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Research Article

Optimal Allocation Method of Discrete Manufacturing Resources for Demand Coordination between Suppliers and Customers in a Fuzzy Environment

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Discrete manufacturing products are often assembled from multiple parts through a series of discrete processes. How to effectively configure resources in a discrete manufacturing environment is an important research topic worthy of attention. Based on an in-depth analysis of the discrete manufacturing operation model and the manufacturing resource allocation process, this paper fully considers the uncertainty factors of the manufacturing resource customers and the interests of the manufacturing resource suppliers and proposes a bilevel planning model under a fuzzy environment that comprehensively considers the customers' expectation bias and the suppliers' profit maximization. The method firstly uses a language phrase to collect the language evaluation of the customers and suppliers for manufacturing tasks and uses a trapezoidal fuzzy number to convert the language evaluation phrase into a value that can be calculated. Then, we use the prospect theory to optimize the constraint indicators based on the language evaluation of customers and suppliers. Next, the bilevel planning model for optimal configuration of manufacturing resources in discrete manufacturing environment is established under the consideration of the respective interests of both the customers and the suppliers, and the fast nondominated sorting genetic algorithm (NSGA-II) is used to solve the model. Finally, an example is given to verify the validity and feasibility of the model.

1. Introduction

With the rapid economic growth, customer demand for products has become more diverse. How to effectively grasp customer demand, shorten lead time, lower production cost, and increase product quality are key factors for companies to achieve sustainable development [1]. Due to unpredictable market changes, this requires the manufacturing systems to be able to rapidly reconstruct in response to rapid market changes. Discrete manufacturing has gradually become the mainstream model of manufacturing industry because of its advantages such as noncontinuity and reconfigurability [2]. With lots of manufacturing units that provide the same functionality but have different parameters in a discrete system, effective resource configuration which can reflect customer needs is often considered as a key technology [3].

Manufacturing resource configuration (MRC) plays a very important role in discrete systems, especially when manufacturing systems have to cope with shorter product life cycles [4]. In order to fulfill the dynamic customer needs, it always needs discrete systems to invoke several manufacturing units in sequence and combine them together fast. Due to complexity and diversity of manufacturing resources, resource optimal configuration has become a key issue in discrete systems and has been widely studied in both industrial community and academia. Despite of significant progress achieved by the researchers in manufacturing resource configuration, grey relational analysis [5], manufacturing grids [6], the idea of Pareto [7], graph theoretic methods [8], artificial intelligence-based methods [9], and other methods have been proposed successively. Most of current MRC algorithms where the data of MRC are in the form of real number are not suitable for discrete systems environment because the MRC of discrete systems is often fuzzy and uncertain. For example, when MRD describe the quality of products, they can better express their customers' perception by using language evaluation words of "good," "bad," and so on. Therefore, this paper proposes a resource optimization configuration that considers the customers' expectation bias and considers the suppliers' profit maximization under fuzzy environment.

The remainder of this paper is organized as follows. After reviewing the related literature in Literature Reviews, some basic theories such as prospect theory and bilevel programming model are introduced in Preliminary Knowledge. Problem Description and Symbol Introduction presents the issues of the thesis research and some basic symbols. In The Proposed Method, it proposes a novel method for discrete manufacturing resource optimization configuration under fuzzy environment. An illustrative example is given to demonstrate the use of the proposed method in Illustrative Example. Conclusions and discussions are drawn with brief comments in Conclusions and Discussion.

2. Literature Reviews

MRC has emerged because of the need for manufacturing organizations to cope with shorter product life cycles, time-to-market, and a shift to respond to demands for MRD [10]. In the past years, many approaches, models, and methodologies have been proposed for solving manufacturing resource configuration problems. Among them, the main research algorithms are as follows:

(i) Grey relational analysis

(ii) Manufacturing grid

(iii) The idea of Pareto

(iv) Graph theoretic methods

(v) Artificial intelligence-based methods

Zhang used grey relational analysis to further study manufacturing machine and manufacturing cell (MC) of multigranularity resource configuration process. During resource modeling, advanced information and sensor technologies are adopted to construct the information models of resources, which make the traditional production process more transparent, traceable, and on-line controllable [5]. Based on the quantum evolution theory, Zhang and Hu proposed a hybrid chaotic quantum evolutionary algorithm (CQEA) for resource combinatorial optimization (RCO) problems. Using an example to prove the proposed CQEA is effective, efficient, and scalable for the RCO problem in manufacturing grid system [6]. Li et al. gave a resource configuration method based on binary decision diagram (BDD) which is a directed acyclic graph (DAG) based on Shannon's decomposition. This method extends the scale of the reliability system. Through the results of three case studies, it is found that the decision graph expansion method is more computationally efficient than the traditional BDD [7]. Xiang et al. introduce a new multiobjective optimization algorithm based on the combination of the idea of Pareto solution and group leader algorithm (GLA), which study of quality of service (QoS) and energy consumption assessment (EnCon) [8]. Tao et al. gave a parallel intelligent algorithm of resource configuration, which can minimize implementation time and cost and maximize the reliability of MGrid resource service composition paths [9].

Although there are many research results on the optimal configuration of resources, there are two obvious shortcomings in the current research results. First of all, the existing research results can promote and facilitate quicker and smarter decisions for service composition, but it cannot play any role in the fuzzy problem in the discrete system. That is, most of the existing research methods use real number, but the evaluation of manufacturing resources in discrete systems is often fuzzy and uncertain. Secondly, most of the existing research results are single objective, which can only consider the interests of one of the MRD or the MRP, and there are a few multiobjective research results, which consider the interests of both the MRD and the MRP, but when modeling, the multiobjective is converted into a single objective by using the weighted operator, and it is not truly multiobjective.

This paper proposes a bilevel programming model considering customer expectation under a fuzzy environment. Based on the prospect theory, we calculate the expected deviations of cost, quality, time, and green indicators of manufacturing resource customers and establish the objective function, then considering the efficiency, coordination, agility indicators of the manufacturing resource suppliers, we establish the objective function. Based on bilevel programming theory, the objective function and constraint conditions of MRD and MRP are established, respectively, and the fast nondominated sorting genetic algorithm (NSGA-II) is used to solve the model.

3. Preliminary Knowledge

3.1. Trapezoidal Fuzzy Number and Language Evaluation Phrases

3.1.1. Trapezoidal Fuzzy Numbers. Let $\tilde{A}$ be a fuzzy set, and a fuzzy subset a of $\tilde{A}$ is defined with a membership function $v_a(x)$ that maps each element x in a to a real number in the interval [0, 1]. The function value of $v_a(x)$ signifies the grade of membership of x in a [11]. A trapezoidal fuzzy number a represented with four points as follows: $a = (a^1, a^2, a^3, a^4)$, $a^1 \le a^2 \le a^3 \le a^4$ (see Figure 1). Its membership function $v_a(x)$ is defined as

$$v_a(x) = \begin{cases} 0, & x < a^1, \\ \dfrac{x - a^1}{a^2 - a^1}, & a^1 \le x \le a^2, \\ 1, & a^2 \le x \le a^3, \\ \dfrac{x - a^4}{a^3 - a^4}, & a^3 \le x \le a^3, \\ 0, & a^4 \le x, \end{cases} \tag{1}$$

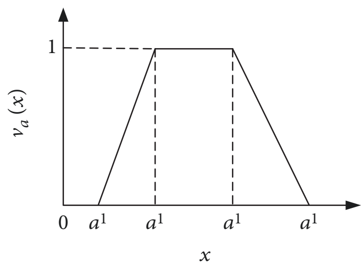

FIGURE 1: A triangular fuzzy number a.

where a^1, a^2, a^3, and a^4 are real numbers and these constants reflect the fuzziness of the evaluation data [12]. As shown in Figure 1, the trapezoidal fuzzy numbers can be denoted by (a^1, a^2, a^3, a^4). The x in interval $[a^2, a^3]$ gives the maximal grade of $v_{\tilde{a}}(x)$, that is, $v_{\tilde{a}}(x) = 1$, and it is the most probable value of the evaluation data. a^1 and a^4 are the lower and upper limits of the available area for the evaluation data, and they reflect the fuzziness of the evaluation data. If $a^2 = a^3$, then $\tilde{a} = (a^1, a^2, a^3, a^4)$ is reduced to a triangular fuzzy number $\tilde{a} = (a^1, a^M, a^4)$, where $a^M = a^2 = a^3$.

Let $a = (a^1, a^2, a^3, a^4)$ and $b = (b^1, b^2, b^3, b^4)$. When $a > 0$ and $b > 0$, the basic arithmetic operations are as follows [13]:

(1) $a + b = (a^1 + b^1, a^2 + b^2, a^3 + b^3, a^4 + b^4)$.

(2) $a - b = (a^1 - b^1, a^2 - b^2, a^3 - b^3, a^4 - b^4)$.

(3) $a \times b = (a^1 \times b^1, a^2 \times b^2, a^3 \times b^3, a^4 \times b^4)$.

(4) $a/b = ((a^1/b^4), (a^2/b^3), (a^3/b^2), (a^4/b^1))$.

Definition 1 (see [14]). There are two trapezoidal fuzzy numbers $a = (a^1, a^2, a^3, a^4)$ and $b = (b^1, b^2, b^3, b^4)$. When $a^1 \geq b^4$, it can be said that a is greater than b and recorded as $a > b$; when $a^1 = b^1$, $a^2 = b^2$, $a^3 = b^3$, and $a^4 = b^4$, it can be said that a is equal to b and recorded as $a = b$; when $b^1 \geq a^4$, it can be said that a is less than b and recorded as $a < b$.

