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FUZZY DYNAMIC CLUSTERING OF MOLD GRID RESOURCES BASED ON F-TEST

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ABSTRACT

Fuzzy dynamic clustering algorithm of mold grid resources associated with the total lifecycle of mold based on F-test was constructed in this paper. To classify and establish mold manufacturing grid resources conveniently, this paper divides mold grid resources into seven types. Generally time (T), quality (Q), cost (C), service (S), reputation (R), liability (L) and environment (E) are chosen to be evaluation criterion for mold grid resources, according to the requirement of different manufacturing system. The weight of each index was calculated with AHP, and then mold grid resources are clustered and identified by fuzzy cluster method on the base of these. A reasonable classification number by using F- test is found, and best resources classification is obtained and similarity-based resources are clustered. Finally, simulation experiments are carried out with specific application for mold grid resources classification. The results show that the method is effective, and the paper applies fuzzy cluster analysis to sort the gird resources reasonably. It can improve search speed and utilization of mold grid resources, and the response time can be decreased in resources selection.

Keywords: *Fuzzy Dynamic Clustering, F-test, Manufacturing Grid, Mold Grid Resources*

1 INTRODUCTION

Manufacturing grid is the first application of combining advanced grid technology with traditional manufacturing industry, which is a brand new phase of manufacturing informatization, especially of grid-based manufacturing. Mold manufacturing grid has the same qualities of distribution, resources sharing, dynamic and diversity as normal manufacturing grid.

Mold manufacturing grid resources generally refers to the sum of human, financial, and material in manufacturing enterprise [1]. It includes equipment, materials, personnel and the sum of all physical elements which to complete the entire life cycle of mold production activities .In the network environment, mold grid resources owned by different organizations, and distributed in different physical locations and heterogeneous platforms.

Even though the mold grid resources are distributive, the information can be sufficiently shared. Similarly the demands of mold grid user change, including dynamically increase and dynamically decrease. In addition, mold grid resources are heterogeneous and diverse. Allowing the coexistence of resources with different systems and classification, the diversified mold resources in the grid environment faces the challenge of unified connection [2].

In the grid environment, it needs to integrate these manufacturing resources to make these resources in the mold manufacturing grid system under the unified management and coordination of work. Traditional resources classification, modeling has been the development of manufacturing grid can not meet the urgent need for a new resources classification and modeling unified description of resources and management.

Therefore we need to make clustering mold grid resources, this provide premise and guarantee for the next step of resources searching and scheduling. After the resources have been clustered, we just need to search the source of clustering units that is the closest to the task requested information, which greatly improved the resources searching and locating efficient [3].

The paper studied how to cluster mold grid resources by using the fuzzy clustering method of fuzzy mathematics theory, according to the features of mold grid resources. The paper proposed fuzzy dynamic clustering method to classify the mold manufacturing resources in manufacturing grid. Firstly, the weight of each index was calculated with AHP, and then mold grid resources are clustered and identified by fuzzy cluster method on the base of these. A reasonable classification number by using F- test is found, and best resources classification is

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obtained and similarity-based resources are clustered.

2 DYNAMIC CLUSTERING METHOD BASED FUZZY EQUIVALENT RELATION

Cluster analysis [3] is a method to classify things under certain regulation, and fuzziness is the feature of the classification. The cluster analysis algorithm is not just widely used to pattern recognition, image segmentation and feature matching, also to the fields of psychology, biology, medical and geography etc.

At present, the clustering analysis method can divided into two catalogues[4]: one is the dynamic clustering method based on the fuzzy equivalent relation, also called as system-clustering method; the other one is fuzzy iterative self-organizing datum analysis method (ISODATA method) based on fuzzy classification, also called as gradual clustering method. This paper use the dynamic clustering method based on the fuzzy equivalent relation.

The basic steps to dynamically cluster resources based on the fuzzy equivalent relation include classification objects identification, data standardization, fuzzy equivalence matrix developing, clustering and cluster result analyzing.

2.1 Mold Grid Resources Description

This paper, to classify and establish mold grid resources conveniently , divides it into mold design and analysis resources, mold manufacturing equipment resources, mold information service resources ,mold knowledge and technology resources and mold talent resources and so on , according to the features during the mold design and manufacturing process is[5].

Among them , the design and analysis resources include CAD/CAE/CAPP/CAM software ,testing and inspection equipment ,include such as UG, Pro/E, Cimatron, CATIA, Moldflow, Deform, Dynaform, ANSYS, MARC and soft about rapidly prototyping and reverse engineering.

