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Manufacturing resources modeling based on features for manufacturability

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Abstract

Manufacturability evaluation is the effective way to shorten the period of development, optimize the manufacturing process and reduce the product costs. The manufacturability of a product depends on the processing ability of specific manufacturing resources. The building of the manufacturing resources model is the foundation for manufacturability evaluation. To better utilize the information of manufacturing resources, the hybrid algorithm of fuzzy c-means clustering algorithm (FCM) and genetic algorithm (GA) is implemented in this paper to group manufacturing resources based on manufacturing and geometric features. The information model of manufacturing resources is built by using the object-oriented method and the framework of manufacturability evaluation based on the manufacturing resources is defined. An application sample is exploited and its results are analyzed. The grouping result shows that the hybrid algorithm is reliable and effective.
Keyword: fuzzy c-means clustering; genetic algorithm; manufacturability; manufacturing resources model

1.Introduction

In the recent years, the increasing global competition is challenging the manufacturing industry. In order to 'design it right the very first time', designer must ensure that their products are both functional and easy to manufacture. The manufacturability analysis system [1-3] is becoming such a tool to evaluate various manufacturability aspects in the design phase, thereby reducing the cost and time to market of the designed product, and promoting the development of virtual manufacturing. Manufacturability evaluation of a proposed design involves determining whether or not it is manufacturable on the given manufacturing resources, and, if it is, finding the associated manufacturing efficiency. A product can be produced quickly at lower cost and high quality in some manufacturing resources environment but in another one it can be produced at high cost even can not be produced. In the same manufacturing resources environment, a product can be produced at different cost and efficiency by using different equipments. Manufacturing resource not only provides supports to production design, process design and manufacturing but also has restriction on them. So the building of manufacturing resources model is very important for manufacturability evaluation. The building of manufacturing resources model includes two parts: grouping of processing equipments and information modeling of manufacturing resources.

Concept of manufacturing resources has its narrow sense and broad sense. In broad sense the manufacturing resources involve all the elements needed which are concerned with design, processing, maintenance and etc in the whole life cycle of a product. In narrow sense, the manufacturing resources involve equipments, cutting tools, materials, fixtures, measures and etc, which are only concerned with processing. Information of manufacturing resources provides not only supports for product design, process design and manufacture but also constraints on them. To cluster the processing equipments will decrease the searching space and time of manufacturability evaluation and utilize the manufacturing resources more efficiently. Clustering method aims to organize a group of objects into classes or clusters, so that objects belonging to the same cluster are similar enough to infer that they are the same type, and objects belonging to different clusters are similar enough to infer that they are different types [4].

Process capacity refers to the actual processing capacity of the production process in a stable state within a certain period of time, which reflects the overall dispersion of the product quality characteristics of a process in a stable state. The process capacity of modern processing equipments is growing and the process capacity between different equipments is more and more fuzzy. In this paper, the hybrid algorithm of genetic algorithm and the fuzzy c-means clustering based on genetic algorithm is proposed to group the manufacturing resources according to the features which can be processed by the manufacturing resources. The hybrid algorithm has not only the global searching ability of GA, but also the local searching ability of fuzzy clustering algorithm. In this way, the optimum number of clusters and optimum partition can be obtained simultaneously that can decrease the searching time and searching space for proper processing equipments. Then the information model of manufacturing resources is built by using the object-oriented method on the basis of analyzing the related information which is needed in the processing about manufacturing resources. In this paper, the features such as hole, plane, step, and so on are also involved in the manufacturing resources model. Finally the framework of manufacturability evaluation based on manufacturing resources constraints is built.