Definition 2 (see [14]). There are two trapezoidal fuzzy numbers $a = (a^1, a^2, a^3, a^4)$ and $b = (b^1, b^2, b^3, b^4)$. The distance between the trapezoidal fuzzy numbers $a = (a^1, a^2, a^3, a^4)$ and $b = (b^1, b^2, b^3, b^4)$ is defined as $d(a, b)$.

$$d(a,b) = \|a-b\| = \frac{1}{3}\sqrt{\left(a^1-b^1\right)^2 + \left(a^2-b^2\right)^2 + \left(a^3-b^3\right)^2 + \left(a^4-b^4\right)^2}. \tag{2}$$

3.1.2. Language Evaluation Phrases. Let $G = \{g_0, g_1, \ldots, g_l\}$ be the preestablished finite and totally ordered linguistic term set with odd cardinalities, where g_i denotes the ith linguistic term of set G, and $l + 1$ is the cardinality of G. The middle term in linguistic term set G is thought to be represented an assessment of "approximately 0.5" and the remaining terms of G are thought to be placed around it symmetrically [15].

TABLE 1: Linguistic scales.

Linguistic variables and semantics	Trapezoidal fuzzy numbers
g_0 = very unsatisfied (VU)	(0, 0, 0.077, 0.154)
g_1 = unsatisfied (U)	(0.077, 0.154, 0.231, 0.308)
g_2 = slightly unsatisfied (SU)	(0.231, 0.308, 0.385, 0.462)
g_3 = middle (M)	(0.385, 0.462, 0.538, 0.615)
g_4 = slightly satisfied (SS)	(0.538, 0.615, 0.692, 0.769)
g_5 = satisfied (S)	(0.692, 0.769, 0.846, 0.923)
g_6 = very satisfied (VS)	(0.846, 0.923, 1, 1)

For example, a linguistic term set with seven terms can be expressed as follows.

Let $G = \{g_0, g_1, g_2, g_3, g_4, g_5, g_6\}$ be a linguistic term set, where g_0 = very unsatisfied (VU); g_1 = unsatisfied (U); g_2 = slightly unsatisfied (SU); g_3 = middle (M); g_4 = slightly satisfied (SS); g_5 = satisfied (S); g_6 = very satisfied (VS).

Therefore, g_i can be approximately expressed as a triangular fuzzy number $a = (a^1, a^2, a^3, a^4)$ using the following formula [16]:

$$a = \left(a^1, a^2, a^3, a^4\right) = \left(\max\left\{\frac{2i-1}{2l+1}, 0\right\}, \frac{2i}{2l+1}, \frac{2i+1}{2l+1}, \min\left\{\frac{2i+2}{2l+1}, 1\right\}\right). \tag{3}$$

For example, by (3), each linguistic term in a linguistic term set with seven terms, $G = \{g_0, g_1, g_2, g_3, g_4, g_5, g_6\}$, can be expressed as the corresponding trapezoidal fuzzy numbers listed in Table 1, where $l = 6$ and $i = 0, 1, 2, \ldots, 6$.

3.2. Prospect Theory. Tversky and Kahneman believe that the actual decision-making behavior of an individual under uncertainty is deviated from the basic principle of expected utility. The uncertainty foreground f is a function from the natural state set S to the result set X, that is, $f: S \to X$. The foreground f is a sequence of (x_i, S_i) sequences, where S_i is a division of S which is called S_i event. When event S_i occurs, it produces a result of x_i. If $i > j$, then $x_i > x_j$. The result x_i of each foreground is arranged in ascending order, that is, $x_{-m} \leq x_{-m+1} \leq \cdots \leq x_0 \leq x_1 \leq \cdots \leq x_n$. If you choose x_0 as the reference point and its value is "0," the profit is $x_i > 0$ and the loss is $x_i < 0$.

In 1992, Tversky and Kahneman proposed the cumulative prospect theory [17] based on the prospect theory [18]. Cumulative prospect theory has introduced capacity theory, which can better solve the problem of dominant advantage and deal with problems with multiple results. The capacity value can be expressed as w^+ and w^-, then the value of the foreground $f = (x_i, S_i)$, $(-m \leq i \leq n)$ is expressed as

$$V(f) = V\left(f^+\right) + V\left(f^-\right), \tag{4}$$

where $V(f^+)$ and $V(f^-)$ can be obtained by (5) and (6), respectively.

$$V(f^+) = \sum_{i=0}^{n} w_i^+ v(x_i), \tag{5}$$

$$V(f^-) = \sum_{i=0}^{m} w_i^- v(x_i). \tag{6}$$

Here, $w_i^+ = w^+(S_i \cup \cdots \cup S_n) - w^+(S_{i+1} \cup \cdots \cup S_n), 0 \le i \le n-1$; $w_i^- = w^-(S_{-m} \cup \cdots \cup S_i) - w^-(S_{-m} \cup \cdots \cup S_{i-1}), 1-m \le i \le 0$.

If the result of event S_i is probabilistic, the decision problem can be seen as a probabilistic prospect, that is, $f = (x_i, S_i) \to f = (x_i, p_i)$. Here, $p(S_i) = p_i$ represents the probability of occurrence of event S_i. Under these circumstances, $w_i^+ = w^+(p_i \cup \cdots \cup p_n) - w^+(p_{i+1} \cup \cdots \cup p_n), 0 \le i \le n-1$; $w_i^- = w^-(p_{-m} \cup \cdots \cup p_i) - w^-(p_{-m} \cup \cdots \cup p_{i-1}), 1-m \le i \le 0$.

The core content of the cumulative prospect theory is the value function v and the weight function p, which can be expressed as

$$V(f) = \sum_{i=-m}^{n} v(x_i)p_i. \tag{7}$$

3.2.1. The Weight Function. The weight function converts the probability into the decision weight, so the calculation formulas for the probability weight of the profit and loss are

$$p_1^+ = \frac{p_1^\gamma}{\left(p_1^\gamma + (1-p_1)^\gamma\right)^{1/\gamma}}, \tag{8}$$

$$p_2^- = \frac{p_2^\delta}{\left(p_2^\delta + (1-p_2)^\delta\right)^{1/\delta}}, \tag{9}$$

where p is the probability; γ and δ are that parameters that indicate the degree of curvature of the probability weight function.

3.2.2. The Value Function. A great breakthrough in the expectation theory is to replace the traditional utility function with a value function, so that the carriers concerned can be implemented in the value change rather than the final amount [19]. The value function is to convert surface value into decision value. The specific form of the value function of Tversky and Kahneman is [17]

$$v(x) = \begin{cases} x^a, & x \ge 0, \\ -\lambda(-x)^\beta, & x < 0. \end{cases} \tag{10}$$

Here, when $x \ge 0$, $v(x)$ indicates profit; when $x < 0$, $v(x)$ indicates loss. α and β indicate the degree of roughness of the value function in the region of profit and loss, that is, the rate of decline in the sensitivity of decision-makers, $0 < \alpha < 1$ and $0 < \beta < 1$ [20]. λ indicates that the loss area of the value function is steeper than the income area, that is, it reflects the degree of loss avoidance of decision-makers. If $\lambda > 1$, it denotes that the decision-maker is more sensitive to the loss. People tend to risk gambling when faced with conditions of considerable loss but tend to accept certainty profits when faced with fairly favorable earnings. The happiness caused by profit is not equal to that caused by the same amount of loss. The latter is greater than the former [21].

When people evaluate a thing or make a choice, they always intentionally or unintentionally compare it with a certain reference, which is called the reference point from the definition of mathematics. The reference point is a very important feature of the value function, because the profit or loss is always compared with a certain reference point. The value of the profit or loss from the reference point is located on the right side of the profit or loss to indicate positive evaluation, while the left side of the profit or loss indicates negative evaluation [22]. The reference point is used as an evaluation criterion. It is subjectively determined by an individual and will change due to different evaluation topics, environmental time, and the like.

This paper selects the expectations of MRD as a reference point for the value function. At the same time, we divide the decision indicators into benefit type and cost type. The profitability index means that the larger the index value, the better; and the cost index means that the smaller the index value, the better. According to (7) and Definition 2, the value function of the profitability index and cost index is, respectively,

$$V_{ijk}^{r_1} = \begin{cases} \left(h_{ijk}^r - \theta_{ik}^r\right)^{\alpha^k}, & h_{ijk}^r - \theta_{ik}^r \ge 0, \\ -\lambda^k\left(\theta_{ik}^r - h_{ijk}^r\right)^{\beta^k}, & h_{ijk}^r - \theta_{ik}^r < 0, \end{cases} \tag{11}$$

$$V_{ijk}^{r_2} = \begin{cases} \left(\theta_{ik} - h_{ijk}\right)^{\alpha^k}, & h_{ijk} - \theta_{ik} \le 0, \\ -\lambda^k\left(h_{ijk} - \theta_{ik}\right)^{\beta^k}, & h_{ijk} - \theta_{ik} > 0, \end{cases} \tag{12}$$

where θ_{ik}^r is the reference point (i.e., expectation) given by the MRD B_k for the r index of the manufacturing task TS_i; h_{jk}^r indicates that the r index of the selected manufacturing unit MS_{ij} gives the manufacturing resource customers' perception after completing the manufacturing task. When $h_{ijk}^r - \theta_{ik}^r \ge 0$, $V_{ijk}^{r_1}$ and $V_{ijk}^{r_2}$ are referred to as the value of the profit generated by the MAD relative to the reference point θ_{ik}^r; on the contrary, when $h_{ijk}^r - \theta_{ik}^r < 0$, $V_{ijk}^{r_1}$ and $V_{ijk}^{r_2}$ are referred to as the value of the loss generated by the MAD relative to the reference point θ_{ik}^r; α^k and β^k are the degree of roughness of the profit area and the loss area of the value function, and λ^k is the loss aversion coefficient [20, 21]. In actual decision analysis, these parameters are usually obtained by nonlinear regression of experimental data [23].

