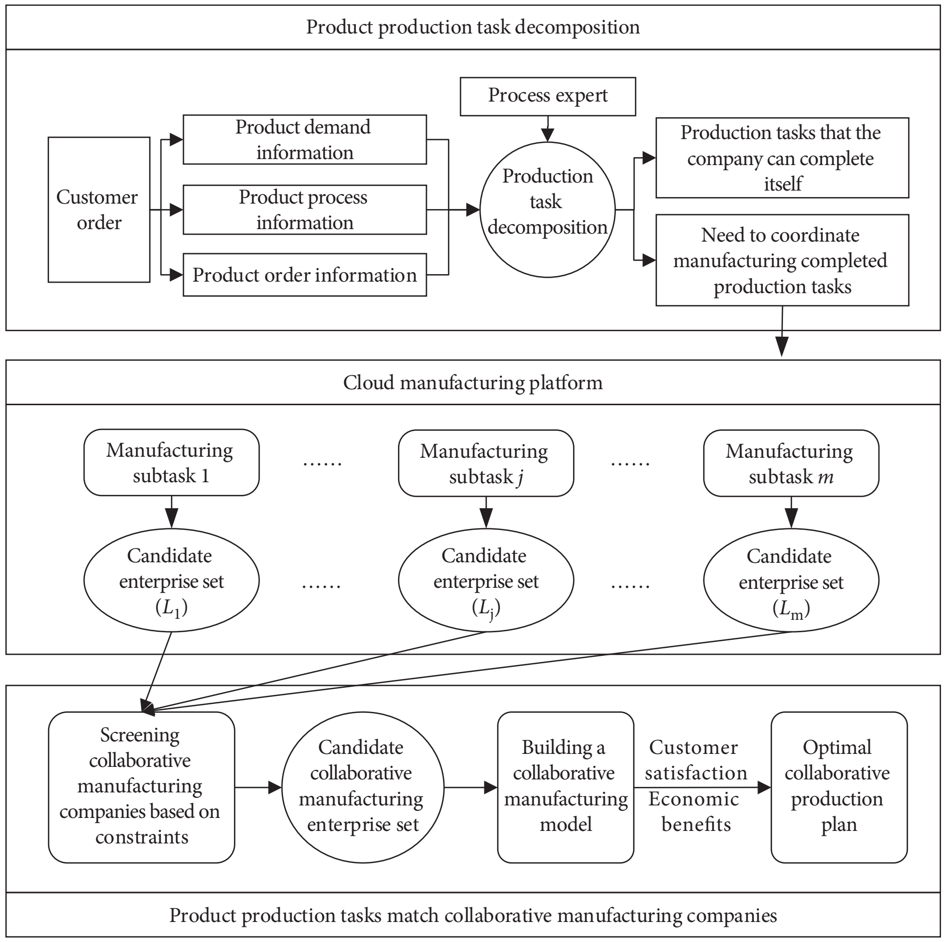

Figure 1: The process of manufacturing resources optimization configuration.

It can be seen from Figure 1 that the collaborative manufacturing resource optimization configuration of the customized product involves the customer layer, the enterprise layer, the collaborative enterprise layer, and so on, which needs to consider many factors. Customers pursue the maximization of satisfaction, hoping that product quality, delivery time, purchase cost, and so on can meet their maximum expectations. However, manufacturing enterprises pursue the maximization of enterprise customization economic benefits, hoping to obtain the maximization of enterprise economic benefits through the smallest production input. For the same order, the maximization of customer satisfaction and the maximization of enterprise economic benefits cannot always reach the maximum at the same time. There is always a certain contradiction between them. Therefore, in the process of optimizing configuration of manufacturing resources for middle and lower batch customization enterprises in cloud manufacturing environment, not only the maximization of enterprise customization economic benefits but also the maximization of customer satisfaction should be considered. Through the game between them, we can get the balance which makes the economic benefits of customization and customer satisfaction reach the maximum at the same time.

4. The Proposed Method

4.1. Preliminary Knowledge

4.1.1. Kano Model. Kano model is a mathematical model proposed by Professor N. Kano, which can obtain customer demand classification, priority ranking, and the nonlinear relationship between customer satisfaction and customer demands [13]. Kano thinks that the customer satisfaction is essentially the difference between actual perception and expectation perception, that is, when the customer compares the perception of the product or service with the actual perception, the happiness or disappointment generated by the customer is the customer satisfaction. According to the relationship between customer demand characteristics and customer satisfaction, we divide customer demand characteristics into Must-be Quality (M), One-dimensional Quality (O), Attractive Quality (A), Indifferent Quality (I), and Reverse Quality (R) [14], as shown in Figure 2.

(1) Must-Be Quality (M). It refers to the characteristics that customers believe should be included in the products or services provided by enterprises. Must-be quality is positively related to customer satisfaction.

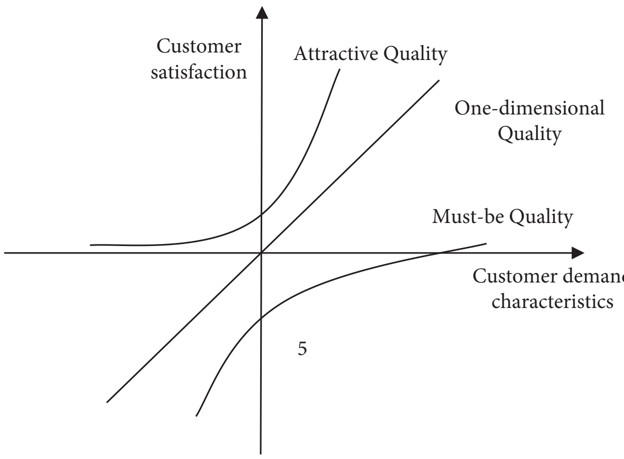

Figure 2: The model diagram of Kano.

(2) One-Dimensional Quality (O). It means that the customer wants the product or service provided by the company to contain this characteristic.

(3) Attractive Quality (A). It means that the products or services provided by the company contain characteristics that the customer did not think. If the company provides this characteristic, customer satisfaction can grow rapidly; if the company does not provide this feature, customer satisfaction will not be reduced.

(4) Indifferent Quality (I). It means that the increase or decrease in the characteristics of the products or services provided by the company will not affect the increase or decrease of customer satisfaction.

(5) Reverse Quality (R). It means that the characteristics that the customer does not want the products or services provided by the company. Reverse quality is inversely related to customer satisfaction.

4.1.2. QFD Model. Because the customer demands of products or services expression are comprehensive, it is necessary to adopt the basic principle of QFD to refine the customer demand characteristics.

