THE APPLICATION OF DATA-PROCESS INTERACTION MODEL IN COST ALLOCATION

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ABSTRACT: Cost allocation methods were studied based on the theory of process management in a manufacturing enterprise. Through establishing a dynamic mapping relationship between production process data and production operations on site, the interaction behavior was described and theory structure and data structure were established based on the data-process interaction model for the collection of cost resource information. Cost management data was extracted from complex process data and history data. Combining data envelopment analysis (DEA) and cooperative game theory, the allocation problems of cost resources in the production process were studied. Three nucleolus-based cost allocation models were proposed, as well as their algorithms, including the genetic algorithm. Finally, the proposed methods were validated in practice.

KEY WORDS: Complicated production environment, Data-Process interaction model, Cost management, Cost Allocation.

1 INTRODUCTION

Manufacturing enterprises with complex production processes have been accumulating increasing amounts of production cost data. Industrial site data and historical data with potential application value were extracted for further guidance for cost management and control of the production process. This has become a topic of broad and intense interest in research of cost management in recent years. Cost resource optimization and management problems based on both data and process of industrial production have sporadically been studied internationally in recent years, but mainly only in a specific production environment. However, theoretical and application results have been very limited, and the method based on both data and process has not formed a coherent theoretical system.

At present, the research on product data acquisition and management has mainly been concentrated on monitoring the production execution process and data management of Manufacturing Execution System (MES) globally. Some researchers put forward the assembly process design scheme by using an auxiliary flow chart (Chen et al., 2017; Jung et al., 2017; Renu and Mocko, 2016; Liu et al., 2016; Liu et al., 2016). The manufacturing process and order was described by way of a flow chart based on analyzing the process characteristics of products. Some researchers proposed a production process monitoring method based on Agent to access material information and execution status information on site (Shamsuzzoha et al., 2017; Metzger et al., 2015). Mahmood Mehdiloozada proposed the general structure for a data collection system on the production field from the angle of system building (Mehdiloozada et al., 2015). The above studies only focused on the collection of process data from the perspective of data collection and monitoring. However, the integrated management problem of product data acquisition process control and multi-source data collection was not effectively solved in the complex environment. There has been very little study on the subsequent processing of these data where the collected data was changed to information format required by the cost management and the data mining of implicit information.

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Using data envelopment analysis (DEA) theory to solve the cost resource allocation problem is a topic of broad and intense interest among scholars in the field of DEA research in recent years (Foroughi, 2013; Imanirad et al., 2015; Guimarães and Junior, 2017). Based on the decision making unit (DMU) efficiency invariance hypothesis and Pareto minimality, Cook first applied the DEA method to the cost allocation problem. Since then, cook proposed the efficiency invariance hypothesis and Mostafaee expanded studies. Based on the overall average efficiency maximization, Hatami-Marbini established a nonlinear cost allocation model (Cook and Zhu, 2005; Mostafaee, 2013; Hatami-Marbini et al., 2017; Salahi and Toloo, 2017). Kim held that when the evaluation index contained the cost resource input, the fixed cost and the existing cost investment should be combined and the corresponding fixed cost allocation model should be established (Lam et al., 2014). However, the above studies did not consider the mutual game relationship between decision making units. In process of the actual manufacturing costs resource allocation, when manufacturing costs apportioned to any DMU (i.e., cost object) was reduced, the cost assigned to anther DMU increased, and vice versa.

To effectively solve the cost resource optimization management and control problems in the complex conditions of manufacturing enterprises, and to overcome the existing defects in the modeling and optimization of cost management problems in the complex conditions the traditional modeling method and the commonly used optimization methods should be combined with advanced cost management thought and methods in the field of cost accounting. Drawing lessons from the research results of accounting science researchers and the practical experience of experts, the production process management, data integration, and cooperative game theory knowledge and technology were integrated. By making use of advanced cost management ideas and technology, the cost resources allocation system was established, with the data-process interaction model as the core, to improve the quality of product cost information.

2 PROCESS MODELING AND DATA MANAGEMENT ORIENTED TO THE PRODUCTION SITE

2.1 Production process analysis and data classification

The production process model is developed related to process management and the corresponding production operation. The relationships among process definition, process instance, and workflow related to process management are shown in figure 1.

