Dual-objective Programming Model for Equipment Resource Allocation and Its Algorithm Implementation

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Abstract. This paper in view of the allocation of equipment resources in enterprise groups is studied. Firstly, it introduces the 0-1 decision variable, and takes the order group self-made processing period, equipment resource condition and self-made parts processing status as constraints, emphasizing the processing quality control of the self-made parts required for key important features. A dual-objective programming model of equipment resource allocation based on quality and cost is constructed, and the dual-objective function is transformed into a single objective function by linear weighting method, and then, the improved honey evolutionary genetic algorithm is used to solve it. Finally has carried on the simulation analysis, the simulation analysis results show that the resource allocation dual-objective programming model and the algorithm are effective.

1. Introduction
Equipment resources as the core strategic resource of enterprise group, its effective configuration is crucial for enterprises to control the processing period, improve the processing quality, control the production cost and improve the utilization rate of manufacturing resources. In view of the importance of resource equipment configuration, domestic and foreign scholars about the equipment resource optimal allocation problem in a series of studies [1-3]. Considering that the previous research did not attach importance to the quality processing requirements of self-made parts for key important features, and some limitations of the algorithms involved. This paper emphasizes the quality control of the manufacturing process for the self-made parts required by the key important features, establishes the optimization model of equipment resource allocation with the dual-objective of processing quality and cost control, and solves it with the improved honey evolutionary genetic algorithm. Overcoming the insufficient local search ability in the traditional genetic algorithm often leads to premature convergence of the algorithm, the limitations of late efficiency is not high.

2. Establishment of a dual-objective planning model for equipment resource allocation
2.1. Description of equipment resource allocation and introduction of 0-1 decision variables
The essence of the equipment resource allocation is driven by the order task, and the idle or redundant processing equipment resources in the current contract period are selected from the same or different geographical locations to complete the processing of self-made parts, that is, the optimal equipment
resources are configured to complete the overall processing task of the order group.

For the problem of equipment resource allocation, in order to study the convenience of the problem and the operability of the method, it is assumed that a number of self-made parts groups are formed by grouping parts and each group is composed of several manufacturing features. The manufacturing features correspond to the processing operation, and the processing order is determined and independent of each other. The processing quality, processing time and processing cost corresponding to each process are determined.

Under the above assumptions, the resource optimal allocation problem studied in this paper can be described as follows: Let an enterprise group's self-made task set \( \{ SM_i \} \) represents the j-th self-made task under the \( OG_i \) of the order group, and the process and equipment resource group \( \{ R_v \} \) represents the equipment used in the v-th process corresponding to the manufacturing feature \( MF_v \) (the corresponding relationship between the manufacturing feature and the process and equipment is m:n, and the process corresponds to the selected equipment one by one). The enterprise group must be under the conditions of guaranteeing the construction period, etc. Through the optimal allocation of resources within the group, the optimal comprehensive goal is achieved. Firstly, the 0-1 decision variable \( x_{ijuv} \) is introduced to represent the corresponding relationship between the self-made parts to be processed and the processing equipment resources.

\[
  x_{ijuv} = \begin{cases} 
  1 & \text{self-made parts } SM_j \text{ is processed on equipment } R_v, \\
  0 & \text{self-made parts } SM_j \text{ is not processed on equipment } R_v. 
\end{cases}
\]

The schematic diagram of optimal allocation of equipment resources is shown in Figure 1.

![Figure 1](image.png)

**Figure 1.** Schematic diagram of optimal allocation of equipment resources.

2.2. Determination of the objective function

In order to improve the quality of processing and reduce the cost of production, this paper constructs a dual-objective optimization model of the equipment resource allocation based on quality and cost.

2.2.1. Determination of the quality objective function. In the process of production and processing, considering that the enterprise has requirements for the processing technology of the self-made parts of key important features, require higher qualified rate, and lower scrap rate. Therefore, when considering the quality objective function, this paper separately establishes the quality objective
function of the self-made parts required for key important features and common feature processing techniques.