2. Grouping the processing equipments based on features

Manufacturability evaluation [5, 6] is closely related with manufacturing resources. A product can be produced easily and quickly at lower cost and high quality in some manufacturing resources environment but in another one it can be produced at high cost even can not be produced. In the same manufacturing resources environment, a product can be produced at different cost and efficiency by using different equipments. Manufacturability evaluation does not make sense if not considering the constraints of manufacturing resources. A modern enterprise always has rich processing equipments, in order to utilize them better, increase the efficiency of manufacturability evaluation, and the processing equipments are partitioned. There are different principles of partition. With the development of feature technology, feature-based manufacturability evaluation has become a research hotspot. Features include economic indicators, technical indicators, productivity indicators, and environmental indicators. Different manufacturability evaluation methods are proposed according to different features [7]. The grouping of processing equipments based on features is more favorable for manufacturability evaluation.

In manufacturing process, there are a lot of features such as plane, hole, blind hole, step, slot, blind slot, pocket, cylindrical protrusion, curved surface, and so on. Processing equipments are grouped according to the features that can be processed by the equipments. But the same feature can not always be

processed by the same equipment because of the features, the size of parts, tolerance requirements and other important manufacturing criteria. In this paper, besides features, the size of part and processing accuracy are also considered as the attributes of the processing equipments. In manufacturing resources partition based on features, there are N processing equipments and s features altogether, processing equipment vector is shown as Equation (1) and (2).

$$x_i = \left(x_{i1}, x_{i2}, \mathrm{L}\ \mathrm{L}\ , x_{is}, p_i, a_i\right) \quad i = 1, 2, \mathrm{L}\ \mathrm{L}\ , N \tag{1}$$

$$\begin{aligned} x_{ik} &= \begin{cases} 1 & \text{equipment i can process feature k} \\ 0 & \text{equipment i can not process feature k} \end{cases} \quad k = 1, 2, \mathrm{L}\ , s \\ p_i &= \begin{cases} 1 & \text{equipment i can process large-sized parts} \\ 0 & \text{equipment i only can process small and medium parts} \end{cases} \\ a_i &= \begin{cases} 1 & \text{equipment i can be used in finish machining} \\ 0 & \text{equipment i can not be used in finish machining} \end{cases} \end{aligned} \tag{2}$$

There are a few clustering algorithms, fuzzy c-means algorithm is used to partition the manufacturing resources here.

3. A hybrid algorithm of FCM and GA for grouping manufacturing resource

3.1 Fuzzy c-means algorithm

Fuzzy C-means clustering algorithm is an unsupervised and non-parametric method that can help in cluster analysis of data, which was first proposed in 1973. It is widely used, and FCM has been proved to have good stability and partition quality through some cases, and the algorithm has good convergence[8]. A proof of FCM convergence is given as follows [9-12].

In particular, given a set of objects $X = \left(x_1, x_2, \mathrm{K}\ , x_N\right), x_i \in R^s$ where N is the number of objects and s is the dimension of pattern vectors, use FCM to divide the region and find the optimal partition and the prototype that wants to correspond to minimize the following objective function.

$$J_m\left(U, V\right) = \sum_{j=1}^{C} \sum_{i=1}^{N} u_{ij}{}^m d_{ij}{}^2 \tag{3}$$

C is the number of clusters; U is the matrix of membership functions, μ_{ij} is the element of U, and is the membership value of the ith object of the jth cluster; V is the clustering center vector; m is the index that controls the amount of μ_{ij} cluster overlap and fuzziness; $d_{ij} = \left\| x_i - v_j^{(t)} \right\|$, represents the distance between x_i and v_j, t denotes the tth iteration.

The standard Lagrange multiplier minimization method is invoked in Equation (3) to obtain the updated clustering centroid vector and membership function matrix.