In the production process, a specific production task of a workshop can be considered as a process definition; for example "XXX Type Automobile Engine Assembly Task List". The production task describes the production workshop, operating personnel and production completion time of the production operation. The production of a specific product of the production task is a process instance. A production task includes production of many specific products belonging to the same type of product. These specific products share similar resources and production data of this type of product, but their production processes are independent of each other, and production data of products is independent, such as the completion time of review, quality inspection data, and operating personnel information. Through a series of operations, operating personnel complete the production process. The production workflow is composed of a series of operations. The series of operations is an essential link to complete the task of production, being the most direct link to produce new production data and the source of production data changes. Proper operations can complete the production task smoothly and produce finished data, and improper operations will lead to rework and repair of products, while producing rework and repair data.

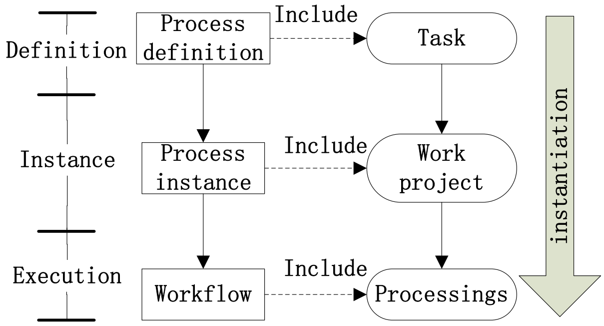

Figure 1. The relationships among concepts of process management

In the workflow process, a large amount of feedback information will constantly appear. The feedback information is the basis of decisions to the workflow. According to the type of feedback in the production process management model and the state of feedback activity, information feedback is divided into real-time feedback and approval feedback. Based on the two modes of feedback, the execution of the production process can be controlled by the state of experience. Throughout the whole activity, various states have been experienced, including task creation, job distribution, execution of activities, suspend of the implementation process, test of execution results. If review is not passed, it must be determined whether a new task needs to be established, and if passed, the test execution process is completed. The state change model is shown in figure 2.

Various stages in the production process are managed by the execution state change model of the production process. However, in this process of management, production activities can start even when the data is incomplete. It is required that the production data are available to drive the entire production process to start. The completed data ensures the accuracy of the production process. At the same time, new data produced in the production process might lead to relevant data changes. The data of the whole production site is partitioned according to its nature. The composition and classification model of data is shown in figure 3.

2.2 Data-process interaction model analysis

In order to realize the integrated management of process and data, the relationship between process and data was analyzed so that the enterprise can realize optimal control of cost resources in the complex production processes. For this purpose, the data-process interaction model for a complex environment was established, as shown in figure 4. The symbol meanings in figure:

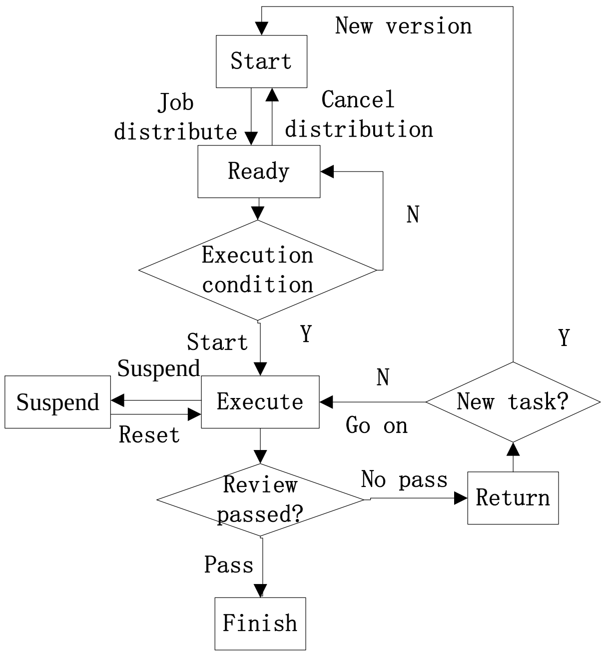

Figure 2. The execution state change model of production process

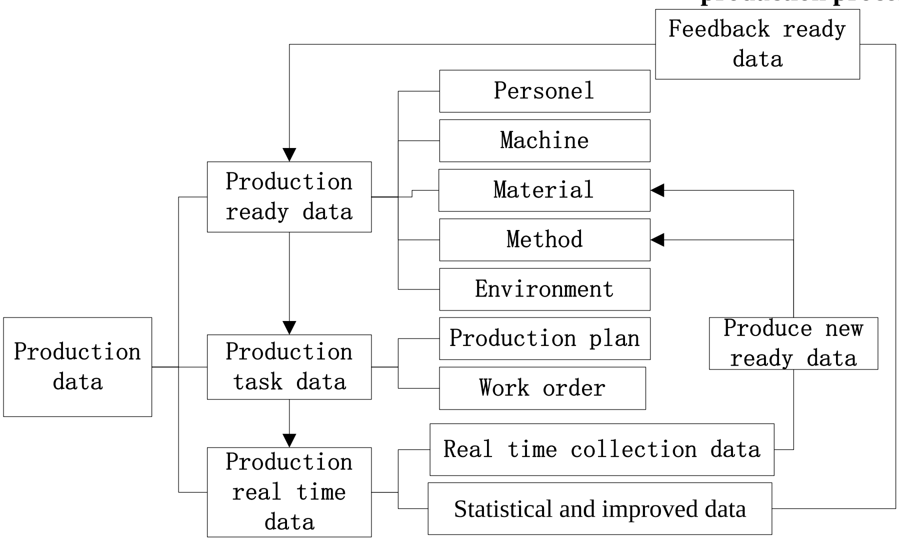

Figure 3. The composition and classification model of production data

E_Z-Raw materials of production;

E_{PG}-Average value of production process;

E_K-After sale service and user satisfaction of product;

PS-Production process, *SP*-Steps in the production process, *PSD*-Related data of process node;

L-Supplier of raw materials, W_E-Entrance of raw materials, W_A-Export of products.

In the overall production process of products, the main production process is accompanied with some parallel production process. The process of production contains its own production sub-processes. The production process and data drive influence each other in each production stage. The interaction behavior can be described by the mapping relation model of the production process and production data, as shown in figure 5. During the execution phase, the product process model and data model will be integrated alternately and interactively by the production data space and the process space. The data-process interaction model is established as shown in figure 6. The model shows that a production project includes a process instance. The process instance is a composite object including information about activities, relevant data, cost of resources and specific implementation personnel. It is a hierarchical mesh activity model and effectively realizes integration management of both the production process and the data.