3.3. The Bilevel Programming. Manufacturing unit configuration is the main form of discrete manufacturing tasks. The process of optimization selection belongs to the typical multi-objective optimization problems (MOP). The traditional MOP solution is to convert MOP into single-object problem solving. Common methods include the main target method, linear weighting method, and hierarchical optimization method. But the discrete manufacturing unit configuration

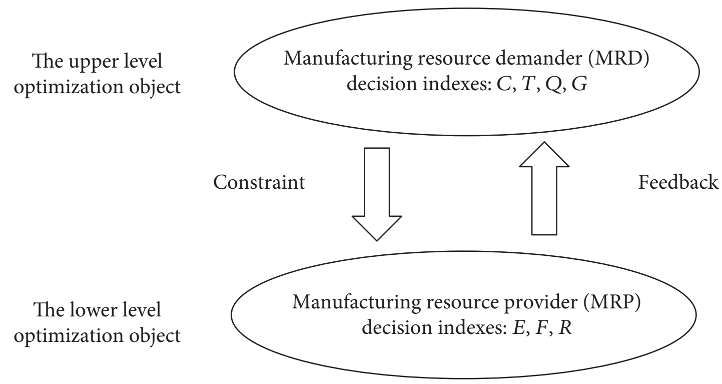

Figure 2: Schematic diagram of the bilevel programming.

optimization process involves the interests of the customers and suppliers, because the customers and suppliers each have a part of the optimization variables, each represents their own interests, and each variable exists between influences and constraints, and it cannot be solved using traditional methods.

The bilevel programming [24] model is a hierarchical model with a master-slave hierarchical structure. In the bilevel programming model, the upper and lower decision-makers have their own objective functions and constraints.

The upper decision-maker makes decisions firstly. According to their objective functions and constraints, the lower decision-maker obtains the optimal solutions within the possible range and sends back their own optimal solutions to the upper decision-maker. Then, the upper decision-maker obtains the global optimal solution of the problem within the possible scope based on the optimal solutions of the lower decision-maker. The mathematical description of the bilevel programming model is as follows:

$$\begin{aligned} (\mathrm{U}) \min_{y} \quad & Z(x, y) \\ \text{s.t.} \quad & G(\mathrm{x}, \mathrm{y})£0, \\ (\mathrm{L}) \min_{y} \quad & f(x, y) \\ \text{s.t.} \quad & g(x, y) \leq 0, \end{aligned} \tag{13}$$

where (U) is the upper plan and (L) is the lower plan; Z is the objective function of the upper plan, x is the determinate variable of the upper plan, and G is the constraint condition of the decision variable x; z is the objective function of the lower plan, y is the decision variable of the lower plan, g is the constraint condition of the decision variable y, and the lower decision variable y is the function of the upper level decision variable x, that is, $y = y(x)$.

The upper and lower optimization problems are relatively independent, and their optimization processes are dependent on each other, so the bilevel programming problems cannot usually be independently solved layer by layer. Not only the interests of MRD but also the interests of MRP must be taken into account in a discrete manufacturing environment. The idea of bilevel programming is used to solve the problem of optimal configuration of manufacturing unit in discrete manufacturing environments, as shown in Figure 2.

4. Problem Description and Symbol Introduction

The optimal configuration of manufacturing resources in discrete environments refers to the process of configuring reasonable manufacturing resources or manufacturing resource combinations according to different manufacturing tasks [5]. After a discrete manufacturing task is issued, the MRP decomposes the total manufacturing task into a set of manufacturing subtasks according to the decomposition preferences. According to the matching principle of manufacturing resources, we find all manufacturing units that can meet the manufacturing subtasks and form a set of manufacturing units. Considering the profit of MRD and MRP, we select the optimal set of manufacturing units to form the optimal manufacturing resource configuration, as shown in Figure 3. With the emergence and development of networked manufacturing technologies, manufacturing units are not only confined to the internal structure of a single company but are also composed of multiple companies in different geographic locations, so the manufacturing resource optimization configurations are distribution, heterogeneity, and dynamics.

Compared with the existing method for optimal configuration of manufacturing resources, this paper proposes an optimization algorithm for manufacturing resources in a fuzzy environment that considers the interests of both MRD and MRP. Firstly, the MRP decomposes the MRD's product demand for the MRP (i.e., the total manufacturing task) according to design preferences and obtains a set of manufacturing subtasks. Secondly, we use the existing infrastructure to match the manufacturing subtasks with the existing manufacturing units. A set of manufacturing units for each subtask is obtained. Next, a questionnaire is used to obtain the MRP and MRD's linguistic evaluation of each manufacturing unit, and u a trapezoidal fuzzy number is used to translate the language phrase into numerical values. Then, we obtain the customer's expected deviation value for each manufacturing unit based on the prospect theory. On this basis, a bilevel planning model that considers the

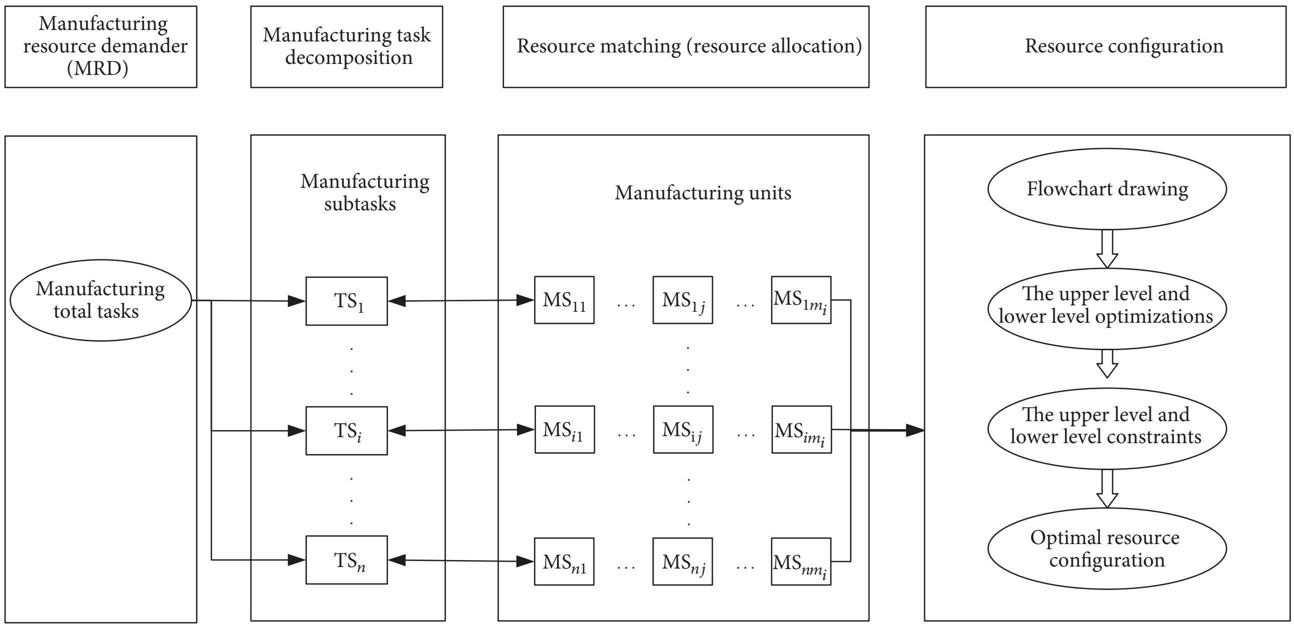

Figure 3: Manufacturing resource configuration diagram.

interests of both MRD and MRP was established and solved using NSGA-II algorithms. Finally, the resource configuration of aircraft-bearing processing was taken as an example to demonstrate the feasibility of the method.

(i) $B = \{B_1, B_2, \dots, B_b\}$ is a set of manufacturing resource customers (MRD), where B_k denotes the kth manufacturing resource customers, $k = 1, \dots, b$.

(ii) $\mathrm{TS} = \{\mathrm{TS}_1, \mathrm{TS}_2, \dots, \mathrm{TS}_n\}$ is a set of manufacturing subtasks, where TS_i denotes the ith manufacturing subtasks, $i = 1, \dots, n$.

(iii) $\mathrm{MS}_i = \{\mathrm{MS}_{i1}, \mathrm{MS}_{i2}, \dots, \mathrm{MS}_{im_i}\}$ is a candidate manufacturing unit set of the ith manufacturing subtasks, which can provide a similar function. Where MS_{ij} denotes the jth manufacturing units of the ith manufacturing subtasks, $i = 1, \dots, n$ and $j = 1, \dots, m_i$.

(iv) $C_i = \{C_{i1}, C_{i2}, \dots, C_{im_i}\}$ is a cost set of the ith manufacturing subtasks, where C_{ij} denotes the cost of the jth manufacturing units of the ith manufacturing subtasks, $i = 1, \dots, n$ and $j = 1, \dots, m_i$.

(v) $T_i = \{T_{i1}, T_{i2}, \dots, T_{im_i}\}$ is a time set of the ith manufacturing subtasks, where T_{ij} denotes the time of the jth manufacturing units of the ith manufacturing subtasks, $i = 1, \dots, n$ and $j = 1, \dots, m_i$.

(vi) $Q_i = \{Q_{i1}, Q_{i2}, \dots, Q_{im_i}\}$ is a quality set of the ith manufacturing subtasks, where Q_{ij} denotes quality of the jth manufacturing units of the ith manufacturing subtasks, $i = 1, \dots, n$ and $j = 1, \dots, m_i$.

(vii) $G_i = \{G_{i1}, G_{i2}, \dots, G_{im_i}\}$ is a green set of the ith manufacturing subtasks, which is the set of environmental protection, where G_{ij} denotes green of the jth manufacturing units of the ith manufacturing subtasks, $i = 1, \dots, n$ and $j = 1, \dots, m_i$.

(viii) $E_i = \{E_{i1}, E_{i2}, \dots, E_{im_i}\}$ is an efficiency set of the ith manufacturing subtasks, where E_{ij} denotes efficiency of the jth manufacturing units of the ith manufacturing subtasks, $i = 1, \dots, n$ and $j = 1, \dots, m_i$.

(ix) $F_i = \{F_{i1}, F_{i2}, \dots, F_{im_i}\}$ is an agility set of the ith manufacturing subtasks, where F_{ij} denotes agility of the jth manufacturing units of the ith manufacturing subtasks, $i = 1, \dots, n$ and $j = 1, \dots, m_i$.

(x) $R_i = \{R_{i1}, R_{i2}, \dots, R_{im_i}\}$ is a coordination set of the ith manufacturing subtasks, where R_{ij} denotes coordination of the jth manufacturing units of the ith manufacturing subtasks, $i = 1, \dots, n$ and $j = 1, \dots, m_i$.