At this time, we need to adopt the basic principles of QFD to decompose the characteristics of customer demand in detail, that is, transforming the customer demand characteristics into the specific engineering characteristics of a product or service [15]. For example, when a customer purchases a car, he gives his first demand characteristic as “fast.” If we use QFD to convert demand characteristics, it requires the car manufacturer to strengthen the engine. Studies have shown that QFD not only can well represent the correlation-degree between customer demand characteristics and engineering characteristics but also can express the autocorrelation-degree between engineering characteristics [16]. Based on this, the function representation relationship between the demand characteristics and the engineering characteristics is determined. Before a QFD optimization model is established, the House of Quality (HoQ) should be constructed at first. A typical HoQ comprises of six main parts as described in Figure 3.

4.1.3. Bi-Level Programming Mode. In the cloud manufacturing environment, the manufacturing resources optimization configuration research should not only consider the maximization of customer satisfaction but also consider the maximization of enterprise customization economic benefits. The process of optimization is a typical Multiobjective Optimization Problem (MOP), so we can use the bi-level programming mode to describe the relationship between the customer and the enterprise.

Compared with the traditional single-level planning model, the bi-level programming model has the following significant advantages. Firstly, the upper and lower decision makers have their own objectives and constraints in the bi-level programming model. Secondly, the upper objective and the lower objective can form their own optimal values through game theory. The mathematical description of the bi-level programming model is as follows [17]:

$$\begin{aligned} (U) \quad & \max Z(x, y), \\ & \text{s.t.}\, G(x, y) \leq 0; \\ (L) \quad & \max f(x, y), \\ & \text{s.t.}\, g(x, y) \leq 0, \end{aligned} \tag{1}$$

where (U) is the the upper objective; (L) is the lower objective; G is the upper constraint; and g is the lower constraint. The lower decision variable y is a function of the upper decision variable x, i.e., $y = y(x)$. This paper adopts the theory of the bi-level programming model to solve the problem of manufacturing resources optimization configuration in the cloud manufacturing environment. The maximum customer satisfaction is the upper objective and the maximum enterprise customization economic benefits are the lower objective, as shown in Figure 4.

4.2. Model Building

4.2.1. Calculation of Customer Satisfaction. Calculating customer satisfaction (CS) and customer disappointment (DS) is the first step in quantitative analysis of the Kano model. EOC Mkpojiogu [18] believes that customers have different demand characteristics for the same product or service, so customer satisfaction (CS) and customer disappointment (DS) which can be said by percentage of customers who are satisfied or dissatisfied; they can be calculated using the following formulas:

$$\mathrm{CS}_i = \frac{M_i + O_i + A_i}{M_i + O_i + A_i + I_i + R_i}, \quad i = 1, \ldots, n, \tag{2}$$

$$\mathrm{DS}_i = \frac{I_i + R_i}{M_i + O_i + A_i + I_i + R_i}, \quad i = 1, \ldots, n, \tag{3}$$

where CS_i and DS_i represent customer satisfaction and customer dissatisfaction with the i-th demand characteristic,

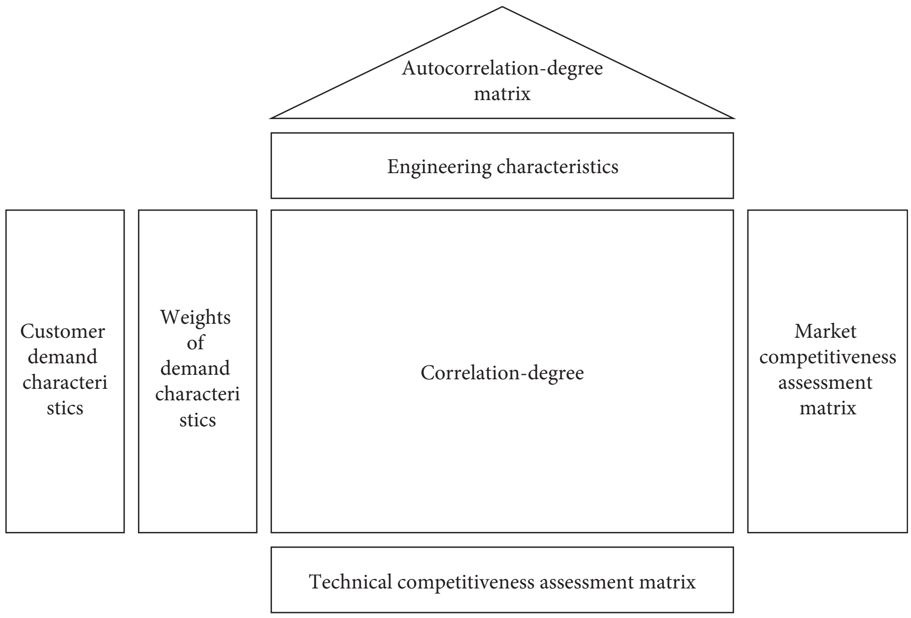

Figure 3: The House of Quality model.

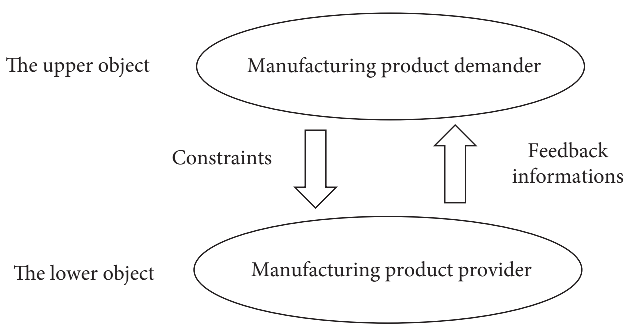

Figure 4: The bi-level programming model.

respectively; M_i, O_i, A_i, I_i, and R_i, respectively, indicate the number of people who think that the i-th demand characteristics are Must-be Quality (M), One-dimensional Quality (O), Attractive Quality (A), Indifferent Quality (I), and Reverse Quality (R).

After obtaining customer satisfaction (CS) and customer disappointment (DS), we can calculate the weight of each demand characteristic i and normalize it using the following formula.

$$\omega_i = \frac{\mathrm{CS}_i - \mathrm{DS}_i}{\sum_{i=1}^{n}\left(\mathrm{CS}_i - \mathrm{DS}_i\right)}, \quad i = 1, \ldots, n, \tag{4}$$

where ω_i represents the weight of the i-th demand characteristic.