The manufacturing equipment resources include various kinds of machining and form equipment ,include the CNC machine tools, machining centers, large precision expensive machine (such as nanometer ultra-precision machine tools, precision injection molding machine, laser machine tools, etc.), rapid prototyping and manufacturing equipment (including LOM, SLA, FDM, SLS,RP equipment, etc.), the pressing machines, the high-speed milling, the high-speed punch, etc..

The information service resources include markets, customers, management and service after sale.

The knowledge and technology resources include utilization of knowledge library, living example library, the standard of equipment and software.

The talents resources are experts and employees' level, experiment and other abilities.

Each mold grid resource has its corresponding manufacturing index, such as manufacturing cost and service quality etc. Generally time (T), quality (Q), cost (C), service (S), reputation (R), liability (L) and environment (E) are chosen to be evaluation criterion for mold manufacturing resources, according to the requirement of different manufacturing system. A cluster analysis of the maximum similarity resources is based on the resources properties, so the way of describing resources influences the clustering result [6]. On the basis of comprehensively property analysis of mold grid node resources, the paper defined 7 indexes to describe the resources properties in the system.

2.2 Define Classification Objective

Set the domain $S=\{y_1,y_2,\cdots,y_n\}$ as the object to be classified, each object has m properties, can be expressed as $y_i=(y_{i1},y_{i2},\cdots,y_{im})$ （$i=1,2,\cdots,\ n$）. Therefore, the original matrix is obtained as the following:

$$S=\begin{Bmatrix} y_{11} & y_{12} & \cdots & y_{1m} \\ y_{21} & y_{22} & \cdots & y_{2m} \\ \vdots & \vdots & \cdots & \vdots \\ y_{n1} & y_{n2} & \cdots & y_{nm} \end{Bmatrix} \quad (1)$$

The weight vectors of m properties are decided by AHP [8]:

$$h=(h_1,h_2,\cdots,h_m)\ (\sum_{l=1}^{m}h_l=1) \quad (2)$$

By endowing the weight to each vector $y_i^{'}$

$$y_i^{'}=(y_{i1}^{'},y_{i2}^{'},\cdots,y_{im}^{'}) \quad (3)$$

2.3 Data Standardization

Different targets determine different dimensions and dimension units since the object property could be benefit-type (such as quality and service), or cost-type (such as time and cost). To compare the quantities of different dimensions, usually the data need to be dealt with dimensionless method. The

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paper adopted the standard 0-1 transform method to make the index being non-dimensional [7].

Using formula (4) to transform the benefit-type objectives:

$$x_{ij} = \left(y_{ij}^{'} - y_j^{'\min}\right) / \left(y_j^{'\max} - y_j^{'\min}\right) \quad (4)$$

Using formula (5) to transform the cost-type objectives:

$$x_{ij} = \left(y_j^{'\max} - y_{ij}^{'}\right) / \left(y_j^{'\max} - y_j^{'\min}\right) \quad (5)$$

In the formula, $y_j^{'\max}$ and $y_j^{'\min}$ are the maximum and minimum value of $y_{1j}^{'}, y_{2j}^{'}, \cdots, y_{nj}^{'}$. The optimal value is 1 and the poorest value is 0 for all the properties after transformation, and the transformed values are linear.

2.4 Fuzzy Equivalent Matrix Development And Clustering

To determine similar coefficient and to develop fuzzy similar matrix according to the traditional clustering method, the similarity degree $r_{ij} = R(x_i, x_j) \in [0,1]$ of x_i and x_j, i,j=1,2,⋯,n. The main methods to determine $r_{ij} = R(x_i, x_j) \in [0,1]$ are constructing similar coefficients by using the Cosine method of traditional clustering method, Euclidean Distance method, maximum and minimum method, geometric average minimum method and other methods etc. The paper adopted the maximum and minimum method to develop the fuzzy similar matrix:

$$r_{ij} = \sum_{k=1}^{m} \min(x_{ik}, x_{jk}) / \sum_{k=1}^{m} \max(x_{ik}, x_{jk}) \quad (6)$$

Usually the fuzzy equivalent matrix t(R) is obtained by using the fuzzy equivalent closure method. Starting from fuzzy similar matrix R, in turn to do squaring: $R \to R^2 \to R^4 \to \cdots \to R^{2^k} \to \cdots$. It means R_k has transmissibility when $R^k \cdot R^k = R^k$ first appears and R_k is the transitive closure t(R) we desire. After the fuzzy equivalent matrix is obtained, we assign a proper confidence level value $\lambda \in [0, 1]$ to t(R) and cluster λ matrix in a descending order. And then a corresponding series classification can be obtained and form a dynamic clustering figure.