5. The Proposed Method

5.1. Discrete Manufacturing Index Optimization Based on Prospect Theory. Prospect theory thinks that people are bounded rational. For example, when a person gains or loses the same item, the loss caused by the loss is much greater than the joy after harvest. Therefore, the prospect theory can be used to indicate people's satisfaction with products or equipment. The prospect theory focuses on the difference in customer psychology, not just the customer's final value. In this paper, MRD expectation is used as a reference point to optimize the MRD indexes and MRP indexes.

5.1.1. Index Constraint Optimization of MRD

(1) Cost Constraint. In a discrete manufacturing system, the cost indicators of each manufacturing unit include not only the fixed costs of manufacturing units but also the logistics costs between manufacturing units. The optimization of the cost constraint index is based on the prospect value of the MRD for the cost index. It can be calculated as

$$\begin{aligned} V(C) &= \sum_{i=1}^{n} V(C_i) \\ &= \sum_{i=1}^{n}\sum_{j=1}^{m_i}\left\|C_{ij} - \theta_{ij}^{c}\right\| H_{ij}, \quad i = 1, \ldots, n, j = 1, \ldots, m_i. \end{aligned} \tag{14}$$

Here, $V(C)$ denotes the total cost prospect value of manufacturing units selected by MRD; H_{ij} can be expressed as

$$H_{ij} = \begin{cases} 1, & \text{the } i\text{th manufacturing subtask is completed by the manufacturing unit } \mathrm{MS}_{ij}, \\ 0, & \text{the } i\text{th manufacturing subtask is not completed by the manufacturing unit } \mathrm{MS}_{ij}. \end{cases} \tag{15}$$

The traditional cost constraint is that the cost of completing the task for the selected manufacturing units' combination cannot be greater than the maximum cost required by the MRD. On the basis of the prospect theory, the traditional cost constraint conditions are transformed into that the combined cost prospect value of the selected manufacturing units cannot be greater than the maximum cost prospect value given by the MRD, which can be expressed as

$$V(C) \le V(C)_{\max}. \tag{16}$$

(2) Time Constraint. In discrete manufacturing systems, the time of each manufacturing unit mainly refers to the total time from which the raw material to workshop to finished product leaving workshop. Each manufacturing unit time involves the time of the unit running and the product twisting time between the manufacturing units. The optimization of the time constraint index is based on the prospect value of the MRD for the time index. It can be calculated as

$$\begin{aligned} V(T) &= \sum_{i=1}^{n} V(T_i) \\ &= \sum_{i=1}^{n}\sum_{j=1}^{m_i}\left\|T_{ij} - \theta_{ij}^{T}\right\| H_{ij}, \quad i = 1, \ldots, n, j = 1, \ldots, m_i. \end{aligned} \tag{17}$$

Here, $V(T)$ denotes the total time prospect value of manufacturing units selected by MRD; H_{ij} can be expressed as

$$H_{ij} = \begin{cases} 1, & \text{the } i\text{th manufacturing subtask is completed by the manufacturing unit } \mathrm{MS}_{ij}, \\ 0, & \text{the } i\text{th manufacturing subtask is not completed by the manufacturing unit } \mathrm{MS}_{ij}. \end{cases} \tag{18}$$

The traditional time constraint is that the time required for the selected manufacturing unit combination to complete the task cannot be greater than the longest delivery time required by the MRD. On the basis of the prospect theory, the traditional time constraint conditions are transformed into that the combined time prospect value of the selected manufacturing units cannot be greater than the maximum time prospect value given by the MRD.

$$V(T) \le V(T)_{\max}. \tag{19}$$

(3) Quality Constraint. In the discrete manufacturing system, the quality index of each manufacturing unit refers to the quality of each manufacturing unit to complete the relevant manufacturing tasks, that is, the quality qualification rate for each manufacturing unit to complete the relevant manufacturing tasks. The optimization of the quality constraint index is based on the prospect value of the MRD for the quality index. It can be calculated as

$$\begin{aligned} V(Q) &= \sum_{i=1}^{n} V(Q_i) \\ &= \sum_{i=1}^{n}\sum_{j=1}^{m_i}\left\|Q_{ij} - \theta_{ij}^{Q}\right\| H_{ij}, \quad i = 1, \ldots, n, j = 1, \ldots, m_i, \end{aligned} \tag{20}$$

where $V(T)$ denotes the total quality prospect value of manufacturing units selected by MRD; H_{ij} can be expressed as

$$H_{ij} = \begin{cases} 1, & \text{the } i\text{th manufacturing subtask is completed by the manufacturing unit } \mathrm{MS}_{ij}, \\ 0, & \text{the } i\text{th manufacturing subtask is not completed by the manufacturing unit } \mathrm{MS}_{ij}. \end{cases} \quad (21)$$

The traditional quality constraint is that the quality qualification rate of any manufacturing unit in the selected manufacturing units' combination should not be less than the minimum quality qualification rate required by the MDR. On the basis of the prospect theory, the traditional quality constraint conditions are transformed into that the quality prospect value of any manufacturing unit in the selected manufacturing unit combination should not be less than the minimum quality prospect value required by the MRD, which can be expressed as

$$V\left(Q_{ij}\right) \geq V(Q)_{\min}, \quad i = 1, \ldots, n, j = 1, \ldots, m_i. \quad (22)$$

(4) Green Constraint. Green is based on the requirements of the current low carbon environmental protection. The evaluation of the environmental indicators includes carbon emissions and processing material losses in the manufacturing process of manufacturing units. In discrete manufacturing systems, the green index of each manufacturing unit is the degree of pollution to the environment by which the selected manufacturing units are combined to complete the related manufacturing tasks. The optimization of the green constraint index is based on the prospect value of the MRD for the green index. It can be calculated as

$$\begin{aligned} V(G) &= \sum_{i=1}^{n} V\left(G_i\right) \\ &= \sum_{i=1}^{n}\sum_{j=1}^{m_i} \left\| G_{ij} - \theta_{ij}^{G} \right\| H_{ij}, \quad i = 1, \ldots, n, j = 1, \ldots, m_i, \end{aligned} \quad (23)$$

where $V(G)$ denotes the total green prospect value of manufacturing units selected by MRD; H_{ij} can be expressed as

$$H_{ij} = \begin{cases} 1, & \text{the } i\text{th manufacturing subtask is completed by the manufacturing unit } \mathrm{MS}_{ij}, \\ 0, & \text{the } i\text{th manufacturing subtask is not completed by the manufacturing unit } \mathrm{MS}_{ij}. \end{cases} \quad (24)$$

The traditional environmental protection constraint is that the pollution rate of any manufacturing unit in the selected manufacturing unit combination cannot be greater than the highest manufacturing pollution rate required by the MRD. On the basis of the prospect theory, the traditional environmental constraints are translated into that the prospect value of pollution of any manufacturing unit in the selected combination of manufacturing units cannot be greater than the maximum prospect value of pollution required by the MRD, which can be expressed as

$$V\left(G_{ij}\right) \leq V(G)_{\max}, \quad i = 1, \ldots, n, j = 1, \ldots, m_i. \quad (25)$$

5.1.2. Index Constraint Optimization of MRP. Manufacturing tasks in discrete manufacturing systems are susceptible to changes in manufacturing tasks and changes in manufacturing resources, making it impossible to complete manufacturing tasks with high quality and efficiency. Therefore, it is very important for manufacturing tasks to consider the factors in the process of optimizing the configuration of manufacturing resources.

(1) The Efficiency of the Manufacturing Units' Configuration. The efficiency of the configuration of manufacturing units in a discrete manufacturing system refers to the number of qualified products that the manufacturing unit produces within a unit time after the manufacturing task is reached. The efficiency index of manufacturing units' configuration mainly includes the functional efficiency of each manufacturing unit E_{ij}^{n} and the decomposition capability of the manufacturing unit E_{ij}^{f}, which can be expressed as

$$\begin{aligned} \max E &= \max \sum_{i=1}^{n}\sum_{j=1}^{m_i} \left(E_{ij} H_{ij}\right) \\ &= \max \left\{ \sum_{i=1}^{n}\sum_{j=1}^{m_i} \left(E_{ij}^{n} H_{ij}\right) + \sum_{i=1}^{n}\sum_{j=1}^{m_i} \left(E_{ij}^{f} H_{ij}\right) \right\}, \\ & \qquad i = 1, \ldots, n, j = 1, \ldots, m_i. \end{aligned} \quad (26)$$

Here,

$$H_{ij} = \begin{cases} 1, & \text{the } i\text{th manufacturing subtask is completed by the manufacturing unit } \mathrm{MS}_{ij}, \\ 0, & \text{the } i\text{th manufacturing subtask is not completed by the manufacturing unit } \mathrm{MS}_{ij}. \end{cases} \quad (27)$$

The functional efficiency E_{ij}^n of any manufacturing units cannot be less than the minimum functional efficiency $E_{\min}^n$ required by MRP; and the decomposition capability of the manufacturing unit E_{ij}^f of any MRP in the manufacturing unit's configuration cannot be less than the minimum decomposition capability of the manufacturing unit $E_{\min}^f$ required by MRP. They can be expressed as

$$\begin{aligned} &E_{ij}^n \geq E_{\min}^n, \quad i = 1, \ldots, n, j = 1, \ldots, m_i, \\ &E_{ij}^f \geq E_{\min}^f, \quad i = 1, \ldots, n, j = 1, \ldots, m_i. \end{aligned} \quad (28)$$

(2) The Agility of the Manufacturing Units' Configuration. The agility of the manufacturing unit configuration in a discrete manufacturing environment refers to the manufacturing units' configuration ability to react quickly and successfully complete the manufacturing task when the content of the manufacturing task changes or a manufacturing resource withdraws for some reason. So that enterprises can cope with the rapidly changing and unpredictable market demand, thus obtaining long-term economic benefits of enterprises. The agility index of manufacturing units' configuration mainly includes the functional diversity F_{ij}^d and the manufacturing resource types F_{ij}^z of each manufacturing unit, which can be expressed as

$$\begin{aligned} \max F &= \max \sum_{i=1}^{n}\sum_{j=1}^{m_i}\left(F_{ij}H_{ij}\right) \\ &= \max\left\{\sum_{i=1}^{n}\sum_{j=1}^{m_i}\left(F_{ij}^d H_{ij}\right) + \sum_{i=1}^{n}\sum_{j=1}^{m_i}\left(F_{ij}^z H_{ij}\right)\right\}, \\ &\qquad i = 1, \ldots, n, j = 1, \ldots, m_i, \end{aligned} \quad (29)$$

where

$$H_{ij} = \begin{cases} 1, & \text{the } i\text{th manufacturing subtask is completed by the manufacturing unit } \mathrm{MS}_{ij}, \\ 0, & \text{the } i\text{th manufacturing subtask is not completed by the manufacturing unit } \mathrm{MS}_{ij}. \end{cases} \quad (30)$$