We quantify the relationship between customer satisfaction (CS) and the customer demand satisfaction of demand characteristics (CR), recorded as $S_i = (y_i, a, b)$, where y_i indicates the degree of satisfaction for the i-th demand characteristic and a_i and b_i are the Kano model adjustment factors for different demand characteristics [19]. If the i-th demand characteristic is a Must-be Quality (M), the satisfaction function is expressed as $S_i = a_i(-e^{-y_i}) + b_i$. The adjustment factors a_i and b_i can be calculated by

$$a_i = \frac{e\left(\mathrm{CS}_i - \mathrm{DS}_i\right)}{e-1}, \qquad b_i = \frac{e\mathrm{CS}_i - \mathrm{DS}_i}{e-1}, \quad i = 1, \ldots, n. \tag{5}$$

If the i-th demand characteristic is a One-dimensional Quality (O), the satisfaction function is expressed as $S_i = a_2 y_i + b_2$. The adjustment factors a_i and b_i can be calculated by

$$a_i = \mathrm{CS}_i - \mathrm{DS}_i, \qquad b_i = \mathrm{DS}_i, \quad i = 1, \ldots, n. \tag{6}$$

If the i-th demand characteristic is a Attractive Quality (A), the satisfaction function is expressed as $S_i = a_2 e^{y_i} + b_2$. The adjustment factors a_i and b_i can be calculated by

$$a_i = \frac{\mathrm{CS}_i - \mathrm{DS}_i}{e-1}, \qquad b_i = \frac{\mathrm{CS}_i - e\mathrm{DS}_i}{e-1}, \quad i = 1, \ldots, n. \tag{7}$$

By integrating the three cases in Table 1, the CS-CR function can be expressed in general form: $S_i = a_i f(y_i) + b_i$, where $f(y_i)$ is the basic function to determine the shape of the relationship curve and a_i and b_i are adjustment coefficients of the Kano model with different demand characteristics.

4.2.2. Demand Characteristics and Engineering Characteristics Conversion Based on QFD. The "0–9" scoring method is used to score the autocorrelation-degree of engineering characteristics and the correlation-degree between demand

Table 1: CS-CR relational functions.

KC	a_i	b_i	$f(y_i)$	$S_i = a_i f(y_i) + b_i$
A	$(\mathrm{CS}_i - \mathrm{DS}_i)/(e-1)$	$(\mathrm{CS}_i - e\mathrm{DS}_i)/(e-1)$	e^{y_i}	$S_i = ((\mathrm{CS}_i - \mathrm{DS}_i)/(e-1))e^{y_1} + ((\mathrm{CS}_i - e\mathrm{DS}_i)/(e-1))$
O	$\mathrm{CS}_i - \mathrm{DS}_i$	DS_i	y_i	$S_i = (\mathrm{CS}_i - \mathrm{DS}_i)y_i + \mathrm{DS}_i$
M	$e(\mathrm{CS}_i - \mathrm{DS}_i)/(e-1)$	$(eCS_i - DS_i)/(e-1)$	$-e^{-y_i}$	$S_i = (e(\mathrm{CS}_i - \mathrm{DS}_i)/(e-1))e^{-y_1} + ((e\mathrm{CS}_i - \mathrm{DS}_i)/(e-1))$

characteristics and engineering characteristics, where “0” means no correlation and “9” means the strongest correlation. r_{ij} denotes the correlation-degree between the i-th demand characteristic and the j-th engineering characteristic; g_{kj} denotes the autocorrelation-degree of the j-th engineering characteristic.

Based on this, we can further obtain the association relationship between the i-th demand characteristic and the j-th engineering characteristic, as shown in the following formula:

$$R_{ij} = \sum_{k=1}^{m} r_{ik} g_{kj}, \quad i = 1, \ldots, n,\ j = 1, \ldots, m, \tag{8}$$

where R_{ij} denotes association relationship between the i-th demand characteristic and the j-th engineering characteristic.

In order to effectively improve the accuracy of the calculation results, the obtained association relationship needs to be normalized by

$$\widehat{R}_{ij} = \frac{R_{ij}}{\max\{R_{ij}\}}, \quad i = 1, \ldots, n,\ j = 1, \ldots, m. \tag{9}$$

Based on the normalized association relationship, the functional relationship between the i-th demand characteristic and the j-th engineering characteristic is further determined to be $Y = \widehat{R}X$, that is,

$$y_i = \widehat{R}_{ij} x_j, \quad i = 1, \ldots, n,\ j = 1, \ldots, m, \tag{10}$$

where $Y = \{y_1, \ldots, y_n\}$ is a set of customer demand characteristics, y_i denotes the i-th demand characteristic of customer and $X = \{x_1, \ldots, x_m\}$ is a set of engineering characteristics, x_j denotes the j-th engineering characteristic.

Combined with equations (5)–(10), the customer satisfaction function expression is

$$S(y_1, \ldots, y_n) = \sum_{i=1}^{n} \omega_i s_i, \quad i = 1, \ldots, n. \tag{11}$$

That is,

$$s_i = \begin{cases} \dfrac{\mathrm{CS}_i - \mathrm{DS}_i}{e-1} e^{\widehat{R}_{ij} x_j} - \dfrac{\mathrm{CS}_i - e\mathrm{DS}_i}{e-1}, (A), \\[2ex] (\mathrm{CS}_i - \mathrm{DS}_i) e^{\widehat{R}_{ij} x_j} + \mathrm{DS}_i, (O), \\[2ex] -\dfrac{e(\mathrm{CS}_i - \mathrm{DS}_i)}{e-1} e^{-\widehat{R}_{ij} x_j} + \dfrac{e\mathrm{CS}_i - \mathrm{DS}_i}{e-1}, (M), \\[2ex] \qquad\qquad\qquad i = 1, \ldots, n, \end{cases} \tag{12}$$

where ω_i denotes the proportion of the i-th demand characteristic to the customer’s entire demand, that is, the weight of the i-th demand characteristic.

4.2.3. Enterprise Customization Economic Benefits Calculation. In economics, economic benefits refer to the proportional relationship between the gross production value and production costs which is the ultimate comprehensive indicator for measuring all economic activities [20]. The enterprise customization economic benefits proposed in this paper refer to the economic benefits of enterprise under the environment of mass customization.

The enterprise customization economic benefits value can be expressed by the difference between the input values (I) and the output values (O) in the production process [21], as in the following equation:

$$E = O - I, \tag{13}$$

where E denotes the enterprise customization economic benefits.

The input value in the production process of an enterprise can be divided into direct costs C_1, indirect costs C_2, and hidden costs C_3.

Direct costs include the cost of raw materials used to purchase primary or auxiliary materials, the cost of purchasing production equipment, the product transportation costs for semifinished or finished products, and the labor costs of production and assembly staff. Indirect costs include the depreciation costs incurred by equipment production operations, the operating costs for normal production (e.g., plant lease fees, utility bills, etc.), and the labor costs of the operation management personnel. The hidden costs include the opportunity cost lost due to the capital flow being occupied and the cost of collaborative production with other companies, as shown in Table 2.

The sales output value of the enterprise mainly refers to the sales value of the products customized by the customer. For example, if the number of customized products is N and the price of each product is p, the sales output value is $N \times P$, that is, $I = N \times P$.