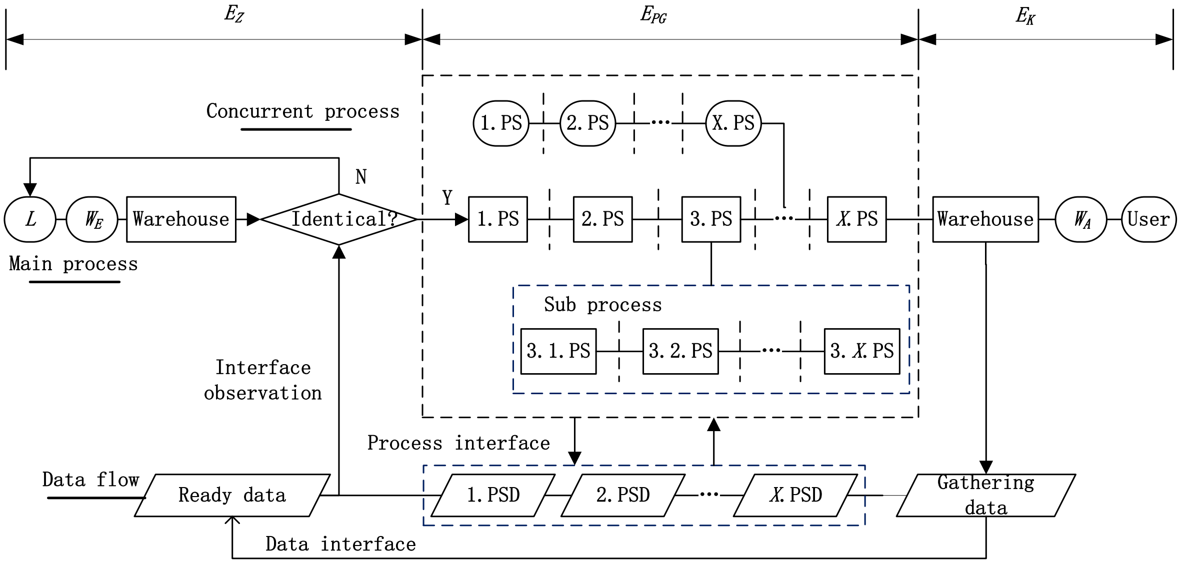

Figure 4. The Data-process interaction model for a complex environment

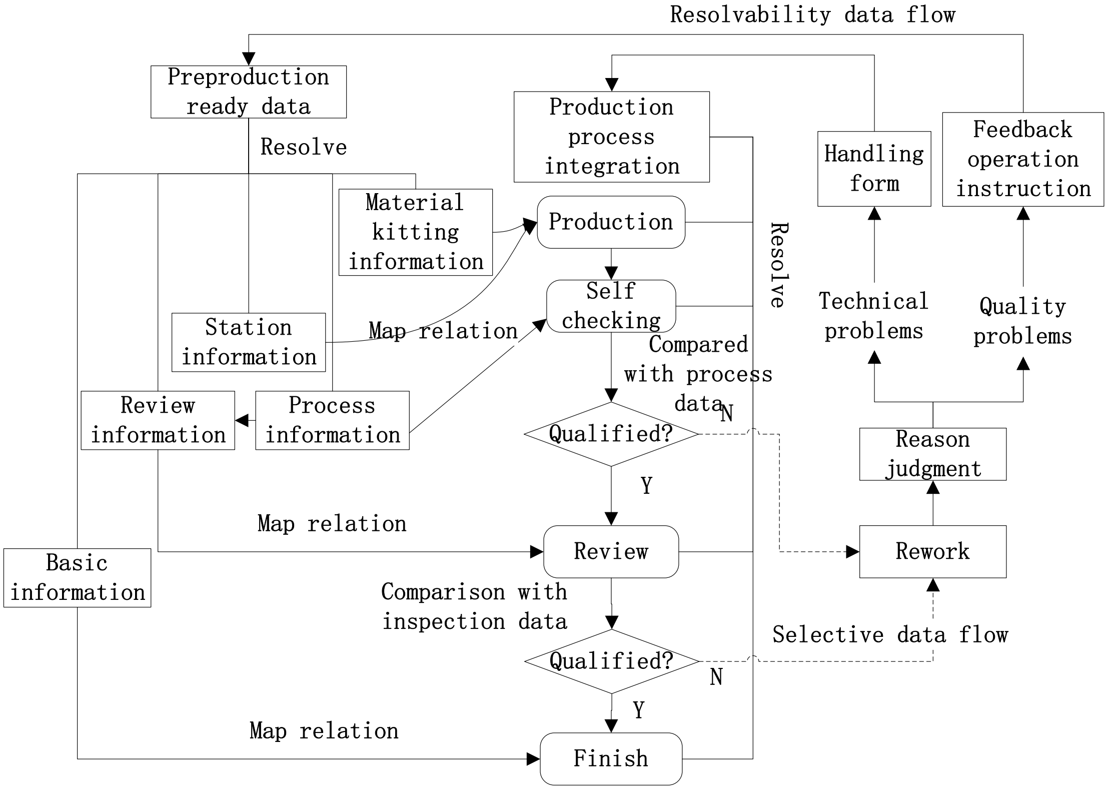

Figure 5. The map relation model of production process and data

3 COST RESOURCES ALLOCATION BASED ON DATA-PROCESS INTERACTION MODEL

The forming process of product cost includes the production resources being shifted to the cost object through a series of operations. This is the process of rational allocation of resources. The choice of an appropriate cost resources allocation model for manufacturing and the determination of a suitable model solution algorithm is the key to obtaining high quality cost information. It provides strong information support for the process cost control, the optimization of the allocation of resources and operating cost analysis and other activities. Making use of the complex production process management and integrated data management based on the data-process interaction model, cost process data and basic data were extracted. Manufacturing cost resources allocation scheme was determined by combining DEA theory with the alliance game analysis method. Firstly, it was determined that the decision-making unit of the individual MDU and the whole MDU was effective. Then, the feature function of cooperative games was defined. Finally, the distribution model of manufacturing cost resources was developed.