The functional diversity F_{ij}^d of any manufacturing unit cannot be less than the minimum functional diversity $F_{\min}^n$ required by the MRP; the type of manufacturing resources F_{ij}^z provided by any MRP in the manufacturing units' configuration should not be less than the minimum type of manufacturing resource $F_{\min}^z$ required by the MRP. They can be expressed as

$$\begin{aligned} &F_{ij}^d \geq F_{\min}^d, \quad i = 1, \ldots, n, j = 1, \ldots, m_i, \\ &F_{ij}^z \geq F_{\min}^z, \quad i = 1, \ldots, n, j = 1, \ldots, m_i. \end{aligned} \quad (31)$$

(3) The Coordination of the Manufacturing Units' Configuration. The coordination of the manufacturing units' configuration in discrete manufacturing environment refers to manufacturing units that can coordinate and efficiently complete manufacturing task when the manufacturing task comes down. The coordination index of manufacturing units' configuration mainly includes the reliability of the manufacturing unit R_{ij}^k and the compatibility of the manufacturing unit R_{ij}^x, which can be expressed as

$$\begin{aligned} \max R &= \max \sum_{i=1}^{n}\sum_{j=1}^{m_i}\left(R_{ij}H_{ij}\right) \\ &= \max\left\{\sum_{i=1}^{n}\sum_{j=1}^{m_i}\left(R_{ij}^k H_{ij}\right) + \sum_{i=1}^{n}\sum_{j=1}^{m_i}\left(R_{ij}^x H_{ij}\right)\right\}, \\ &\qquad i = 1, \ldots, n, j = 1, \ldots, m_i, \end{aligned} \quad (32)$$

where

$$H_{ij} = \begin{cases} 1, & \text{the } i\text{th manufacturing subtask is completed by the manufacturing unit } \mathrm{MS}_{ij}, \\ 0, & \text{the } i\text{th manufacturing subtask is not completed by the manufacturing unit } \mathrm{MS}_{ij}. \end{cases} \quad (33)$$

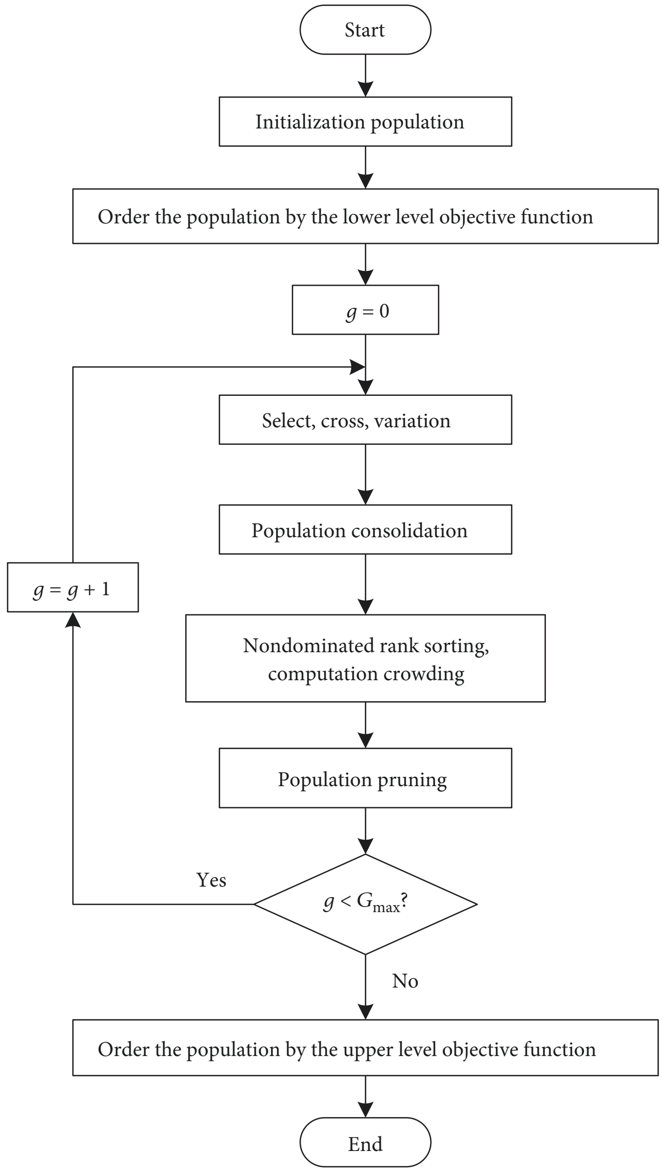

Figure 4: The NSGA-II algorithm for bilevel programming.

Table 2: Set of candidate manufacturing units.

Manufacturing subtasks	TS_1	TS_2	TS_3	TS_4	TS_5	TS_6	TS_7	TS_8
Manufacturing units	MS_{11}	MS_{21}	MS_{31}	MS_{41}	MS_{51}	MS_{61}	MS_{71}	MS_{81}
	MS_{12}	MS_{22}	MS_{32}	MS_{42}	MS_{52}	MS_{62}	MS_{72}	MS_{82}
	MS_{13}	MS_{23}	MS_{33}	MS_{43}	MS_{53}	MS_{63}	MS_{73}	MS_{83}
		MS_{24}	MS_{34}		MS_{54}	MS_{64}		MS_{84}
		MS_{25}				MS_{65}		

The reliability of any manufacturing unit R_{ij}^k in the manufacturing units' configuration cannot be less than the minimum reliability $R_{\min}^k$ required by the MRP. The coordination of any manufacturing unit R_{ij}^x in the manufacturing unit combination cannot be less than the minimum coordination $R_{\min}^x$ required by the MRP. They can be expressed as

$$\begin{aligned} R_{ij}^k &\geq R_{\min}^k, \quad i = 1, \ldots, n, j = 1, \ldots, m_i, \\ R_{ij}^x &\geq R_{\min}^x, \quad i = 1, \ldots, n, j = 1, \ldots, m_i. \end{aligned} \tag{34}$$

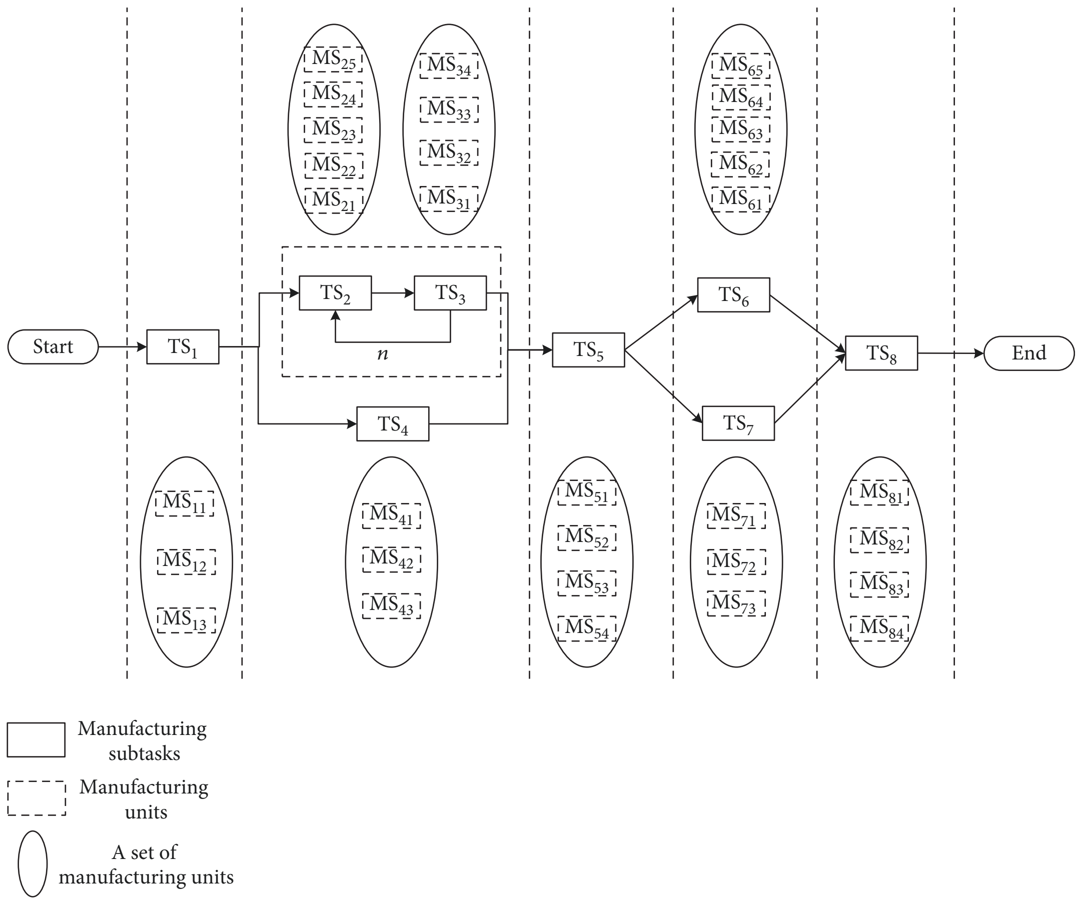

Figure 5: Manufacturing task flow chart.

5.2. Discrete Manufacturing Optimization Model Based on Bilevel Programming. In discrete manufacturing, it is difficult for MRD and MRP to express their preference for a certain characteristic with an explicit or implicit "utility function," but it is generally easy to determine what level of expectation a certain target achieves and according to the actual situation to adjust the level of the object expected to reach. In these elements that influence multiobjective decision-making in discrete manufacturing environment, they may contain both integer variables and fractional variables and may be continuous or discontinuous [25].