Based on the above analysis, the enterprise customization economic benefits E can be expressed as

$$E = N \times P - (C_1 + C_2 + C_3). \tag{14}$$

4.2.4. The Bi-Level Programming Mode for Manufacturing Resources Optimization Configuration. Considering the different objective functions of the supply and demand sides, customer satisfaction is selected as the upper objective function and the enterprise customization economic benefits

Table 2: Production input values.

Direct costs	Symbol	Indirect costs	Symbol	Hidden costs	Symbol
Raw material cost	c_{11}	Depreciation cost	c_{21}	Opportunity cost	c_{31}
Production equipment cost	c_{12}	Manager cost	c_{22}	Collaborative cost	c_{32}
Transportation cost	c_{13}	Operating cost	c_{23}		
Production worker cost	c_{14}				

is used as the lower objective function, and then selecting cost, time, and cost as constraints build the bi-level programming mode, as follows:

$$\max \quad S = \sum_{i=1}^{n} \omega_i s_i, \tag{15a}$$

$$\begin{aligned} \text{s.t.} \quad & p = \left(\sum_{i=1}^{n} \sum_{j=1}^{k_i} c_{ij} x_{ij} + C_1 + C_2 \right) \times (1 + r), \\ & \sum_{j=1}^{k_i} x_{ij} = 1; \\ & \sum_{i=1}^{n} \sum_{j=1}^{k_i} x_{ij} = n; \\ & \sum_{i=1}^{n} k_i = m; \end{aligned} \tag{15b}$$

$$\max \quad E = N \times p - \sum_{i=1}^{n} \sum_{j=1}^{k_i} c_{ij} x_{ij} - (C_1 + C_2), \tag{16a}$$

$$\begin{aligned} \text{s.t.} \quad & T_{\min} \le \sum_{i=1}^{n} \sum_{j=1}^{k_i} t_{ij} x_{ij} \le T_{\max}; \\ & \sum_{i=1}^{n} \sum_{j=1}^{k_i} c_{ij} x_{ij} + C_1 + C_2 \le N \times p; \\ & \frac{\sum_{i=1}^{n} \sum_{j=1}^{k_i} Q_{ij} x_{ij}}{n} \ge Q_{\min}; \\ & \sum_{j=1}^{k_i} x_{ij} = 1; \\ & \sum_{i=1}^{n} \sum_{j=1}^{k_i} x_{ij} = n; \\ & \sum_{i=1}^{n} k_i = m; \\ & x_{ij} = \begin{cases} 1, & EC_j \text{ are assigned to the } j-\text{th companies in the collaborative production enterprise set } B_i, \\ 0, & EC_j \text{ are assigned to the } j-\text{th companies in the collaborative production enterprise set } B_i, \end{cases} \end{aligned} \tag{16b}$$

where (15a) and (16a) denote the upper objective and the lower objective; (15b) and (16b) are upper and lower constraints; r is cost-profit margin; $[T_{\min}, T_{\max}]$ is the production lead time constraints for manufacturing orders; and $Q_{\min}$ is the minimum quality requirement for the product.

4.2.5. Model Solving. The bi-level programming problem is a kind of hierarchical optimization problem with master-slave hierarchical structure, which belongs to NP-hard problem [22]. Genetic algorithm (GA) is an optimization algorithm that simulates the inheritance and evolution of natural organisms.

The GA searches for the optimal solution in the global scope through coding, selection, intersection, and mutation, which can effectively solve the problem of large-scale nonlinear optimization [23, 24]. Aiming at the characteristics of the optimization problem of manufacturing resource configuration, this paper uses a hybrid genetic algorithm embedded in the bi-level programming principle to solve it [25, 26]. The solution process of the algorithm is as follows. Firstly, an initial solution g^0 of the lower objective function is obtained; then, the initial solution is substituted into the upper objective function, and the initial optimal decision variable value G^0 of the upper objective function and its objective function value $z(G^0)$ are obtained; finally, the initial optimal decision variable value of the upper layer is substituted into the lower layer plan to obtain the optimal value $f(G^0)$ of the lower objective function.

Through the selection, crossover, and mutation, the new feasible solution g' of the lower target is obtained. The new decision variable G' and the upper function value $z(G')$ are obtained by substituting g' into the upper objective function, and then, the new decision variable is substituted into the lower objective function to obtain the new lower function value $f(G')$. By iterating over and over again, the nonoptimal feasible solution is eliminated and the optimal solution of the bi-level programming problem is approached gradually. The basic flow chart of the algorithm is shown in Figure 5.

5. Example

We take the large lathe as an example. Enterprise A has received the processing order of CA6140 horizontal lathe from enterprise D. By consulting the relevant literature, we can know that the customer's demand characteristics for lathe are smooth speed (y_1), cutting precision (y_2), good support (y_3), excellent adjustability (y_4), easy to operate (y_5), and stable operation (y_6). According to this customer demand characteristics, we first designed a Kano survey questionnaire and distributed the questionnaire to the 150 respondents (including operators and managers) of the customer D company, and then, equations (2)

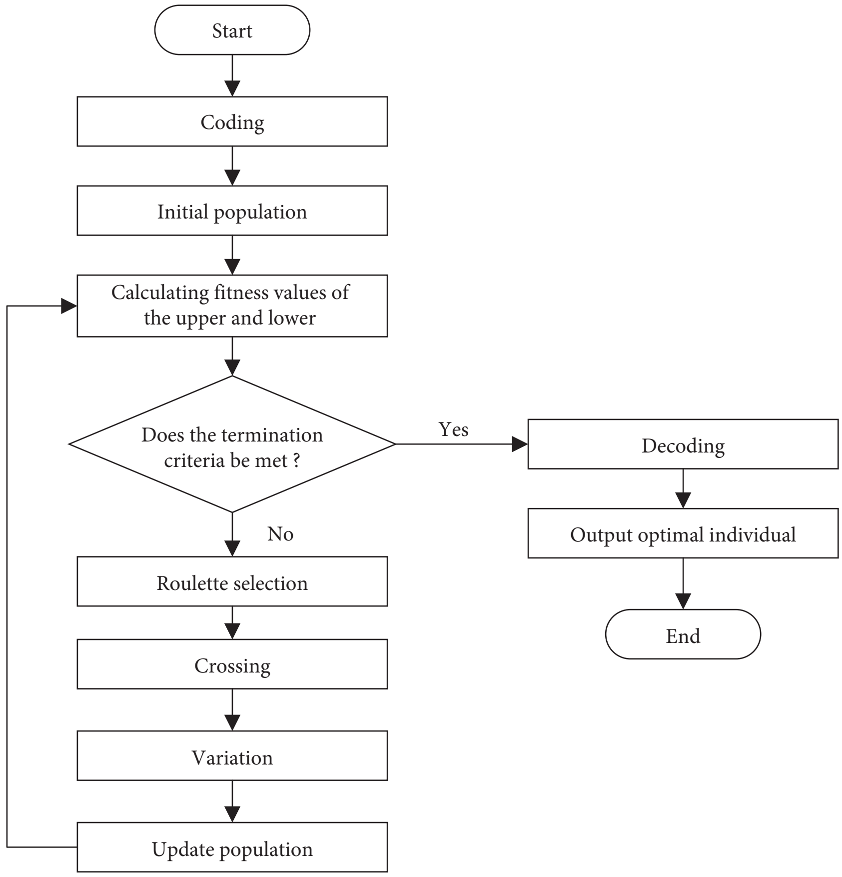

Figure 5: Basic flow chart of hybrid genetic algorithm.

and (3) were used to calculate the CS value, the DS value, and demand characteristics weights, as shown in Table 3.