2.5 Conduct F-Test To Obtain Classification

The classification number does not need to be accurately determined in advance, usually it can be properly classified by adjusting the λ value in dynamic clustering figure. The classification can be varied since different users have different subjective intentions of classification and then infer different λ values. To resolve this shortcoming, the paper adopted F-statistics to determine the optimal λ value and then conduct the classification in the dynamic clustering figure to obtain the optimal classification number.

Set r as the classification number corresponding to λ, set n_i as the number of the *i*-th classification element. Set $\bar{x}_{ik} = \frac{1}{n_i}\sum_{j=1}^{n_i} x_{jk}$ (k=1,2,…,m) as the average value of the *k*-th index of the *i*-th classification element, set $\bar{x}_k = \frac{1}{n}\sum_{j=1}^{n} x_{jk}$ (k=1,2,…,m) as the average value of the *k*-th index of all samples.

Introducing the F-statistics [8]:

$$F = \frac{\sum_{i=1}^{r} n_i \sum_{k=1}^{m} (\bar{x}_{ik} - \bar{x}_k)^2 / (r-1)}{\sum_{i=1}^{r}\sum_{j=1}^{n_i}\sum_{k=1}^{m} (x_{jk} - \bar{x}_{jk})^2 / (n-r)} \quad (7)$$

In the equation, F obeys the distribution with the degrees of freedom r-1 and n-r, the numerator stands for the distance between cluster to cluster and the denominator stands for the distance between element to element within one cluster.

The F_α can be obtained by inquiring the F Critical Values table according to the specified confidence value α. If $F > F_\alpha$, we know the clusters difference are big according to the variance theory of mathematical statistics and assume the classification is reasonable. If there are multiple F_α values fulfill the inequality, choose a satisfactory F_α value from the bigger ones.

3 EXPERIMENT DATABASE

An example of processing a cavity mold part in a mold factory proved the method effectiveness. To finish the part processing, a process equipment unit needs to be searched from manufacturing grid-node. And there are 10 manufacturing grid-nodes

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providing resource needed by processing the part, table I lists the value of those 10 processing resource under targeted criteria T(time), Q(quality), C(cost), S(service), R(reputation), L(liability) and E(environment). Q, R, L and E are assessed with 5-grading system, S is expressed as percentages. The relative weight of each index is obtained by conducting importance analysis for seven feature indexes with AHP method, the weights are listed in Table II.

Table I : Raw Data Sheet From Resources

Index	T (hour)	Q	S	C ($)	R	L	E
y_1	2	5	0.6	4	5	3	4
y_2	4	4	0.45	5	4	4	3
y_3	3	3	0.8	2	2	5	5
y_4	5	5	0.5	4	3	3	3
y_5	3	4	0.6	5	3	5	4
y_6	4	4	0.4	3	4	2	3
y_7	2	5	0.5	4	5	4	2
y_8	4	2	0.9	5	3	5	1
y_9	3	4	0.5	3	5	5	4
y_{10}	2	3	0.7	4	4	3	5

Table II : Relative Weight Of Each Index

Index	T	Q	S	C	R	L	E
Relative Weight	0.16	0.17	0.18	0.05	0.12	0.21	0.11

Table III: Processed Data After The Weighs Calculated

Index	T (hour)	Q	S	C ($)	R	L	E
y_1	0.32	0.85	0.108	0.2	0.6	0.63	0.44
y_2	0.64	0.68	0.081	0.25	0.48	0.84	0.33
y_3	0.48	0.51	0.144	0.1	0.24	1.05	0.55
y_4	0.8	0.85	0.09	0.2	0.36	0.63	0.33
y_5	0.48	0.68	0.108	0.25	0.36	1.05	0.44
y_6	0.64	0.68	0.072	0.15	0.48	0.42	0.33
y_7	0.32	0.85	0.09	0.2	0.6	0.84	0.22
y_8	0.64	0.34	0.162	0.25	0.36	1.05	0.11
y_9	0.48	0.68	0.09	0.15	0.6	1.05	0.44
y_{10}	0.32	0.51	0.126	0.2	0.48	0.63	0.55

Use the relative weigh data in Table II to conduct importance analysis for the data in Table 1, and then we got the calculated sample values, as shown in Table III.