To solve this kind of decision-making problem, this paper proposes a bilevel programming decision method based on the object expectation: selecting index cost (C), time (T), quality (Q), and green (G) as the upper level optimization objectives that affect the MRD of manufacturing resources and then, selecting the index efficiency (E), agility (F), and coordination(R) as the lower level optimization objectives that affect the MRP of manufacturing resources. The bilevel optimization model under the discrete manufacturing environment is established as follows:

$$
\begin{aligned}
(\mathrm{U})\ \min \quad Z = {} & w_c \times \frac{V(C)}{V(C)_{\max}} + w_T \times \frac{V(T)}{V(T)_{\max}} \\
& + w_Q \times \frac{V(Q)}{V(Q)_{\max}} + w_G \times \frac{V(G)}{V(G)_{\max}}
\end{aligned} \tag{35}
$$

$$\text{s.t.} \quad V\left(C_{ij}\right) \le V(C)_{\max}, \tag{36}$$

$$V\left(T_{ij}\right) \le V(T)_{\max}, \tag{37}$$

$$V\left(Q_{ij}\right) \ge V(Q)_{\min}, \tag{38}$$

$$V\left(G_{ij}\right) \ge V(G)_{\min}, \tag{39}$$

$$(L)\ \max \quad z = (E, F, R)^{\mathrm{T}} \tag{40}$$

$$\text{s.t.} \quad E_{ij}^{n} \ge E_{\min}^{n}, \tag{41}$$

$$E_{ij}^{f} \ge E_{\min}^{f}, \tag{42}$$

$$F_{ij}^{d} \ge F_{\min}^{d}, \tag{43}$$

$$F_{ij}^{z} \ge F_{\min}^{z}, \tag{44}$$

$$R_{ij}^{k} \ge R_{\min}^{k}, \tag{45}$$

$$R_{ij}^{x} \ge R_{\min}^{x}. \tag{46}$$

Here, (35) denotes the upper-level optimization object given by the MRD, and (36) and (39) denote the quality, cost, time, and green indicator constraints of the upper-level optimization objectives; (40) denotes the lower-level optimization object given by the MRP, and (41) and (46) denote the

Table 3: Language evaluation of the MRD (one MRD's example).

Manufacturing units	C	T	Q	G
MS_{11}	Between S and VS	Between M and VS	Between SU and M	Between M and SS
MS_{12}	Greater than M	Between U and M	Greater than M	Between M and VS
MS_{13}	Greater than M	Lower than M	Greater than M	Between VU and S
MS_{21}	Between U and M	Greater than S	Between U and M	Lower than M
MS_{22}	Between M and SS	Greater than M	Between S and VS	Between SS and S
MS_{23}	Between M and S	Between U and M	Greater than M	Greater than SS
MS_{24}	Between M and S	Between VU and SU	Greater than M	Lower than M
MS_{25}	Greater than M	Between M and S	Between U and M	Between U and SS
MS_{31}	Greater than S	Lower than M	Between M and SS	Lower than M
MS_{32}	Between U and M	Between S and VS	Between M and S	Between VU and M
MS_{33}	Greater than M	Greater than M	Between M and S	Greater than M
MS_{34}	Greater than U	Greater than M	Between U and SS	Greater than M
MS_{41}	Between VU and U	Between U and M	Between M and VS	Lower than M
MS_{42}	Between U and M	Between M and SS	Greater than M	Greater than S
MS_{43}	Greater than S	Between M and S	Greater than S	Greater than M
MS_{51}	Greater than S	Between M and S	Between SU and SS	Between U and M
MS_{52}	Between SS and S	Greater than M	Between U and VS	Between VU and SU
MS_{53}	Between VU and U	Between S and VS	Between M and VS	Between M and S
MS_{54}	Between M and S	Greater than S	Between VU and M	Lower than M
MS_{61}	Between U and S	Between S and VS	Lower than M	Between S and VS
MS_{62}	Lower than M	Lower than M	Greater than S	Greater than M
MS_{63}	between SS and S	Between U and M	Greater than M	Greater than M
MS_{64}	Greater than M	Greater than M	Between U and M	Between U and M
MS_{65}	Between VU and M	Between S and VS	Between VU and SU	Between M and SS
MS_{71}	Greater than M	Greater than S	Between M and S	Between M and S
MS_{72}	Lower than M	Lower than M	Greater than M	Between M and S
MS_{73}	Greater than S	Greater than SS	Greater than M	Between S and VS
MS_{81}	Greater than M	Greater than S	Between U and M	Between M and S
MS_{82}	Between U and M	Greater than S	Between U and SS	Greater than M
MS_{83}	Between VU and SU	Between SS and S	Between M and VS	Lower than M
MS_{84}	Between M and S	Between VU and U	Between U and S	Between U and M
Expectation value	M	SS	S	M

efficiency, coordination, and agility indicator constraints of the lower-level optimization object.

5.3. Model Solving. There are more famous algorithms for resource configuration optimization, such as genetic algorithm, ant colony algorithm, particle swarm optimization, and simulated annealing algorithm, but these algorithms have certain constraints when solving the bilevel programming model of manufacturing resource optimization configuration in this paper. The bilevel planning is a NP-hard (nondeterministic polynomial, NP) problem. The process of solving such problems is very complicated. The fast nondominated sorting genetic algorithm (NSGA-II) is an improvement of the NSGA algorithm and is one of the best evolutionary multiobjective optimization algorithms [26, 27].

This paper uses the NSGA-II algorithm to solve the bilevel planning model under the discrete manufacturing environment. The general flow is shown in Figure 4.

6. Illustrative Example

6.1. Model Establishment of Discrete Resource Configuration. The MDR submits the manufacturing task to the MDP according to the market demand. On the basis of certain

Table 4: The transformation of trapezoid fuzzy numbers for language evaluation (one MRD's example).

Manufacturing units	C	T	Q	G
MS_{11}	(0.692, 0.769, 1, 1)	(0.385, 0.462, 1, 1)	(0.231, 0.308, 0.538, 0.615)	(0.385, 0.462, 0.692, 0.769)
MS_{12}	(0.385, 0.462, 1, 1)	(0.077, 0.154, 0.538, 0.615)	(0.385, 0.462, 1, 1)	(0.385, 0.462, 1, 1)
MS_{13}	(0.385, 0.462, 1, 1)	(0, 0, 0.538, 0.615)	(0.385, 0.462, 1, 1)	(0, 0, 0.846, 0.923)
MS_{21}	(0.077, 0.154, 0.538, 0.615)	(0.692, 0.769, 1, 1)	(0.077, 0.154, 0.538, 0.615)	(0, 0, 0.538, 0.615)
MS_{22}	(0.385, 0.462, 0.692, 0.769)	(0.385, 0.462, 1, 1)	(0.692, 0.769, 1, 1)	(0.077, 0.154, 0.846, 0.923)
MS_{23}	(0.385, 0.462, 0.846, 0.923)	(0.077, 0.154, 0.538, 0.615)	(0.385, 0.462, 1, 1)	(0.538, 0.615, 0.846, 0.923)
MS_{24}	(0.385, 0.462, 0.846, 0.923)	(0, 0, 0.385, 0.462)	(0.385, 0.462, 1, 1)	(0, 0, 0.538, 0.615)
MS_{25}	(0.385, 0.462, 1, 1)	(0.385, 0.462, 0.846, 0.923)	(0.077, 0.154, 0.538, 0.615)	(0.077, 0.154, 0.692, 0.769)
MS_{31}	(0.692, 0.769, 1, 1)	(0, 0, 0.538, 0.615)	(0.385, 0.462, 0.692, 0.769)	(0, 0, 0.538, 0.615)
MS_{32}	(0.077, 0.154, 0.538, 0.615)	(0.692, 0.769, 1, 1)	(0.385, 0.462, 0.846, 0.923)	(0, 0, 0.538, 0.615)
MS_{33}	(0.385, 0.462, 1, 1)	(0.385, 0.462, 1, 1)	(0.385, 0.462, 0.846, 0.923)	(0.385, 0.462, 1, 1)
MS_{34}	(0.077, 0.154, 1, 1)	(0.385, 0.462, 1, 1)	(0.077, 0.154, 0.692, 0.769)	(0.385, 0.462, 1, 1)
MS_{41}	(0, 0, 0.231, 0.308)	(0.077, 0.154, 0.538, 0.615)	(0.385, 0.462, 1, 1)	(0, 0, 0.538, 0.615)
MS_{42}	(0.077, 0.154, 0.538, 0.615)	(0.385, 0.462, 0.692, 0.769)	(0.385, 0.462, 1, 1)	(0.692, 0.769, 1, 1)
MS_{43}	(0.692, 0.769, 1, 1)	(0.385, 0.462, 0.846, 0.923)	(0.692, 0.769, 1, 1)	(0.385, 0.462, 1, 1)
MS_{51}	(0.692, 0.769, 1, 1)	(0.385, 0.462, 0.846, 0.923)	(0.231, 0.308, 0.692, 0.769)	(0.077, 0.154, 0.538, 0.615)
MS_{52}	(0.538, 0.615, 0.846, 0.923)	(0.385, 0.462, 1, 1)	(0.077, 0.154, 1, 1)	(0, 0, 0.385, 0.462)
MS_{53}	(0, 0, 0.231, 0.308)	(0.692, 0.769, 1, 1)	(0.385, 0.462, 1, 1)	(0.385, 0.462, 0.846, 0.923)
MS_{54}	(0.385, 0.462, 0.846, 0.923)	(0.692, 0.769, 1, 1)	(0, 0, 0.538, 0.615)	(0, 0, 0.538, 0.615)
MS_{61}	(0.077, 0.154, 0.849, 0.923)	(0.692, 0.769, 1, 1)	(0, 0, 0.538, 0.615)	(0.692, 0.769, 1, 1)
MS_{62}	(0, 0, 0.538, 0.615)	(0, 0, 0.538, 0.615)	(0.692, 0.769, 1, 1)	(0.385, 0.462, 1, 1)
MS_{63}	(0.538, 0.615, 0.846, 0.923)	(0.077, 0.154, 0.538, 0.615)	(0.385, 0.462, 1, 1)	(0.385, 0.462, 1, 1)
MS_{64}	(0.385, 0.462, 1, 1)	(0.385, 0.462, 1, 1)	(0.077, 0.154, 0.538, 0.615)	(0.077, 0.154, 0.538, 0.615)
MS_{65}	(0, 0, 0.538, 0.615)	(0.692, 0.769, 1, 1)	(0, 0, 0.385, 0.462)	(0.385, 0.462, 0.692, 0.769)
MS_{71}	(0.385, 0.462, 1, 1)	(0.692, 0.769, 1, 1)	(0.385, 0.462, 0.846, 0.923)	(0.385, 0.462, 0.846, 0.923)
MS_{72}	(0, 0, 0.538, 0.615)	(0, 0, 0.538, 0.615)	(0.385, 0.462, 1, 1)	(0.385, 0.462, 0.846, 0.923)
MS_{73}	(0.692, 0.769, 1, 1)	(0.538, 0.615, 0.846, 0.923)	(0.385, 0.462, 1, 1)	(0.692, 0.769, 1, 1)
MS_{81}	(0.385, 0.462, 1, 1)	(0.692, 0.769, 1, 1)	(0.077, 0.154, 0.538, 0.615)	(0.385, 0.462, 0.846, 0.923)
MS_{82}	(0.077, 0.154, 0.538, 0.615)	(0.692, 0.769, 1, 1)	(0.077, 0.154, 0.692, 0.769)	(0.385, 0.462, 1, 1)
MS_{83}	(0, 0, 0.385, 0.462)	(0.538, 0.615, 0.846, 0.923)	(0.385, 0.462, 1, 1)	(0, 0, 0.538, 0.615)
MS_{84}	(0.385, 0.462, 0.846, 0.923)	(0, 0, 0.231, 0.308)	(0.077, 0.154, 0.846, 0.923)	(0.077, 0.154, 0.538, 0.615)
Expectation value	(0.385, 0.462, 0.538, 0.615)	(0.538, 0.615, 0.692, 0.769)	(0.692, 0.769, 0.846, 0.923)	(0.385, 0.462, 0.538, 0.615)