From Table 3, it can be seen that smooth speed (y_1), cutting precision (y_2), and stable operation (y_6) are Must-be Qualities; good support (y_3) is One-dimensional Quality; which is the expected demand in customer demand characteristics; excellent adjustability (y_4) and easy to operate (y_5) are Attractive Qualities. At the same time, we can get the values of customer satisfaction (CS) and customer disappointment (DS). Then, we can calculate the weight value of each demand characteristic by using equation (4).

$$\begin{aligned}
\omega_1 &= \frac{0.9333 - 0.0667}{4.7064} = 0.1841,\\
\omega_2 &= \frac{0.9667 - 0.0333}{4.7064} = 0.1983,\\
\omega_3 &= \frac{0.9133 - 0.0867}{4.7064} = 0.1756,\\
\omega_4 &= \frac{0.8533 - 0.1467}{4.7064} = 0.1501,\\
\omega_5 &= \frac{0.8933 - 0.1067}{4.7064} = 0.1671,\\
\omega_6 &= \frac{0.7933 - 0.2067}{4.7064} = 0.1246.
\end{aligned} \tag{17}$$

Equations (5) and (7) were used to calculate the adjustment coefficients a_i and b_i of Kano model with different demand characteristics in Table 1, as shown in Table 4.

Next, we use QFD to translate the six demand characteristics of CA6140 lathe into six engineering characteristics. For example, the smooth speed of customer demand is converted into corresponding engineering characteristics, that is, the headstock (x_1) is working well. The other demand characteristics can be transformed into engineering characteristics: tool holder (x_2), tailstock (x_3), feed box (x_4), sliding box (x_5), and lathe bed (x_6), respectively. Then, we hired seven experienced process experts to score the autocorrelation-degree of engineering characteristics and the correlation-degree between engineering characteristics and demand characteristics using the "0–9" scoring method. The relationship matrix is obtained as follows:

$$\begin{aligned}
r &= \begin{bmatrix} 9 & 5 & 7 & 2 & 5 & 5\\ 5 & 9 & 6 & 1 & 4 & 4\\ 2 & 2 & 9 & 2 & 3 & 1\\ 3 & 3 & 1 & 9 & 6 & 2\\ 1 & 4 & 3 & 6 & 9 & 3\\ 5 & 6 & 2 & 4 & 5 & 9 \end{bmatrix},\\
g &= \begin{bmatrix} 9 & 4 & 5 & 4 & 3 & 2\\ 4 & 9 & 4 & 6 & 2 & 3\\ 5 & 4 & 9 & 3 & 7 & 1\\ 4 & 6 & 3 & 9 & 4 & 5\\ 3 & 2 & 7 & 4 & 9 & 3\\ 2 & 3 & 1 & 6 & 3 & 9 \end{bmatrix}.
\end{aligned} \tag{18}$$

Table 3: Analysis of questionnaire results.

Demand characteristics	M	O	A	I	R	Total	KC	CS	DS
Smooth speed (y_1)	79	50	11	10	0	150	M	0.9333	0.0667
Cutting precision (y_2)	67	36	42	5	0	150	M	0.9667	0.0333
Good support (y_3)	56	61	20	12	1	150	O	0.9133	0.0867
Excellent adjustability (y_4)	45	23	60	22	0	150	A	0.8533	0.1467
Easy to operate (y_5)	47	35	52	15	1	150	A	0.8933	0.1067
Stable operation (y_6)	50	24	45	31	0	150	M	0.7933	0.2067

Table 4: Adjustment coefficient and satisfaction function.

Demand characteristics	KC	a_i	b_i	$s_i = (y_i, a_i, b_i)$
y_1	M	1.3709	1.4376	$s_1 = a_1(-e^{-y_1}) + b_1$
y_2	M	1.4766	1.5099	$s_2 = a_2(-e^{-y_2}) + b_2$
y_3	O	0.8266	0.0867	$s_3 = a_3 y_3 + b_3$
y_4	A	0.4112	0.2645	$s_4 = a_4 e^{y_4} + b_4$
y_5	A	0.4578	0.3511	$s_5 = a_5 e^{y_5} + b_5$
y_6	M	0.9280	1.1347	$s_6 = a_6(-e^{-y_6}) + b_6$

Further, we obtain the association relationship R between the demand characteristic and the engineering characteristic by using equation (8) and normalize the association relationship R to obtain $\widehat{R}$.

$$\widehat{R} = \begin{bmatrix} 0.1861 & 0.1608 & 0.1916 & 0.1707 & 0.1696 & 0.1211 \\ 0.1688 & 0.1888 & 0.1875 & 0.1763 & 0.1588 & 0.1200 \\ 0.1664 & 0.1534 & 0.2348 & 0.1534 & 0.2052 & 0.0869 \\ 0.1480 & 0.1669 & 0.1553 & 0.2177 & 0.1713 & 0.1408 \\ 0.1318 & 0.1563 & 0.1793 & 0.1970 & 0.1984 & 0.1372 \\ 0.1522 & 0.1700 & 0.1463 & 0.2045 & 0.1534 & 0.1736 \end{bmatrix}. \tag{19}$$

From equation (10), we can get the relationship between demand characteristics and engineering characteristics as follows:

$$\begin{aligned} y_1 &= 0.1861x_1 + 0.1608x_2 + 0.1916x_3 + 0.1707x_4 + 0.1696x_5 + 0.1211x_6; \\ y_2 &= 0.1688x_1 + 0.1888x_2 + 0.1875x_3 + 0.1763x_4 + 0.1588x_5 + 0.1200x_6; \\ y_3 &= 0.1664x_1 + 0.1534x_2 + 0.2348x_3 + 0.1534x_4 + 0.2052x_5 + 0.0869x_6; \\ y_4 &= 0.1480x_1 + 0.1669x_2 + 0.1553x_3 + 0.2177x_4 + 0.1713x_5 + 0.1408x_6; \\ y_5 &= 0.1318x_1 + 0.1563x_2 + 0.1793x_3 + 0.1970x_4 + 0.1984x_5 + 0.1372x_6; \\ y_6 &= 0.1522x_1 + 0.1700x_2 + 0.1463x_3 + 0.2045x_4 + 0.1534x_5 + 0.1736x_6. \end{aligned} \tag{20}$$

According to the customer order details and the enterprise's production efficiency combined with the QFD method, designers can establish a house of quality model, as shown in Table 5.