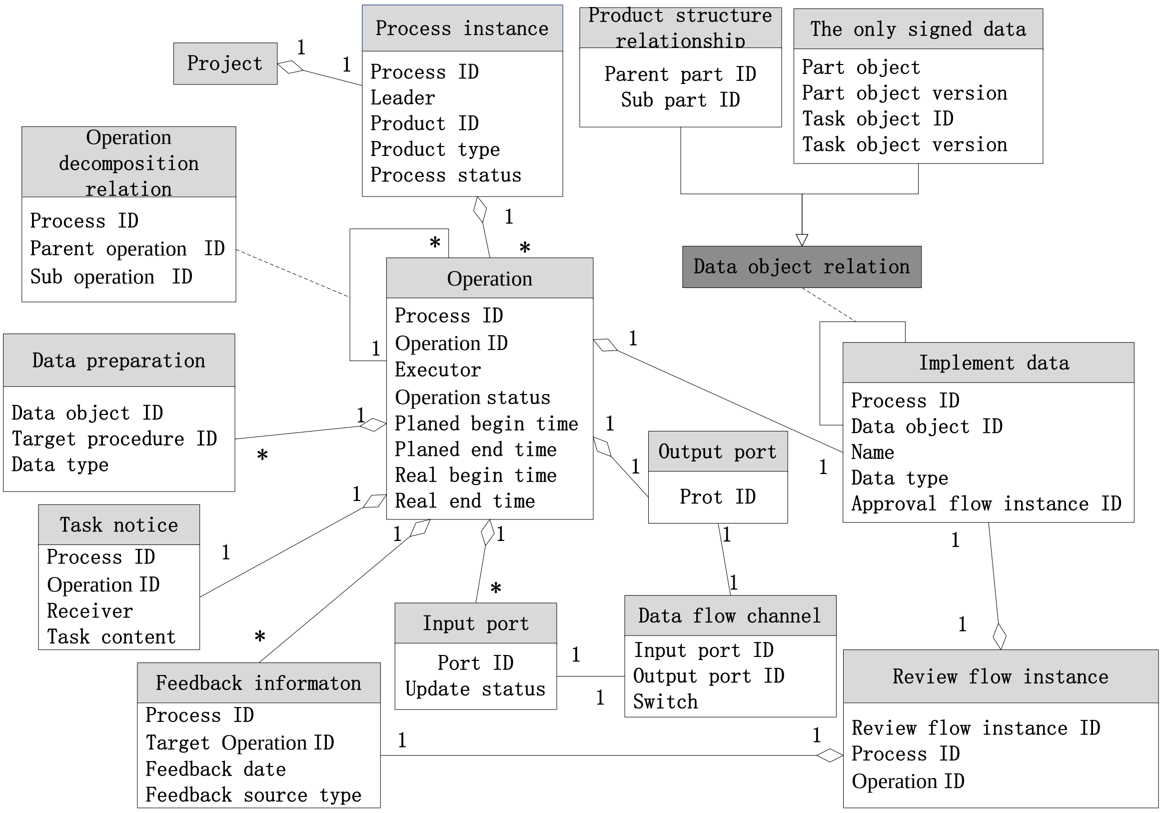

Figure 6. The data-process interaction object model

3.1 DMU efficiency evaluation based on manufacturing cost resources

From the decision making unit MDU (i.e., cost object) from the perspective of the individual, the choice of allocation scheme reaches its maximum relative efficiency. It is supposed that n sub decision making units established in the production process, within the where, the input and output vectors of the sub decision-making unit DMU_j(j=1, 2, ..., n) respectively are $X_j = (x_{1j}, x_{2j}, ..., x_{mj})^T$ and. $Y_j = (y_{1j}, y_{2j}, ..., y_{sj})^T$

$$
\begin{aligned}
& MaxE_d = \frac{\sum_{r=1}^{s} u_r \gamma_{rd}}{\sum_{i=1}^{m} v_i x_{id} + R_d} \\
& s.t. \\
& \qquad E_j = \frac{\sum_{r=1}^{s} u_r \gamma_{rj}}{\sum v_i x_{ij} + R_j} \le 1, \qquad \forall j \\
& \qquad \sum_{j=1}^{n} R_j = R \\
& \qquad u_i, v_i, R_j \ge 0, \qquad \forall r, i, j
\end{aligned}
$$

(1)

In Model (1), v_i(i=1, 2, ..., m) and u_r(r=1, 2, ..., s) are the weight of the corresponding input and output. The weight of R_j is positive. To simplify the calculation, the weight of R_j is assumed as 1. So a set of feasible solutions are determined to make all the efficiency values of DMU are 1 in Model (1). It was proved that all DMU were effective units in Model (1).

3.2 Basic assumptions and characteristic functions of the coalition game

To illustrate the cooperative game relationship between the *DMU*, basic assumptions are as follows:

Basic assumption 1: Every *DMU* is selfish. Minimization cost allocation strategies are taken in the process of cost resource allocation.

Basic assumption 2: Every *DMU* is involved in the cooperative game. Finally, a cost resource allocation scheme that is fair and acceptable for each has been determined.