(1) Quality objective function of self-made parts required by key important features

According to the scrap rate of the self-made parts processing task required by the key important characteristics, the quality objective function with the lowest defect rate is constructed, that is

$$Q_1 = \sum_{x=1}^{n} \sum_{j_1=1}^{m_1} \sum_{j=1}^{k} \sum_{w=1}^{q} x_{ijw} (1-q_{ijw}) / (1-q_{ij})$$  \hspace{1cm} (1)$$

Among them, $q_{ijw}$ is the qualification rate of the self-made parts $SM_{ij}$ in equipment $R_{w}$ required by the key important features; $q_{ij}$ is the minimum qualification rate required for the processing of self-made parts required by the key important features. $j_1 \in \{ \text{the subscript set with self-made parts required for key important features in order group OG}_1 \}$, $x_{ijw}$ are decision variables.

$$x_{ijw} = \begin{cases} 1, & \text{the self-made parts required for key important features SM}_{ij} \text{ is processed on equipment R}_{w}, \\ 0, & \text{the self-made parts required for key important features SM}_{ij} \text{ is not processed on equipment R}_{w}. \end{cases}$$

(2) Quality objective function of self-made parts required by common features

According to the scrap rate of the self-made parts processing task required by the common features, the quality objective function with the lowest defect rate is constructed, that is

$$Q_2 = \sum_{i=1}^{n} \sum_{j_2=1}^{m_2} \sum_{j=1}^{k} \sum_{w=1}^{q} x_{ijw} (1-q_{ijw}) / (1-q_{ij})$$  \hspace{1cm} (2)$$

Among them, $q_{ijw}$ is the qualification rate of the self-made parts $SM_{ij}$ in the equipment $R_{w}$ required by the common features; $q_{ij}$ is the minimum qualification rate required for the $SM_{ij}$ processing of the self-made parts required by the common features,

$$j_2 \in \{ \text{the subscript set with self-made parts required for general important features in order group OG}_2 \} \text{, } x_{ijw}$$

is a 0-1 decision variable, and its definition is similar to $x_{ijw}$.

(3) Determination of the quality objective function

According to the importance attached to the rejection rate of the self-made parts with key important features, the quality objective function of the self-made parts required by the key important features and common features is weighted to determine the total quality objective function.

$$Q = \min \ W_1 Q_1 + W_2 Q_2$$

that is

$$Q = \min \ W_1 \sum_{x=1}^{n} \sum_{j_1=1}^{m_1} \sum_{j=1}^{k} \sum_{w=1}^{q} x_{ijw} (1-q_{ijw}) / (1-q_{ij})$$

$$+ W_2 \sum_{i=1}^{n} \sum_{j_2=1}^{m_2} \sum_{j=1}^{k} \sum_{w=1}^{q} x_{ijw} (1-q_{ijw}) / (1-q_{ij})$$  \hspace{1cm} (3)$$

Let $W_1$ and $W_2$ represent the weights of the self-made mass objective function required by key important features and common features in order, satisfying $W_1 + W_2 = 1$, and the larger the weight
value, indicating that the higher the importance is attached to it.

2.2.2. Determination of the cost objective function. Processing cost and logistics cost are the main considerations for resource allocation of enterprise groups. The cost objective function of this paper is as follows.

\[ C = \sum_{i=1}^{n} \sum_{j=1}^{m} (C_{ij} + CT_{ij}) \]  \hspace{1cm} (4)

Where \( C \) is the total cost of all orders, \( C_{ij} \) is the cost of the order group \( OG_{ij} \), \( CS_{ij} \) is the processing cost of the self-made parts \( SM_{ij} \) in the order group \( OG_{ij} \), and \( CT_{ij} \) is the logistics cost of the self-made parts \( SM_{ij} \). The specific \( CS_{ij} \), \( CT_{ij} \) see (5) and (6).

\[ CS_{ij} = \sum_{i=1}^{n} \sum_{j=1}^{m} k \sum_{u=1}^{q} \sum_{v=1}^{q} x_{ijuv} p_{c_{ijuv}} p_{t_{ijuv}} \]  \hspace{1cm} (5)

\[ CT_{ij} = \sum_{i=1}^{n} \sum_{j=1}^{m} k \sum_{u=1}^{q} \sum_{v=1}^{q} x_{ijuv} x_{ij(u+1)w} \beta_{aw,(u+1)w} l_{c_{ijuw}(u+1)w} \]  \hspace{1cm} (6)