According to the analysis of the process experts of A company, due to the limited manufacturing precision of the enterprise, it is impossible to complete the manufacture of the spindle box and the feed box, and it is necessary to find a company with high manufacturing precision to complete the cooperation.

According to the A enterprise's process expert analysis, A enterprise cannot complete the manufacture of feed box (x_4) and sliding box (x_5) because of its own manufacturing precision; therefore, it is necessary to find a enterprise with high manufacturing precision to complete the cooperation. Due to the high production cost of the enterprise, headstock (x_1), tool holder (x_2), tailstock (x_3), and lathe bed (x_6) need to find companies with lower manufacturing costs to cooperate.

Through the cloud manufacturing platform, the manufacturing enterprises that can complete the system manufacturing tasks are collected and assembled. The manufacturing resource collection is shown in Table 6.

The candidate enterprises sets for engineering characteristics manufacturing tasks x_1, x_2, x_3, x_4, x_5, and x_6 are B_1, B_2, B_3, B_4, B_5, and B_6 in which the number of candidate enterprises in each set is 3, 2, 3, 2, 4, and 2, respectively, and there are 16 enterprises in total.

In other words, for the production orders of D enterprises, it is necessary to select the most suitable 6 enterprises from 16 candidate companies to jointly complete 6 collaborative manufacturing tasks. This not only ensures that the final product can be completed within the customer's allowed delivery time, the price, and the processing quality that can be accepted by the customer but also ensures that the total manufacturing cost is relatively low, maximizing the company's economic benefits.

The D enterprise's custom number of CA6140 ordinary horizontal lathes is 30, that is, $N = 30$; the time allowed for delivery is $[T_{\min}, T_{\max}] = [35, 42]$; the minimum quality pass rate that can be tolerated is 0.86, i.e., $Q_{\min} = 0.86$. The A enterprise's maximum acceptable cost for the CA6140 ordinary horizontal lathe is 200000; the A enterprise's production input cost is 2000, that is, $C_1 + C_2 = 20000$; cost-profit margin is 0.091, that is, $r = 0.091$.

Table 5: Quality of House for CA6140 lathe.

Demand characteristics	ω_i	x_1	x_2	x_3	x_4	x_5	x_6
y_1	0.1841	0.1861	0.1608	0.1916	0.1707	0.1696	0.1211
y_2	0.1983	0.1688	0.1888	0.1875	0.1763	0.1588	0.1200
y_3	0.1756	0.1664	0.1534	0.2348	0.1534	0.2052	0.0869
y_4	0.1501	0.1480	0.1669	0.1553	0.2177	0.1713	0.1408
y_5	0.1671	0.1318	0.1563	0.1793	0.1970	0.1984	0.1372
y_6	0.1246	0.1522	0.1700	0.1463	0.2045	0.1534	0.1736

Table 6: Candidate manufacturing enterprise information.

Manufacturing tasks	Candidate enterprise sets	Candidate enterprises	Time	Cost	Quality
x_1	B_1	B_{11}	15	44	0.93
		B_{12}	12	47	0.96
		B_{13}	14	38	0.88
x_2	B_2	B_{21}	8	24	0.95
		B_{22}	5	26	0.93
x_3	B_3	B_{31}	4	28	0.89
		B_{32}	3	29	0.91
		B_{33}	2	33	0.87
x_4	B_4	B_{41}	12	23	0.78
		B_{42}	10	25	0.86
x_5	B_5	B_{51}	10	27	0.75
		B_{52}	9	29	0.81
		B_{53}	7	34	0.84
		B_{54}	7	36	0.87
x_6	B_6	B_{61}	14	19	0.87
		B_{62}	10	23	0.92

According to the different objective functions of both suppliers and demanders, a bi-level programming model with customer satisfaction and enterprise economic benefits as objective functions is established as follows.

$$\max \quad S = 0.1841s_1 + 0.1983s_2 + 0.1756s_3 + 0.1501s_4 + 0.1671s_5 + 0.1246s_6, \tag{21a}$$

$$\text{s.t.} \quad \begin{aligned} p &= \left(\sum_{i=1}^{n}\sum_{j=1}^{k_i} c_{ij}x_{ij} + 5000\right) \times (1 + 0.091); \\ s_1 &= 1.3709\left(-e^{-y_1}\right) + 1.4376; \\ s_2 &= 1.4766\left(-e^{-y_2}\right) + 1.5099; \\ s_3 &= 0.8266y_3 + 0.0867; \\ s_4 &= 0.4112e^{y_4} + 0.2645; \\ s_5 &= 0.4578e^{y_5} + 0.3511; \\ s_6 &= 0.9280\left(-e^{-y_6}\right) + 1.1347; \\ Y &= \widehat{R}X; \end{aligned} \tag{21b}$$

$$\max \quad E = 50 \times p - \sum_{i=1}^{n}\sum_{j=1}^{k_i} c_{ij}x_{ij} + 5000, \tag{22a}$$

$$\text{s.t.} \quad \begin{aligned} & 35 \le \sum_{i=1}^{n}\sum_{j=1}^{k_i} t_{ij}x_{ij} \le 42; \\ & \sum_{i=1}^{n}\sum_{j=1}^{k_i} c_{ij}x_{ij} + 5000 \le 50 \times p; \\ & \frac{\sum_{i=1}^{6}\sum_{j=1}^{k_i} Q_{ij}x_{ij}}{6} \ge 0.86; \\ & 0.34x_{11} + 0.36x_{12} + 0.29x_{13} = x_1; \\ & 0.48x_{21} + 0.52x_{22} = x_2; \\ & 0.31x_{31} + 0.32x_{32} + 0.37x_{33} = x_3; \\ & 0.48x_{41} + 0.52x_{42} = x_4; \\ & 0.21x_{51} + 0.23x_{52} + 0.27x_{53} + 0.29x_{54} = x_5; \\ & 0.45x_{61} + 0.55x_{62} = x_6; \\ & x_{ij} = \begin{cases} 1, & EC_j \text{ are assigned to the } j\text{-th companies in the collaborative production enterprise set } B, \\ 0, & EC_j \text{ are assigned to the } j\text{-th companies in the collaborative production enterprise set } B_i. \end{cases} \end{aligned} \tag{22b}$$

Selecting the sum of the upper objective function and the lower objective function value as the fitness function, $f = S + E$; the upper and lower cross-over rate is 0.8; the upper and lower variability is 0.05; the initial population size is set to 40. Programming with MATLAB R2016a, the algorithm iterates 500 times, which iterative fitness value is shown in Figure 6.