Then develop the Fuzzy similarity matrix R by using maximum-minimum method to process the standard matrix X.

$$R = \begin{bmatrix} 1.0000 & 0.7299 & 0.6061 & 0.7663 & 0.7247 & 0.7070 & 0.8666 & 0.5180 & 0.7806 & 0.8205 \\ 0.7299 & 1.0000 & 0.6803 & 0.8025 & 0.8281 & 0.8397 & 0.7836 & 0.7297 & 0.8109 & 0.7154 \\ 0.6061 & 0.6803 & 1.0000 & 0.6019 & 0.8332 & 0.5826 & 0.5989 & 0.6996 & 0.7964 & 0.7252 \\ 0.7663 & 0.8025 & 0.6019 & 1.0000 & 0.7180 & 0.7846 & 0.7197 & 0.6234 & 0.6749 & 0.6711 \\ 0.7247 & 0.8281 & 0.8332 & 0.7180 & 1.0000 & 0.6831 & 0.7173 & 0.7532 & 0.9008 & 0.7102 \\ 0.7070 & 0.8397 & 0.5826 & 0.7846 & 0.6831 & 1.0000 & 0.6597 & 0.5824 & 0.7156 & 0.6903 \\ 0.8666 & 0.7836 & 0.5989 & 0.7197 & 0.7173 & 0.6597 & 1.0000 & 0.5992 & 0.7817 & 0.7028 \\ 0.5180 & 0.7297 & 0.6996 & 0.6234 & 0.7532 & 0.5824 & 0.5992 & 1.0000 & 0.6750 & 0.5728 \\ 0.7806 & 0.8109 & 0.7964 & 0.6749 & 0.9008 & 0.7156 & 0.7817 & 0.6750 & 1.0000 & 0.7108 \\ 0.8205 & 0.7154 & 0.7252 & 0.6711 & 0.7102 & 0.6903 & 0.7028 & 0.5728 & 0.7108 & 1.0000 \end{bmatrix}$$

$$t(R) = \begin{bmatrix} 1.0000 & 0.7836 & 0.7836 & 0.7836 & 0.7836 & 0.7836 & 0.8666 & 0.7532 & 0.7836 & 0.8205 \\ 0.7836 & 1.0000 & 0.8281 & 0.8025 & 0.8281 & 0.8397 & 0.7836 & 0.7532 & 0.8281 & 0.7836 \\ 0.7836 & 0.8281 & 1.0000 & 0.8025 & 0.8332 & 0.8281 & 0.7836 & 0.7532 & 0.8332 & 0.7836 \\ 0.7836 & 0.8025 & 0.8025 & 1.0000 & 0.8025 & 0.8025 & 0.7836 & 0.7532 & 0.8025 & 0.7836 \\ 0.7836 & 0.8281 & 0.8332 & 0.8025 & 1.0000 & 0.8281 & 0.7836 & 0.7532 & 0.9008 & 0.7836 \\ 0.7836 & 0.8397 & 0.8281 & 0.8025 & 0.8281 & 1.0000 & 0.7836 & 0.7532 & 0.8281 & 0.7836 \\ 0.8666 & 0.7836 & 0.7836 & 0.7836 & 0.7836 & 0.7836 & 1.0000 & 0.7532 & 0.7836 & 0.8205 \\ 0.7532 & 0.7532 & 0.7532 & 0.7532 & 0.7532 & 0.7532 & 0.7532 & 1.0000 & 0.7532 & 0.7532 \\ 0.7836 & 0.8281 & 0.8332 & 0.8025 & 0.9008 & 0.8281 & 0.7836 & 0.7532 & 1.0000 & 0.7836 \\ 0.8205 & 0.7836 & 0.7836 & 0.7836 & 0.7836 & 0.7836 & 0.8205 & 0.7532 & 0.7836 & 1.0000 \end{bmatrix}$$

Then, obtain the corresponding fuzzy equivalent matrix t(R) by using square method on the fuzzy similarity matrix R.

Set λ to a random value, the dynamic cluster chart of manufacturing grid can be obtained by calculating with corresponding λ cut matrix, as shown in Figure 1.