Where, \( p_{c_{ijuw}} \) is the processing cost of the self-made parts \( SM_{ij} \) on the equipment resource \( R_{uw} \), \( p_{t_{ijuv}} \) is the processing time of the self-made parts \( SM_{ij} \) on the equipment resource \( R_{uv} \), and \( l_{c_{ijuw}(u+1)w} \) is the transportation price of the self-made parts \( VP_{ij} \) from the equipment resource \( R_{fw} \) to the equipment resource \( R_{(u+1)w} \). \( \beta_{aw,(u+1)w} \) is

\[ \beta_{aw,(u+1)w} = \begin{cases} 1, & \text{equipment } R_{aw} \text{ and equipment } R_{(u+1)w} \text{ do not belong to the same manufacturing body;} \\ 0, & \text{equipment } R_{aw} \text{ and equipment } R_{(u+1)w} \text{ belong to the same manufacturing body.} \end{cases} \]

2.2.3. Comprehensive optimization of objective function. In order to be more suitable for the application in practical engineering and the solution of the model, this paper converts the above dual-objective functions about quality and cost into single objective function through the linear weighting method to obtain the comprehensive optimization objective function.

\[ Z = \min \quad w_3 Q + w_4 C. \]  \hspace{1cm} (7)

In the formula: \( w_3 \) and \( w_4 \) represent the weight of the quality and cost targets in turn, satisfying \( w_3 + w_4 = 1 \). The weight coefficient \( w_3 \), \( w_4 \) can be selected according to the specific requirements of the building materials industry for quality and cost.

In addition, for the bi-objective programming problem, the dimension problem should be taken into account in the actual solution. For the specific treatment method, please refer to the following contents of the multi-text model solution algorithm to realize the corresponding design of some fitness functions.

3. Determination of model constraints

(1) Duration constraints

The construction period constraints such as the start time, end time, processing time and
transportation time of the self-made part processing on the equipment resources are shown in equations (8), (9) and (10).

\[ E_{ijuv} = S_{ijuv} + pt_{ijuv}x_{ijuv} \quad (i = 1, \ldots, n, j = 1, \ldots, m, u = 1, \ldots, k, v = 1, \ldots, q) \]  
\[ T_y = \sum_{u=1}^{k} \sum_{v=1}^{q} (E_{ijuv} + l_{ijuv}(u+1)) \]  
\[ T_y < \max[T_i] \quad (i = 1, \ldots, n, j = 1, \ldots, m) \]

Where, \( S_{ijuv} \) is the start time of the self-made parts \( SM_{ij} \) on the device \( R_{uv} \), \( E_{ijuv} \) is the end time of the self-made parts \( SM_{ij} \) on the device \( R_{uv} \), \( T_y \) is the completion time of the self-made parts \( SM_{ij} \), and \( l_{ijuv}(u+1) \) is the self-made parts \( SM_{ij} \) slave \( R_{uv} \) to the device \( R_{(u+1)v} \). Transportation time, \( T_i \) is the total completion time of the order group \( OG_i \).

(2) Equipment resources and self-made parts constraints

In order to ensure that the model device resources are not in a state of conflict, a device resource can only process at most one self-made parts at the same time (in order to simplify the problem, it is not considered that one device resource can process multiple self-made parts at the same time), that is

\[ \sum_{i=1}^{n} \sum_{j=1}^{m} x_{ijuv} \leq 1 \quad (u = 1, \ldots, k, v = 1, \ldots, q) \]

A self-made part has at most one device resource to process it at a time, that is

\[ \sum_{v=1}^{q} x_{ijuv} \leq 1 \quad (u = 1, \ldots, k, i = 1, \ldots, n, j = 1, \ldots, m), \]

A self-made part must complete the processing of all features according to the process requirements, that is

\[ \sum_{u=1}^{k} \sum_{v=1}^{q} x_{ijuv} = k \quad (i = 1, \ldots, n, j = 1, \ldots, m) \]