It can be seen from Figure 5 that the algorithm obtains the optimal fitness value individually when iterating to 200 times. The optimal fitness value was 232924.3. The optimal chromosome coding scheme is 0100100101000101, which means that the production of manufacturing task x_1 is assisted by enterprise B_{12}; the production of manufacturing task x_2 is assisted by enterprise B_{22}; the production of manufacturing task x_3 is assisted by enterprise B_{33}; the production of manufacturing task x_4 is assisted by enterprise B_{42}; the production of manufacturing task x_5 is assisted by enterprise B_{54}; and the production of manufacturing task x_6 is assisted by enterprise B_{62}.

6. Discussion

This paper takes customer satisfaction and enterprise economic benefit as the objective functions, establishes a bi-

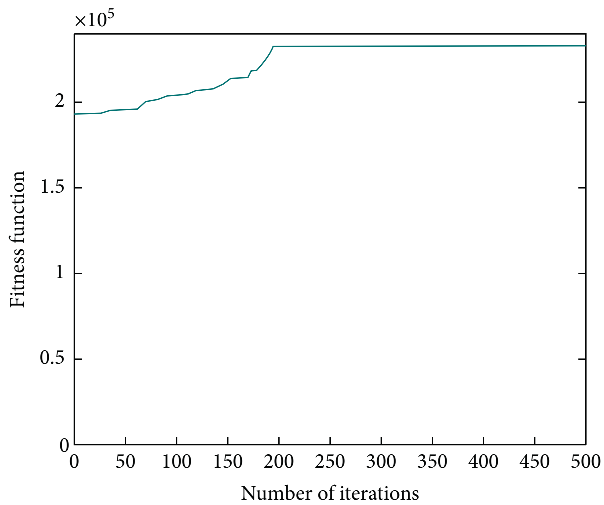

Figure 6: Individual optimal fitness value.

level planning model for manufacturing resource optimization configuration in cloud manufacturing environment and solves the model by intelligent algorithm.

However, the customer satisfaction function calculated in this paper is the absolute satisfaction value, ignoring the impact of the competitive enterprise on customer satisfaction. Relevant research shows that competing companies in the same industry will affect customer satisfaction to a certain extent. If we consider the impact of competing firms on customer satisfaction values when establishing the upper objective function, we can establish a new bi-level programming model as follows.

$$\max \quad S = \sum_{i=1}^{n} \omega_i s_i - \sum_{t=1}^{k} \mathrm{com}^t, \tag{23a}$$

$$\begin{aligned} \text{s.t.} \quad & p = \left(\sum_{i=1}^{n} \sum_{j=1}^{k_i} c_{ij} x_{ij} + C_1 + C_2 \right) \times (1 + r); \\ & \sum_{j=1}^{k_i} x_{ij} = 1; \\ & \sum_{i=1}^{n} \sum_{j=1}^{k_i} x_{ij} = n; \\ & \sum_{i=1}^{n} k_i = m; \end{aligned} \tag{23b}$$

$$\max \quad E = N \times p - \sum_{i=1}^{n} \sum_{j=1}^{k_i} c_{ij} x_{ij} - (C_1 + C_2), \tag{24a}$$

$$\begin{aligned} \text{s.t.} \quad & T_{\min} \le \sum_{i=1}^{n} \sum_{j=1}^{k_i} t_{ij} x_{ij} \le T_{\max}; \\ & \sum_{i=1}^{n} \sum_{j=1}^{k_i} c_{ij} x_{ij} + C_1 + C_2 \le N \times p; \\ & \frac{\sum_{i=1}^{n} \sum_{j=1}^{k_i} Q_{ij} x_{ij}}{n} \ge Q_{\min}; \\ & \sum_{j=1}^{k_i} x_{ij} = 1; \\ & \sum_{i=1}^{n} \sum_{j=1}^{k_i} x_{ij} = n; \\ & \sum_{i=1}^{n} k_i = m. \end{aligned}$$

$$x_{ij} = \begin{cases} 1, & EC_j \text{ are assigned to the } j-\text{th companies in the} \\ & \text{collaborative production enterprise set } B_i, \\ 0, & EC_j \text{ are assigned to the } j-\text{th companies in the} \\ & \text{collaborative production enterprise set } B_i, \end{cases} \tag{24b}$$

where com^t indicates the satisfaction given by the customer when the t-th competition company completes the customer order. (23a) an increase of $\sum_{t=1}^{k} \mathrm{com}^t$ helps the upper objective function can clearly describe customer satisfaction. In this way, scientificity and rationality of the evaluation results can be effectively improved.

7. Conclusion

The existing research literature on manufacturing resources optimization configuration considers only the needs of one side (the product ordering party or the producer of the product), while ignoring the others. This paper is aimed at the deficiency of manufacturing resource optimization configuration in cloud manufacturing environment and fully analyzes the process of manufacturing resource optimization configuration in cloud manufacturing environment to give a dual-objective programming model. The model starts from the expected goal of both enterprise and customer and obtains the optimal solution within the feasible range through the game between the upper object and the lower object. The enterprise obtains the most economic benefits, and the customer obtains the most satisfaction. In this paper, 6 collaborative production tasks and 16 candidate manufacturing enterprises are studied for optimal resource allocation which solved by hybrid genetic algorithm that the time of 500 iterations is 32.21 s. When we increased the problem size to 10 collaborative production tasks and 32 candidate manufacturing companies, the number of iterations increased to 800 and the time taken was 54.33 s. It can be seen that when the candidate company is doubled, the solution efficiency is 1.6 times. The model proposed in this paper has the characteristics of clear thinking, simple operation, and strong practicability. It provides a new way to solve manufacturing resources optimization configuration in cloud manufacturing environment.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors of this study state that there are no conflicts of interest to disclose.

Acknowledgments

This work was financially supported by the Humanities and Social Sciences of Ministry of Education Planning Fund (Grant no. 16YJC630085) in China, the Liaoning Province Planning Office of Philosophy and Social Science (L18BJY029), Liaoning Provincial Financial Research Fund (18C008), the Shenyang Planning Office of Philosophy and Social Science (18ZX019), the Liaoning Province Department of Education Project (WGD2016002), Shenyang Science and Technology Innovation Knowledge Base (SYKJ201807 and 201806), Shenyang Federation Social Science Circles (Grant nos. SYSK2018-05-05), the Key Program of Social Science Foundation of Liaoning Province (Grant no. L15AGL013), and the Natural Science Foundation of Liaoning Province (Grant no. 201602545). The authors wish to acknowledge the contribution of Liaoning Key Lab of Equipment Manufacturing Engineering Management, Liaoning Research Base of Equipment Manufacturing Development, Liaoning Key Research Base of Humanities and Social Sciences, Research Center of Micromanagement Theory, and Shenyang University of Technology.