principles, the MDP decomposes the manufacturing task and gets the set of manufacturing subtasks including 8 manufacturing subtasks ($TS_1, TS_2, \ldots, TS_8$). The MDP uses the function object matching principle to form a set of manufacturing units that complete each subtask, as shown in Table 2. The sequence of tasks is successive, as shown in Figure 5.

The questionnaire method to collect the language evaluation of the MRD is given by the acceptable range and expectation value for the four indexes ($C/T/Q/G$) of each manufacturing unit, as shown in Table 3.

According to (3) and Table 4, the acceptable range and expectation value of the MRD are converted into trapezoidal fuzzy numbers, as shown in Table 4.

Selecting the MRD expectation value as the reference point and referencing literature [28] obtains $\alpha = \beta = 0.88$, $\lambda = 2.25$, and $\delta = 0.56$. Next, we calculate the expected deviation (i.e., value function) of each manufacturing unit, according to Definition 2 and (11) and (12) and then based on (8) and (9) to calculate the decision weights of each manufacturing unit. Finally, according to (7), we can calculate the prospect value of MRD for each manufacturing, which is shown in Table 5.

In the same way, first of all, we get the language evaluation of three indexes (E/F/R) given by the MRP. Then, according to (3) and Table 2, we used formula $a = (a_1 + 2a_2 + 2a_3 + a_4)/6$ to defuzzify the trapezoidal fuzzy numbers, as shown in Table 6.

Assume that the parameters of the bilevel programming model for optimal configuration of manufacturing resources are $w_c = 0.272$, $w_T = 0.231$, $w_Q = 0.301$, $w_Q = 0.196$, $V(C)_{\max} = 0.541$, $V(T)_{\max} = 0.425$, $V(Q)_{\min} = 0.786$, $V(G)_{\min} = 0.775$, $E^n_{\min} = 0.128$, $E^f_{\min} = 0.128$, $F^d_{\min} = 0.205$, $F^z_{\min} = 0.205$, $R^k_{\min} = 0.195$, and $R^x_{\min} = 0.180$. According to (35) and (40), a bilevel optimization model for resource optimization configuration is as follows:

$$\begin{aligned}
\text{(U) min} \quad & Z = 0.506V\left(C_{ij}\right) + 0.544V\left(T_{ij}\right) \\
& \quad + 0.382V\left(Q_{ij}\right) + 0.253V\left(G_{ij}\right) \\
\text{s.t.} \quad & V\left(C_{ij}\right) \leq 0.541, \\
& V\left(T_{ij}\right) \leq 0.425, \\
& V\left(Q_{ij}\right) \geq 0.214, \\
& V\left(G_{ij}\right) \geq 0.225,
\end{aligned} \tag{47}$$

$$\begin{aligned}
\text{(L) max} \quad & z = (E, F, R)^{\mathrm{T}} \\
\text{s.t.} \quad & E^n_{ij} \geq 0.128, \\
& E^f_{ij} \geq 0.128, \\
& F^d_{ij} \geq 0.205, \\
& F^z_{ij} \geq 0.205, \\
& R^k_{ij} \geq 0.195, \\
& R^x_{ij} \geq 180.
\end{aligned} \tag{48}$$

6.2. Model Solving. NSGA-II algorithm was used to solve the model study (48). The initial population of the algorithm is 50; the crossover probability is 0.6; the mutation probability is 0.03; and the largest genetic algebra is 200. In the MATLAB 2016a calculation environment, the average fitness of each population under different fitness functions is calculated [29], as shown in Figure 6. In the 200-generation evolution process, the average fitness value after 50 generations tends to be stable. Therefore, after 50 generations of evolution, the Pareto optimal solution of the lower level optimization object of the manufacturing resource optimization configuration model is obtained. Calculate the Pareto frontier of optimal solution sets consisting of 50 solutions, as shown in Figure 7. Each point in the graph represents a Pareto optimal solution. The entire Pareto optimal solution set is located on the first-level Pareto frontier and distributed uniformly. That is, the ideal Pareto optimal solution set is obtained.

The Pareto optimal solution of the lower-level optimization of the manufacturing unit optimization selection model is regarded as the feasible solution of the upper optimization goal, the corresponding target value of the upper optimization goal is calculated, and the global optimal solution of the optimal selection bilevel programming model is obtained, according to the advantages and disadvantages. The degree is ranked and the first five groups of solutions are listed. The group with the smallest target value is the global optimal solution that satisfies the optimal choice between the customer and the manufacturer.

The Pareto optimal solution of the lower level optimization object of the manufacturing unit optimization model is the feasible solution of the upper level optimization object; then, the corresponding the upper level optimization object values are calculated. Further, we get the global optimal solution of the bilevel programming model and sort them according to their pros and cons and take the first five solutions listed, as shown in Table 7. The group with the smallest object value is the global optimal solution of the optimization problem.

Table 5: The prospect value of MRD (one MRD's example).

Manufacturing units	C	T	Q	G
MS_{11}	0.327	0.307	0.625	0.658
MS_{12}	0.272	0.255	0.520	0.547
MS_{13}	0.272	0.255	0.520	0.547
MS_{21}	0.205	0.192	0.391	0.412
MS_{22}	0.112	0.105	0.214	0.225
MS_{23}	0.205	0.193	0.392	0.413
MS_{24}	0.205	0.193	0.392	0.413
MS_{25}	0.273	0.255	0.520	0.547
MS_{31}	0.327	0.307	0.625	0.658
MS_{32}	0.205	0.192	0.391	0.412
MS_{33}	0.272	0.255	0.520	0.547
MS_{34}	0.328	0.307	0.626	0.659
MS_{41}	0.327	0.307	0.625	0.658
MS_{42}	0.205	0.192	0.391	0.412
MS_{43}	0.327	0.307	0.625	0.658
MS_{51}	0.327	0.307	0.625	0.658
MS_{52}	0.226	0.212	0.431	0.454
MS_{53}	0.327	0.307	0.625	0.658
MS_{54}	0.205	0.192	0.391	0.412
MS_{61}	0.279	0.261	0.532	0.560
MS_{62}	0.272	0.255	0.520	0.547
MS_{63}	0.226	0.212	0.431	0.454
MS_{64}	0.272	0.255	0.520	0.547
MS_{65}	0.272	0.255	0.520	0.547
MS_{71}	0.272	0.255	0.520	0.547
MS_{72}	0.272	0.255	0.520	0.547
MS_{73}	0.327	0.307	0.625	0.658
MS_{81}	0.272	0.255	0.520	0.547
MS_{82}	0.207	0.194	0.395	0.416
MS_{83}	0.287	0.269	0.548	0.577
MS_{84}	0.205	0.192	0.391	0.412

Table 6: Evaluation information of MRP.