It is assumed that the coalition *S* is a sub set of players set *N*= {1, 2, ..., *n*}. The input and output of *S* respectively are $x_i(S)=\sum_{j\in S} x_{ij}$ and $y_r(S)=\sum_{j\in S} y_{rj}$. The goal of the alliance is to obtain the minimum allocated cost. Then the minimum distribution cost of the alliance S is the minimum value of the following linear programming formula:

$$\begin{cases} V(S) = \min\left|\sum_{r=1}^{s} u_r y_r(S) - \sum_{i=1}^{m} v_i x_i(S)\right| \\ s.t. \\ \quad \sum_{j=1}^{n}\left|\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij}\right| = R \\ \quad R_j = \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \ge 0 \\ \quad u_r, v_i \ge 0, \forall r, j \end{cases}$$

(2)

Conclusions can be obtained from Model (2):

Conclusion 1: *V*(*f*)=0, *V*(*N*)=*R*

V(*S*) as a characteristic function of coalition *S*, reflects its selfishness characteristics. This is in line with actual cost allocation. The game constituted by all *DMU* can be defined as (*N*, *V*).

Conclusion 2: The characteristic function (*N*, *V*) is super additive; that is for any *S*⊂*N*, *T*⊂*N*, and *S*∩*T*=*f*, there is *V*(*S*)+*V*(*T*)≤*V*(*S*+*T*).

3.3 Nucleolus-based cost allocation models

For any alliance *S*, the total cost of its union members must be below the sum cost of its members separately running. Otherwise, *DMU* will not join the alliance *S*. The importance degree of every alliance *S* is different in the core solutions. So, dissatisfaction degrees of allocation scheme *Z* for the manufacturing cost are defined separately for *S*. Based on this, the following allocation model of manufacturing cost resource is established.

Scheme 1: All alliances *S* are treated equally, without considering the differences among *S*. The dissatisfaction degree of alliance *S* is applied to scheme *Z*.

$$\varepsilon_1(S) = \sum_{j\in S} z_j - V(S), \qquad 1 < |S| < n$$

(3)

The $\varepsilon_1(S)$ is clearly larger, and *S* is not more satisfied. In order to make the minimum dissatisfaction of alliance *S* be the most dissatisfied, the following model is established.

$$\begin{cases} \underset{u_r v_i}{Min}\,\varepsilon \\ s.t. \\ \quad \varepsilon \ge \varepsilon_1(S), \qquad 1 < |S| < n \\ \quad \sum_{j\in S} z_j \ge V(S), \qquad 1 < |S| < n \\ \quad V(\{j\}) \le z_j \le \Delta(j) \\ \quad \sum_{j=1}^{n} z_j = R \\ \quad z_j = \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \\ \quad u_r, v_j \ge 0, \qquad \forall r, j \end{cases}$$

(4)

In Model (4), the first constraint delineates an upper limit for the degree of dissatisfaction degree of *S*. All players in the model only have a common set of weights.

Scheme 2: There will be a difference in the number of members of the alliance *S*. So the importance of each *S* is determined by its number of members; the more members *S* is more important. Then the dissatisfaction degree of alliance is:

$$\varepsilon_2(S) = \frac{\sum_{j\in S} z_j - V(S)}{|S|}, \qquad 1 < |S| < n$$

(5)

In order to make the minimum average dissatisfaction degree of all *DMU* of *S*, Model (6) is established with the same constraint conditions as Model (4).

$$\begin{aligned}
&\underset{u_r v_i}{Min}\varepsilon \\
&s.t. \\
&\quad \varepsilon \geq \varepsilon_2(S), \qquad 1 <| S |< n \\
&\quad \sum_{j \in S} z_j \geq V(S), \qquad 1 <| S |< n \\
&\quad V(\{j\}) \leq z_j \leq \Delta(j) \\
&\quad \sum_{j=1}^{n} z_j = R \\
&\quad z_j = \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \\
&\quad u_r, v_j \geq 0, \qquad \forall r, j
\end{aligned}$$

(6)

Scheme 3: Because of the difference between the alliance S, the importance of each S is determined by the characteristics function $V(S)$. $V(S)$ is greater, and the importance of S is greater. The dissatisfaction of S is defined in Model (7):

$$\varepsilon_3(S) = \frac{\sum_{j \in S} z_j - V(S)}{V(S)}, \qquad 1 <| S |< n$$

(7)

The following model is established.

$$\begin{aligned}
&\underset{u_r v_i}{Min}\varepsilon \\
&s.t. \\
&\quad \varepsilon \geq \varepsilon_3(S), \qquad 1 <| S |< n \\
&\quad \sum_{j \in S} z_j \geq V(S), \qquad 1 <| S |< n \\
&\quad V(\{j\}) \leq z_j \leq \Delta(j) \\
&\quad \sum_{j=1}^{n} z_j = R \\
&\quad z_j = \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \\
&\quad u_r, v_j \geq 0, \qquad \forall r, j
\end{aligned}$$