Different λ cut sets corresponded to different λ values, therefore the classifications are different. Different λ cut sets are calculated by orderly setting λ to 1、0.8666、0.8397、0.8332、0.8281、0.8025、0.7836&0.7532, and we get different classifications.

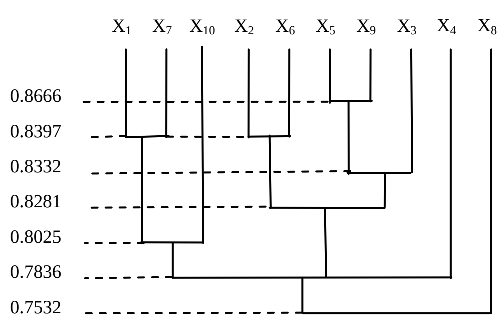

Figure 1 Dynamic Cluster Chart

When λ=1, it divided into 10 classifications: {y_1}, {y_2}, {y_3}, {y_4}, {y_5}, {y_6}, {y_7}, {y_8}, {y_9} {y_{10}}; When λ=0.8666, it divided into 9 classifications: {y_5, y_9}, {y_1}, {y_2}, {y_3}, {y_4}, {y_6}, {y_7}, {y_8}, {y_{10}};When λ=0.8397, it divided into 7 classifications: {y_1, y_7}, {y_2, y_6}, {y_5, y_9}, {y_3}, {y_4}, {y_8}, {y_{10}};When λ=0.8332, it divided into 6

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classifications: $\{y_1,y_7\},\{y_2,y_6\},\{y_3,y_5,y_9\},\{y_4\},\{y_8\},\{y_{10}\}$;When λ=0.8281, it divided into 5 classifications: $\{y_1, y_7\}$, $\{y_2, y_3, y_5, y_6, y_9\}$, $\{y_4\}$, $\{y_8\}$, $\{y_{10}\}$; When λ=0.8025, it divided into 4 classifications: $\{y_1, y_7, y_{10}\}$, $\{y_2, y_3, y_5, y_6, y_9\}$, $\{y_4\}$, $\{y_8\}$; When λ=0.7836, it divided into 2 classifications: $\{y_1, y_2, y_3, y_4, y_5, y_6, y_7, y_9, y_{10}\}$, $\{y_8\}$; When λ=0.7532, all the manufacturing resource is classified into one category.

The classification result shows that the categories are narrower and classifications are more precise with the increasing of the λ value, which increases the standard of resource searching.

Use formula 7 to calculate the F value that corresponds to different λ values according to the obtained clustering result and then determine the optimal value of clustering level λ, the result shows in Table IV. Table IV shows there are 2 F values fulfill the inequality $F > F_{0.05}$ by setting the significant level to 0.05, then by checking $F- F_{0.05}$ we find out $F- F_{0.05}$=1.52 is the maximum value when λ=0.8332. Therefore, the optimal classification is to divide the resource into 6 categories by setting λ to 0.8332. In this situation, the manufacturing resource is divided into 6 resource domain, meaning the 1st resource domain $\{y_1, y_7\}$, the 2nd one $\{y_2, y_6\}$, the 3rd one $\{y_3, y_5, y_9\}$, the 4th one $\{y_4\}$, the 5th one $\{y_8\}$ and the 6th one $\{y_{10}\}$.

Table IV: Clustering Result Table

λ	1	0.8666	0.8397	0.8332
R class	10	9	7	6
F	0	11.24	8.48	7.78
$F_{0.05}$		239	8.94	6.26
$F-F_{0.05}$		-227.76	-0.46	1.52
λ	0.8281	0.8025	0.7836	0.7532
R class	5	4	2	1
F	6.02	4.13	2.11	0
$F_{0.05}$	5.19	4.76	5.32	
$F-F_{0.05}$	0.83	-0.63	-3.21	

4 CONCLUSION

There is a large amount of mold grid resources in the mold manufacturing grid environment. How to quickly, accurately and comprehensively find out the necessary resources and schedule it has became the key to successfully implement a mold manufacturing grid, also it is a important aspect of the difference between manufacturing grid and internet. The paper dynamically clustered the mold grid resources by using fuzzy dynamic clustering method, it not just classified the information resources with similar semantic, but also provided premise and guarantee for the next step of resources searching and scheduling. Finally the feasibility and validity of method was validated through an instant analysis, the result shows the proposed resources clustering algorithm can effectively achieve the classification of mold grid resources.

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