Manufacturing units	The functional efficiency E_{ij}^{n}	The decomposition capability E_{ij}^{f}	The functional diversity F_{ij}^{d}	The manufacturing resource types F_{ij}^{z}	The reliability R_{ij}^{k}	The compatibility R_{ij}^{x}
MS_{11}	0.872	0.718	0.423	0.577	0.682	0.572
MS_{12}	0.718	0.346	0.718	0.718	0.682	0.417
MS_{13}	0.718	0.282	0.718	0.419	0.329	0.286
MS_{21}	0.346	0.872	0.346	0.282	0.818	0.561
MS_{22}	0.573	0.718	0.861	0.483	0.682	0.542
MS_{23}	0.650	0.346	0.718	0.714	0.682	0.415
MS_{24}	0.650	0.205	0.718	0.282	0.329	0.201
MS_{25}	0.714	0.654	0.346	0.423	0.548	0.489
MS_{31}	0.872	0.282	0.577	0.282	0.621	0.242
MS_{32}	0.346	0.872	0.654	0.282	0.621	0.561
MS_{33}	0.718	0.718	0.654	0.718	0.402	0.618
MS_{34}	0.564	0.718	0.423	0.718	0.682	0.618
MS_{41}	0.128	0.346	0.718	0.282	0.682	0.277
MS_{42}	0.346	0.577	0.718	0.872	0.828	0.591
MS_{43}	0.872	0.654	0.872	0.718	0.475	0.583
MS_{51}	0.872	0.654	0.500	0.346	0.536	0.464
MS_{52}	0.731	0.718	0.564	0.205	0.682	0.454
MS_{53}	0.128	0.872	0.718	0.654	0.268	0.680
MS_{54}	0.654	0.872	0.282	0.282	0.268	0.561
MS_{61}	0.501	0.872	0.282	0.872	0.828	0.750
MS_{62}	0.282	0.282	0.872	0.718	0.682	0.382
MS_{63}	0.731	0.346	0.718	0.718	0.329	0.417
MS_{64}	0.718	0.718	0.346	0.346	0.195	0.499
MS_{65}	0.282	0.872	0.205	0.577	0.621	0.655
MS_{71}	0.718	0.872	0.654	0.654	0.682	0.680
MS_{72}	0.282	0.282	0.718	0.654	0.682	0.361
MS_{73}	0.872	0.731	0.718	0.872	0.329	0.673
MS_{81}	0.718	0.872	0.346	0.654	0.389	0.680
MS_{82}	0.345	0.872	0.410	0.718	0.682	0.701
MS_{83}	0.205	0.731	0.718	0.282	0.475	0.485
MS_{84}	0.654	0.128	0.500	0.346	0.276	0.180

6.3. Analysis of Algorithm Results. The results of the solution of the example are compared with the results of the traditional algorithm to prove the validity of the model example.

The upper-level optimization objective of the bilevel programming model, presents the objective of the traditional manufacturing resource configuration model. The exhaustive method is used to calculate the functional target decision-making scheme, and all the obtained data are ranked according to the degree of pros and cons. The top 10 groups are listed, as shown in Table 8.

From Tables 7 and 8, the five optimal solutions (groups 1, 3, 4, 7, and 9 in Table 7) of the model study in this paper all contain the optimal top 10 optimal solutions. Therefore, the results of the model calculation in this paper not only satisfy the upper level optimization object but also satisfy the lower level optimization object of the model.

7. Discussion

In this paper, when establishing a bilevel programming of the discrete manufacturing resource optimization configuration model, the upper level optimization object is to select the smallest comprehensive value of the MRD and the lower level optimization object is to consider the maximum demand of the MRP.

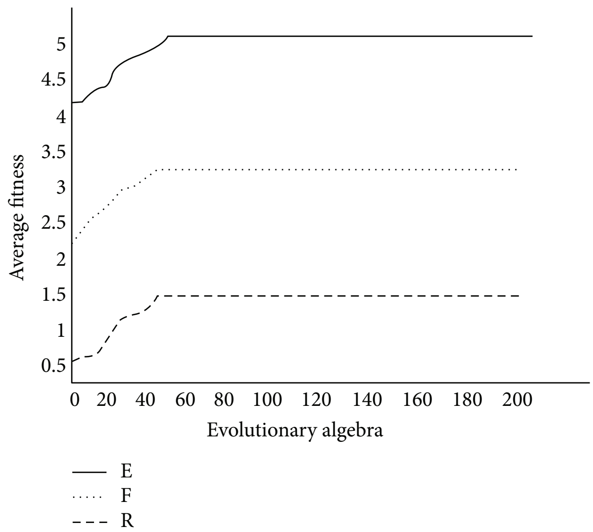

Figure 6: Average fitness curve of population.

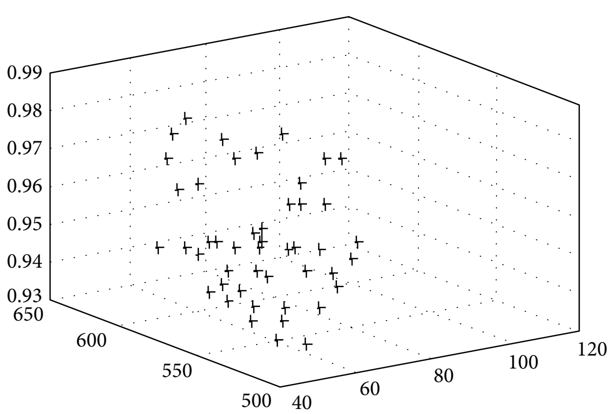

Figure 7: The Pareto frontier of optimal solution sets.

The upper level optimization goal is to select the upper level to consider the resource suppliers' comprehensive foreground value to be the smallest and the lower layer to consider the resource supply-side demand maximization, while the upper and lower layer constraints are. There are no interactions between the constraints imposed by the resource suppliers and the resource customers. The upper level and lower level give their own constraints, but the constraints are given by the MRD and the MRP, respectively, so there is no interaction between the constraints. We add a constraint condition which is strongly related to the upper level optimization object to the lower-level. A new bilevel programming model is established as follows:

$$
\begin{aligned}
\text{(U) min}\quad & Z = w_c \times \frac{V(C)}{V(C)_{\max}} + w_T \times \frac{V(T)}{V(T)_{\max}} + w_Q \times \frac{V(Q)}{V(Q)_{\max}} + w_G \times \frac{V(G)}{(VG)_{\max}} \\
\text{s.t.}\quad & V\left(C_{ij}\right) \leq V(C)_{\max}, \\
& V\left(T_{ij}\right) \leq V(T)_{\max}, \\
& V\left(Q_{ij}\right) \geq V(Q)_{\min}, \\
& V\left(G_{ij}\right) \geq V(G)_{\min},
\end{aligned}
\tag{49}
$$

$$\text{(L) max}\quad z = (E, F, R)^{\mathrm{T}} \tag{50}$$

$$\text{s.t.}\quad V_{ij} \leq V_{\max}, \tag{51}$$

$$E_{ij}^{n} \geq E_{\min}^{n}, \tag{52}$$

$$E_{ij}^{f} \geq E_{\min}^{f}, \tag{53}$$

$$F_{ij}^{d} \geq F_{\min}^{d}, \tag{54}$$

$$F_{ij}^{z} \geq F_{\min}^{z}, \tag{55}$$

$$R_{ij}^{k} \geq R_{\min}^{k}, \tag{56}$$

$$R_{ij}^{x} \geq R_{\min}^{x}. \tag{57}$$

In the lower constraint, add (51) which represent the foreground value constraint of the MRD for each manufacturing unit. By adding (51) to the lower constraint conditions, when the MDP is optimizing the manufacturing resource configuration, it is a priority to discharge the prospect value of the MRD, thus simplifying the complexity of computing, speeding up the calculation speed, and further improving the interactivity between the upper level and the lower level.

8. Conclusions

The traditional discrete manufacturing object decision-making method only considers the requirements of the MRD and ignores the practical difficulties of the MRP or only from the perspective of the MRP to provide self-perceived the MRD satisfaction and then through the linear weighting method to convert the multiobjective optimization problem into a single-objective optimization problem to solve. This paper analyzes the importance and current deficiencies of manufacturing resource optimization configuration in a discrete manufacturing environment and considers uncertainties such as manufacturing resource changes and manufacturing task changes. On this basis, according to the process and characteristics of manufacturing resource configuration in a discrete manufacturing environment, and from the interests of different participants, a bilevel programming mathematical model for manufacturing resource optimization configuration was built. It not only ensures the interests of different participants but also ensures the smooth progress of the manufacturing service. Finally, it uses NSGA-II to solve the model. The method presented in this paper has the characteristics of clear concept and simple calculation process and has strong operability and practicality. It provides a new way to solve the problem of multiobjective resource optimization configuration.

Table 7: Discrete manufacturing optimal solution sorting of NSGA-II.

Sequence	Manufacturing resource configuration plan	U	L
1	MS_{11}, MS_{25}, MS_{34}, MS_{42}, MS_{58}, MS_{66}, MS_{87}	1.5938	1.4936
2	MS_{15}, MS_{28}, MS_{31}, MS_{41}, MS_{55}, MS_{74}, MS_{83}	1.5940	1.4867
3	MS_{13}, MS_{23}, MS_{34}, MS_{42}, MS_{55}, MS_{73}, MS_{83}	1.5939	1.4902
4	MS_{15}, MS_{22}, MS_{31}, MS_{44}, MS_{58}, MS_{66}, MS_{81}	1.5940	1.4897
5	MS_{13}, MS_{25}, MS_{34}, MS_{42}, MS_{55}, MS_{65}, MS_{81}	1.5937	1.4899

Table 8: The order of optimal solutions obtained by the exhaustion method.

Sequence	Manufacturing resource configuration plan	U	L
1	MS_{11}, MS_{25}, MS_{34}, MS_{42}, MS_{58}, MS_{66}, MS_{87}	1.5938	1.4936
2	MS_{15}, MS_{22}, MS_{31}, MS_{44}, MS_{58}, MS_{66}, MS_{81}	1.5938	1.4891
3	MS_{15}, MS_{28}, MS_{31}, MS_{41}, MS_{55}, MS_{74}, MS_{83}	1.5940	1.4867
4	MS_{13}, MS_{23}, MS_{34}, MS_{42}, MS_{55}, MS_{73}, MS_{83}	1.5939	1.4902
5	MS_{15}, MS_{25}, MS_{31}, MS_{41}, MS_{55}, MS_{74}, MS_{83}	1.5937	1.4871
6	MS_{13}, MS_{23}, MS_{34}, MS_{42}, MS_{56}, MS_{73}, MS_{87}	1.5931	1.4894
7	MS_{15}, MS_{22}, MS_{31}, MS_{44}, MS_{58}, MS_{66}, MS_{81}	1.5940	1.4897
8	MS_{11}, MS_{28}, MS_{34}, MS_{42}, MS_{55}, MS_{66}, MS_{87}	1.5934	1.4937
9	MS_{13}, MS_{25}, MS_{34}, MS_{42}, MS_{55}, MS_{65}, MS_{81}	1.5937	1.4899
10	MS_{13}, MS_{22}, MS_{34}, MS_{42}, MS_{58}, MS_{73}, MS_{87}	1.5936	1.4890

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.

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