(8)

4 ALGORITHM FOR THE MODEL

4.1 Genetic Algorithm

Cost management in an enterprise needs refinement under the complex manufacturing condition, and the cost object and the number n of *DMU* in the game is larger. The calculation complexity of the above models is high, and resolving time costs increases with the general linear programming method. Therefore the genetic algorithm (GA) is used to reduce the solution time of the model. GA is a global optimization search algorithm based on Darwin's theory of evolution. GA can quickly calculate complex nonlinear multidimensional data space. According to the individual fitness, its process includes repeated selection, crossover and mutation, restructuring the structure of an individual within the group. The solution structure with better performances is generated to the offspring to enhance the fitness of the offspring, and then generates the optimal or suboptimal solution. The model corresponds to the optimization problem. Feasible solutions to a problem can be transformed from the solution space into the search space that GA can handle, and the chromosome coding is the primary problem. Here, allocation of resources is directly mapped to the chromosome encoding by the floating point coding mode.

4.2 Calculation of the model

In order to guarantee the convergence of the genetic algorithm for resolving the model, the manufacture cost resource allocation model must be transformed into the model without restraints. Based on the above Model (4) as an example, considering the dissatisfaction of constraints, assumptions for the arbitrary allocation scheme Z, dissatisfaction of all S is arranged from large to small $(\varepsilon_1(Z), \cdots, \varepsilon_{2^n-1}(Z))$, and the weight ω_i meets the decreasing size relationship $\omega_1 > \omega_2 > \cdots > \omega_{2^n-1}$. Model (4) can be transformed into an unconstrained model as follows:

$$\underset{Z}{Min} \sum_i \omega_i \varepsilon_i(Z) + \omega_0 \mid \sum_{j=1}^{n} R_j - R \mid$$

(9)

The second item of Model (9) is penalty of the objective function. Its objective is to eliminate the constraint condition $\sum_{j=1}^{n} R_j = R$ of Model (4) and the weight must meet $\omega_0 \gg \omega_1$. The GA fitness function of Model (4) is as follows.

$$F(Z) = -\sum_i \omega_i \varepsilon_i(Z) + \omega_0 \mid \sum_{j=1}^{n} R_j - R \mid$$

(10)

Obviously for the allocation scheme, $F(Z)$ is the larger, it is the better. So the value of $F(Z)$ corresponding to the source allocation scheme is determined in the end to be the largest.

Hamming distance d (the number of different corresponding positions of two chromosomes) is evaluated by chromosome group. This is the basis of the algorithm convergence.

$$d = \sum_{i=1}^{H} (a_i \oplus b_i)$$
(11)

Table 1. The operation data of ten cost objects

Cost object	Manufacture Cost	Operation personnel	Paper profit	Rj
1	1016	122	1756.9	26.23
2	591	61	660	9.03
3	515	48	320.3	3.36
4	723	64	771.3	10.67
5	477	52	843	12.9
6	612	40	461.6	6.42
7	446	44	128.8	0.01
8	791	70	673.2	8.75
9	1236	71	1286.4	20.2
10	1248	63	301.9	2.41

Here H is the length of chromosomes. Symbol $\oplus$ represents "exclusive or" operation of the corresponding bits of the two chromosomes.

It is assumed that a manufacturing cost 1,000,000 was put into "XXX automobile engine assembly task", and ten cost objects assumed this cost. According to the technical requirements, the relevant operation indexes of the cost object were selected from the previous year. The input indexes include manufacturing costs and operating personnel, and the output indexes are the book profit. A DMU object corresponds to a cost object, so the calculation complexity of the allocation scheme is relatively high. GA is suitable for resolving the allocation scheme. Coefficients are set as follows: ω0 =10000, ωi =1/i, i=1, 2, ..., 210-1. For example, for Model (4), in accordance with the above algorithm calculation process, the maximum fitness function value F(Z)=24.425 can be obtained and the corresponding distribution results are shown in Table 1.