Given a fixed number C ($2 \le C < N$), m ($1 < m < \infty$) and ε, a small positive constant, the FCM

algorithm starts with a set of initial cluster centers. Then generate randomly a fuzzy c-partition and set iteration number $t=0$, $t=(0,1,2,\mathrm{L}\ \mathrm{L})$. A three step iterative process works as follows:

Setp1. Given the membership values $\mu_{ij}^{(t)}$, the cluster centre vector V is calculated by:

$$v_j^{(t)} = \frac{\sum_{i=1}^{N}\left(\mu_{ij}^{(t-1)}\right)^m x_i}{\sum_{i=1}^{N}\left(\mu_{ij}^{(t-1)}\right)^m} \qquad j=1,\mathrm{K}\ \mathrm{K}\ C \tag{4}$$

Setp2. Given the new cluster centers $V^{(t)}$, the membership values $\mu_{ij}^{(t)}$ are update by:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{d_{ij}}{d_{ik}}\right)^{\frac{2}{(m-1)}}} \qquad i=1,\mathrm{K}\ \mathrm{K}\ ,N \quad j=1,\mathrm{K}\ \mathrm{K}\ C \tag{5}$$

Setp3. Compare $U^{(t)}$ to $U^{(t+1)}$ in a convenient matrix norm: if $\left\|U^{(t+1)}-U^{(t)}\right\|<\varepsilon$, then stop; otherwise, set $t=t+1$ and return to setp1.

3.2 The genetic algorithm

In 1975, Professor J. Holland proposed the genetic algorithm (GA). GA is inspired by the evolutionist theory explaining the origin of species. In nature, weaker species become extinct by natural selection. Stronger species emerge from natural selection to pass on their genes to future generations. In the long run, dominant populations tend to be the species that carry the correct combination of genes. During the slow evolution of a species, genes can change at any time. If these changes are aided by natural selection, then a new species will form. Conversely, if these changes do not help in natural selection, natural selection will eliminate unsuccessful changes as the challenge of survival continues to increase. Because GA replaces many computationally expensive deterministic optimization methods, it is becoming increasingly popular in the engineering field [13-15].

3.3 The hybrid fuzzy clustering algorithm

Since the FCM algorithm is a local search algorithm, it is good in some regions, but does not satisfy people in general [16]. The algorithm is particularly sensitive to initialization, leading to easy access to local optima during the computation [17]. GA has the advantages of simpleness, universality, good robustness, fitness for concurrent processing and it is a global optimization algorithm widely used in practice. Based on these advantages of GA, a Fuzzy c-means algorithm based on GA has not only the ability of global searching of GA but also the ability of local searching of FCM. The hybrid algorithm can solve

the problem that the FCM is sensitive to initialization and increase the convergence speed of convergence. In this way, the clustering can be done more efficiently.

The FCM algorithm is difficult to determine the number of initial clusters without effective guidance before performing clustering. The hybrid fuzzy clustering algorithm is composed of the outer iteration and the inner iteration. The outer iteration determine the optimal number of cluster dynamically by using GA and the inner iteration determine the optimal partition corresponding to the optimal number of cluster by using FCM clustering based on GA.

3.4 The inner iteration

Since a hybrid algorithm of GA and FCM is introduced in the internal iteration, the optimal classification matrix corresponding to the number of clusters can be easily obtained and the optimal classification is obtained according to the principle of maximum membership. The main contents of the hybrid algorithm are encoding, constructing fitness function, selecting genetic operators, determining parameters.

3.4.1 Encoding

Real coding on the clustering center v is the coding method. A chromosome is expressed as $chr = v_1 v_2 \mathrm{L}\ v_c, v_i\left(i = 1,2,\mathrm{L}\ ,c\right)$ where C is the number of clusters. In each cluster there are S characters, so the length of a chromosome is $c \times s$. A chromosome is expressed as $\left\{v_{11}, v_{12}, \mathrm{K}\ , v_{1s}, v_{21}, v_{22}, v_{2s}, \mathrm{K}\ \mathrm{K}\ , v_{c1}, v_{c2}, \mathrm{K}\ , v_{cs}\right\}$.