In conclusion, the dual-objective planning model of equipment resources is as follows:

\[ \min \quad Z = \min \quad w_3 Q + w_4 C \]

Where \( Q \) is the quality objective function and \( C \) is the cost objective function, whose specific expressions are shown in equations (3) and (4).
4. Realization of solving algorithm of equipment resource allocation dual objective programming model

As a kind of intelligent optimization algorithm, genetic algorithm has the characteristics of fewer requirements for professional knowledge, good robustness and irrelevant iterative solution process and gradient information [4]. However, the traditional legacy algorithm has insufficient local search ability in the later search process often leads to the limitation of premature convergence and low efficiency of the algorithm [5], this paper applies an improved honey evolutionary genetic algorithm to solve the above-mentioned equipment resource allocation bi-objective programming model.

4.1. Coding method

This paper adopts the decimal coding method. According to the construction period, equipment resources and self-made parts constraints, each group of feasible solutions can be expressed as the only configuration of the self-made parts and equipment resources to be processed.

4.2. Generation of initial population

Randomly generated initial population, in order to improve the quality of initial population, make initial population evenly distributed in the feasible solution space. According to the characteristics of the honey evolutionary genetic algorithm, the generalized Hamming distance is used to quantify the difference between individuals in the initial population, and satisfy \( GH_{ij} \geq 30 \) (where \( GH_{ij} \) is the generalized Hamming distance between individuals \( i \) and \( j \)).

4.3. Design of fitness function

The fitness of the population is the bigger the better, and the dual objective function of the equipment resource-planning model established in this paper is the smaller the better, at the same time, considering the dual-objective function dimension problem. So here you need to first standardized dimensionless treatment was carried out on the double goals (formula (15)), and then further take its
reciprocal are fitness function (formula (16)).

\[
f(x) = w_1 \frac{Q_{\text{max}} - Q(x)}{Q_{\text{min}}} + w_2 \frac{C_{\text{max}} - C(x)}{C_{\text{min}}}, \text{where } x \in M
\]  

(15)

\[
F(x) = \frac{1}{f(x)}, \text{where } x \in M
\]  

(16)

Where, \( M \) is the population set, \( Q_{\text{max}} = \max Q(M), Q_{\text{min}} = \min Q(M), C_{\text{max}} = \min C(M), C_{\text{min}} = \max C(M) \), initial according to the population before iteration, compare with the current maximum and minimum values during evolution, and update.

4.4. Genetic manipulation

Genetic manipulation mainly involves selection, crossover and variation.

(1) Choice

By introducing weight parameters, a comprehensive selection probability related to fitness and degree of difference is determined, and uses it as a selection criterion to participate in the roulette wheel selection. When the difference degree between large, it is more conducive to the generation of new generations. The genotype can effectively avoid the premature convergence of traditional genetic algorithms. The specific steps are as follows:

1) The selection probability of individual fitness in the population is

\[
P_{i1} = F_i / \sum_{i=1}^{N} F_i
\]  

(17)

Where \( F_i \) is the fitness value of individual \( i \) in the population and \( N \) is the population size.

2) The selection probability of individual difference degree in the population is

\[
P_{i2} = GH_{i,\text{queen}} / N \times GH_{\text{ave,queen}}
\]  

(18)

Where, \( GH_{i,\text{queen}} \) is the generalized Hamming distance between the individual \( i \) and the queen bee, and represents the degree of difference between the individual \( i \) and the queen bee, and \( GH_{\text{ave,queen}} \) is the average generalized Hamming distance between the population and the queen bee.

3) The comprehensive selection probability of individual \( i \) in the population is

\[
P_i = \alpha P_{i1} + (1-\alpha)P_{i2}
\]  

(19)

Where \( \alpha \) is the selection weight value \( (0 < \alpha < 1) \), and the weight value should be determined according to the specific problems. The above-mentioned individual comprehensive selection probability is used as the selection criterion to participate in the roulette selection.

(2) Crossover

Aiming at the problem of equipment resource allocation, POX crossover operator is adopted in this paper [7], this operator can not only inherit the excellent characteristics of the parent generation, but also produce children (new configuration scheme) that are always feasible. Moreover, under the same conditions, this crossover operator works better.