In Table 1, cost objects 7 and 3 have the equivalent input amount. But the output of object 7 was only 1/3 the output of object 3. This illustrates that object 3 benefitted more than object 7 from the use of manufacturing cost, expressed as $R_7^* < R_3^*$. The relationship between cost objects 7 and 6 is similar and the allocation result is $R_7^* < R_6^*$. Cost objects 9 and 10 have an equivalent input amount. But the output of object 9 is four times the output of object 10. This illustrates that object 9 benefitted more than object 10 from the use of manufacturing cost, expressed as $R_9^* > R_{10}^*$. Cost objects 2 and 4 have an equivalent input and output amounts, so the difference of two allocation results is very small.

5 APPLICATION VERIFICATION

Table 2. The data integrated management based on data-process interaction model

Furnace number	Process	Weight	Steel number	Activity driver
2015102030	Oxidation ingredients	19.826	430L	0.203 8
2015102030	Electric furnace smelting	19.826	430L	2.700 5
2015102030	LF refining	19.826	430L	1.783 3
2015102030	VD refining	19.826	430L	1.630 5
2015102030	Ingotting	19.826	430L	0.560 4
2015102030	Annealing	19.826	430L	19.826 0
2015102037	Oxidation ingredients	39.152	42CrMo	0.203 8
2015102037	Electric furnace smelting	39.152	42CrMo	1.885 3
2015102037	LF refining	39.152	42CrMo	1.961 7
2015102037	VD refining	39.152	42CrMo	1.273 8
2015102037	Ingotting	39.152	42CrMo	0.636 9
2015102039	Oxidation ingredients	39.152	42CrMo	0.203 8
2015102039	Electric furnace smelting	39.152	42CrMo	1.910 7
2015102039	LF refining	39.152	42CrMo	2.292 9
2015102039	VDrefining	39.152	42CrMo	1.477 6
2015102039	Ingotting	39.152	42CrMo	0.586 0
2015102033	Oxidation ingredients	20.275	GCr15	0.196 3
2015102033	Electric furnace smelting	20.275	GCr15	2.110 4
2015102033	LF refining	20.275	GCr15	2.748 5
2015102033	VD refining	20.275	GCr15	1.619 6
2015102033	Ingotting	20.275	GCr15	0.638 0
2015102033	Annealing	20.275	GCr15	20.275

2015102035	Oxidation ingredients	39.256	60Si2CrA	0.203 8
2015102035	Electric furnace smelting	39.256	60Si2CrA	2.292 9
2015102035	LF refining	39.256	60Si2CrA	3.948 8
2015102035	*VD refining*	*39.256*	*60Si2CrA*	*1.681 4*
2015102035	Ingotting	39.256	60Si2CrA	0.687 9

Table 3. The results of cost resources optimization configuration

Activity	Activity cost	Cost project	Resource cost	Resource driver	Allocation rule
Oxidation ingredients					Indirect auxiliary activity
Electric furnace smelting	3 915.0	Furnace body	3 915.0	1	Activity
Electric furnace smelting	10 868.0	Electrode	10 868.0	1	Activity
Electric furnace smelting	45.5	Derrick	45.5	1	Activity
Electric furnace smelting	28 093.0	Electric	42 140.0	5	Activity group
LF refining	6 096.0	Ladle	6 096.0	1	Activity
LF refining	1 300.0	Fluorite	1 300.0	1	Activity
LF refining	1 016.0	Oxygen tube	1 581.0	1.8	Activity group
LF refining	8 428.0	Electric	42 140.0	1.5	Activity group
VD refining	565	Oxygen tube	1 581.0	1	Activity group
VD refining	5 619.0	Electric	42 140.0	1	Activity group
Repairing the casting pit	1 997.0	Clay brick	1 997.0	1	Direct auxiliary activity
Ingotting	9 287.0	Ingot mold	9 287.0	1	Activity
Annealing	12 126.0	Electric	12 126.0	1	Activities
Transform					Indirect auxiliary activity

In a complex production environment, the cost resource optimization system is established based on the data-process interaction model and the cooperative game nucleolus-based cost allocation models and is validated by practical application in the enterprises. Cost data is collected and reorganized by the data-process interaction model, as shown in table 2. Cost resources optimal allocation is completed by the manufacturing resource allocation model. The allocation results are shown in table3.

6 CONCLUSIONS

Cost resource information can be applied to integrated management based on data-process interaction model. According to the combination of model and DEA theory and game theory, the manufacturing cost allocation model is proposed and the model algorithm is given. Finally, the effectiveness of the method and suitability of the algorithm are displayed through concrete examples. A suitable allocation scheme is provided for resources allocation that is appropriate for a complex production environment. High quality, effective cost information related to products is provided for the decision-making staff in enterprises.

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