References

[1] Y. F. Zhang, D. Xi, R. Li, and S. D. Sun, "Task-driven manufacturing cloud service proactive discovery and optimal configuration method," *International Journal of Advanced Manufacturing Technology*, vol. 84, no. 1–4, pp. 29–45, 2016.

[2] R. Ranjan, J. Kolodziej, L. Wang, and A. Y. Zomaya, "Cross-layer cloud resource configuration selection in the big data era," *IEEE Cloud Computing*, vol. 2, no. 3, pp. 16–22, 2015.

[3] W. L. Tate, L. M. Ellram, T. Schoenherr, and K. J. Petersen, "Global competitive conditions driving the manufacturing location decision," *Business Horizons*, vol. 57, no. 3, pp. 381–390, 2014.

[4] J. Lartigau, X. Xu, L. Nie, and D. Zhan, "Cloud manufacturing service composition based on QoS with geo-perspective transportation using an improved Artificial Bee Colony optimisation algorithm," *International Journal of Production Research*, vol. 53, no. 14, pp. 4380–4404, 2015.

[5] L. Qu, C. Assi, and K. Shaban, "Delay-Aware scheduling and resource optimization with network function virtualization," *IEEE Transactions on Communications*, vol. 64, no. 9, pp. 3746–3758, 2016.

[6] H. Akbaripour, M. Houshmand, Tom van Woensel, and N. Mutlu, "Cloud manufacturing service selection optimization and scheduling with transportation considerations: mixed-integer programming models," *The International Journal of Advanced Manufacturing Technology*, vol. 95, no. 1–4, pp. 43–70, 2018.

[7] Z. Wu, T. Liu, Z. Gao, Y. Cao, and J. Yang, "Tolerance design with multiple resource suppliers on cloud-manufacturing platform," *The International Journal of Advanced Manufacturing Technology*, vol. 84, no. 1–4, pp. 335–346, 2016.

[8] H. Zheng, Y. Feng, and J. Tan, "A fuzzy QoS-aware resource service selection considering design preference in cloud manufacturing system," *The International Journal of Advanced Manufacturing Technology*, vol. 84, no. 1–4, pp. 371–379, 2016.

[9] Y. Zhang, D. Xi, H. Yang, F. Tao, and Z. Wang, "Cloud manufacturing based service encapsulation and optimal configuration method for injection molding machine," *Journal of Intelligent Manufacturing*, pp. 1–19, 2017.

[10] Y. Cao, S. Wang, L. Kang, and Y. Gao, "A TQCS-based service selection and scheduling strategy in cloud manufacturing," *The International Journal of Advanced Manufacturing Technology*, vol. 82, no. 1–4, pp. 235–251, 2016.

[11] J. Zhang, "An adaptive immune genetic algorithm for machinery manufacturing task scheduling in cloud computing system," *Metallurgical and Mining Industry*, vol. 9, pp. 6–14, 2015.

[12] W. Xu and Y. Yu, "Optimal allocation method of discrete manufacturing resources for demand coordination between suppliers and customers in a fuzzy environment," *Complexity*, vol. 2018, Article ID 1410957, 18 pages, 2018.

[13] N. Kano, N. Seraku, and F. Takahashi, "Attractive quality and must-be quality," *The Journal of Japanese Society for Quality Control*, vol. 41, no. 2, pp. 39–48, 1984.

[14] V. A. Zeithaml, L. L. Berry, and A. Parasuraman, "The nature and determinants of customer expectations of service," *Journal of the Academy of Marketing Science*, vol. 21, no. 1, pp. 1–12, 1993.

[15] X. X. Shen, K. C. Tan, and M. Xie, "An integrated approach to innovative product development using Kano's model and QFD," *European Journal of Innovation Management*, vol. 3, no. 2, pp. 91–99, 2000.

[16] L. He, W. Song, Z. Wu, Z. Xu, M. Zheng, and X. Ming, "Quantification and integration of an improved Kano model into QFD based on multi-population adaptive genetic algorithm," *Computers & Industrial Engineering*, vol. 114, pp. 183–194, 2017.

[17] Y. Kristianto, P. Helo, and R. J. Jiao, "Mass customization design of engineer-to-order products using Benders' decomposition and bi-level stochastic programming," *Journal of Intelligent Manufacturing*, vol. 24, no. 5, pp. 961–975, 2013.

[18] E. O. C. Mkpojiogu and N. L. Hashim, "Understanding the relationship between Kano model's customer satisfaction scores and self-stated requirements importance," *SpringerPlus*, vol. 5, no. 1, p. 197, 2016.

[19] P. Ji, J. Jin, T. Wang, and Y. Chen, "Quantification and integration of Kano's model into QFD for optimising product

designfication and integration of Kano's model into QFD for optimising product design," *International Journal of Production Research*, vol. 52, no. 21, pp. 6335–6348, 2014.

[20] E. Savio, L. De Chiffre, S. Carmignato, and J. Meinertz, "Economic benefits of metrology in manufacturing," *CIRP Annals*, vol. 65, no. 1, pp. 495–498, 2016.

[21] D. Wu, J. Terpenny, and W. Gentzsch, "Economic benefit analysis of cloud-based design, engineering analysis, and manufacturing," *Journal of Manufacturing Science and Engineering*, vol. 137, no. 4, pp. 040903–040909, 2015.

[22] N. Shi and Y. Luo, "Bi-level programming approach for the optimal allocation of energy storage systems in distribution networks," *Applied Sciences Basel*, vol. 7, no. 4, pp. 1–23, 2017.

[23] Z. Huang, C. Yang, X. Zhou, and W. Gui, "A novel cognitively inspired state transition algorithm for solving the linear Bi-level programming problem," *Cognitive Computation*, vol. 10, no. 5, pp. 816–826, 2018.

[24] O. Amirtaheri, M. Zandieh, B. Dorri, and A. R. Motameni, "A bi-level programming approach for production-distribution supply chain problem," *Computers & Industrial Engineering*, vol. 110, pp. 527–537, 2017.

[25] X. Y. Bao and L. Zhang, "Green procurement relationships development under carbon emissions regulations: a Bi-level programming approach," *International Journal of Environmental Research and Public Health*, vol. 15, no. 10, pp. 1–14, 2018.

[26] F. S. Gazijahani and J. Salehi, "Optimal bilevel model for stochastic risk-based planning of microgrids under uncertainty," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 7, pp. 3054–3064, 2018.