(3) Variation
In this paper, insert variation is adopted to randomly select a gene and then insert it into other locations to form a new genotype.

4.5. Introducing the cataclysm operator

In this paper, the method of increasing the mutation rate, at the beginning of the algorithm is to set up a cataclysm countdown. During an iterative process, the gene of the queen bee changes, indicating that the algorithm has strong search ability, if the gene of the queen bee does not produce any change, it means The algorithm may fall into the local optimal solution, and the cataclysm timer is decremented by 1. When the timer returns to zero, the probability of cataclysm increasing the mutation occurs, and expanded new solution space for algorithms. If the gene of the queen bee changes before the cataclysm occurs, indicating that the solution space of the current search still has the value of exploration, reset the timer, and proceed to the next iteration.

5. Simulation analysis

In order to verify the validity of the model and algorithm established in this paper, the following build a simple numerical example, and a comparative simulation test analysis is carried out with the traditional genetic algorithm. The simulation experiment software is MATLAB. Suppose a certain enterprise group receives five order groups, and the construction period is respectively for 30, 20, 45, 50, and 60 days, each order group has a maximum of 30 self-made parts processing tasks, there are 20 processing technology characteristics, of which 12 are key important characteristics, and the processing qualification rate is 99%. There are 8 common characteristics, and the qualification rates are 80%, 85%, 87%, 86%, 88%, 68%, 87% and 78%, respectively. There are 60 resource devices corresponding to the processing technology characteristics, and four processing main body. Where equipment 1-12 belongs to the first processing main body, equipment 13-26 belongs to the second processing main body, equipment 27-45 belongs to the third processing main body, and equipment 46-60 belongs to the fourth processing main body, processing main body between transportation cost and time to see the table below. The problem is to find the best resource allocation scheme to minimize the optimization goal.

| Processing main body | Processing main body | Co.1 | Co.2 | Co.3 | Co.4 |
|----------------------|----------------------|------|------|------|------|
|                      | Cost/yuan | Time/day | Cost/yuan | Time/day | Cost/yuan | Time/day | Cost/yuan | Time/day |
| Co.1                 | 0         | 0        | 200     | 2      | 500     | 3      | 700     | 5      |
| Co.2                 | 200       | 2        | 0       | 0      | 600     | 3      | 560     | 2      |
| Co.3                 | 500       | 3        | 600     | 3      | 0       | 0      | 800     | 4      |
| Co.4                 | 700       | 5        | 560     | 2      | 800     | 4      | 0       | 0      |

The population size is 20 and the gene length is 26, and randomly generated initial population. The minimum generalized Hamming distance of the initial population is 30, the mutation probability is 0.05, the cataclysm probability is 0.5, the weight value of selection operator is 0.4, and the cataclysm timing is 28. Using the improved honey evolutionary genetic algorithm and traditional genetic algorithm are simulated solution, the specific solution results are limited to the length of the paper, omit here. Comparison of the effects of two kinds of algorithms, compare the results are shown in Table 2.
By comparison, it can be seen that the honey evolutionary genetic algorithm in this paper has better performance after comprehensive consideration of mean deviation, maximum deviation and optimal solution proportion.

**Table 2.** Comparison between the improved honey evolutionary genetic algorithm and the traditional genetic algorithm.

| Number of iterations | Mean deviation % | Maximum deviation % | Optimal solution proportion |
|----------------------|------------------|----------------------|-----------------------------|
|                      | Algorithm in this paper | Traditional genetic algorithm | Algorithm in this paper | Traditional genetic algorithm | Algorithm in this paper | Traditional genetic algorithm |
| 60                   | 0.1265            | 0.3021               | 3.11                       | 5.63                        | 63.5                    | 53.6                        |
| 70                   | 0.1357            | 0.2632               | 1.56                       | 4.26                        | 69.6                    | 58.3                        |
| 80                   | 0.1634            | 0.1923               | 1.48                       | 3.67                        | 83.6                    | 65.7                        |
| 90                   | 0.1566            | 0.2136               | 2.35                       | 3.86                        | 85.9                    | 69.3                        |

The simulation analysis results show that the resource allocation dual-objective programming model and algorithm are effective.

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