3.4.2 Fitness function

The purpose of fuzzy clustering is to obtain the minimum objective function (loss function). In fact, it is an optimization problem [18]. How to determine the chromosomal fitness value for the survival probability of the next generation of an individual is a very important issue in the optimization process. The objective function of fuzzy clustering J_m is smaller, the partition is more reasonable and the corresponding fitness function of GA should be bigger. The fitness function is defined as the follow with the objective function J_m:

$$F\left(U,V\right) = \frac{1}{J_m + \varepsilon} \qquad \varepsilon > 0 \tag{6}$$

3.4.3 Crossover and mutation operator

The most important operator in the GA is the crossover operator. Offspring are produced during the crossover process, which is defined as two chromosomes from the parents joining together to form a new chromosome. Iterating the crossover operator, the expected good chromosome genes appear fre-

quently in the population, leading to convergence to an overall good solution. The double-point crossover operator is employed. The two-point crossover operator is a random selection of two crossover points, and the fragments corresponding to the crossover points on the two parental genes are exchanged [19-21].

The variation operator plays a key role in GA by introducing stochastic changes during chromosome evolution. Crossover uses an iterative approach to make chromosomes in a population similar and thus converge the population, while mutation introduces random variation into the population and helps in the search, avoiding local optima. Because the mutation rate is very small, the new chromosomes created by mutation will not be very different.

3.4.4 Selection operator

Nowadays, it is generally accepted that simple genetic algorithms do not guarantee convergence of results to the global optimum in the solution process. But the genetic algorithm with the optimum individual maintaining strategy can obtain the global optimum solution [22-24]. So in this hybrid algorithm, selection is carried out by the combination of the remainder stochastic sampling with replacement and the optimum individual maintaining strategy. The advantage of the remainder stochastic sampling with replacement is that the individuals with high fitness can be preserved in the child generation and the selection error is tinier. The individual with the biggest value of fitness function is maintained in the offspring without genetic manipulation.

3.4.5 FCM optimization of individual

Due to the greater local search capability of FCM, the population is optimized using FCM after each generation of genetic manipulation to generate new populations for subsequent evolution. Using the FCM optimization method, the convergence speed can be improved and the local search capability can be enhanced [25]. The realization of FCM optimization is shown as follows:

(1) The corresponding fuzzy matrix U is derived by calculating the chromosome code through Equation (5);

(2) The new clustering matrix U is calculated by Equation (4) to derive the new clustering centers, which are encoded to generate the new chromosomes;

(3) By recalculating the value of the objective function, the worst individual in the population is found and it is replaced with the individual that always remains the best in the selection.

3.5 The outer iteration

The FCM algorithm must determine the number of clusters in advance, and the process cannot be optimized. A typical genetic algorithm uses outer iterations to determine the optimal number of clusters. A good clustering algorithm takes into account both the degree of separation between different partitions and the degree of compression of a partition. The degree of dispersion between different partitions is expressed as the average distance between clustering centers. The bigger the value of average distance between cluster centers is, the greater the degree of deviation of different partition is. Here, the distance between clustering centers is denoted by D, shown as follows:

$$D = \frac{\sum_{i=1}^{C} \left\| v_i - v_j \right\|}{C} \tag{7}$$

The main purpose of clustering is to partition the dataset in such a way that the distance between different partitions is maximized and the distance between each object in a cluster is minimized. As the number of cluster C increasing, the value of J_m decreases and the value of D increases. The objective function of outer iteration is defined as follows:

$$f = J_m(U,V) + D \tag{8}$$

The fitness function of outer iteration is defined as:

$$F'(U,V) = \frac{1}{J_m(U,V) + D} \tag{9}$$

The encoding method in a typical genetic algorithm is the binary encoding of the number of clusters. The hybrid of the optimum individual maintaining strategy and the remainder stochastic sampling with replacement is employed as the selection operator, the crossover and mutation operator are single point crossover and essential mutation respectively. The number of cluster corresponding to each chromosome is calculated and the corresponding optimum partition in obtained by using the inner iteration.

4. Implementation of algorithm

The hybrid algorithm that introduces the manufacturing resource division consists of two parts: outer iteration and inner iteration, and the program flow chart is shown in Figure 1.

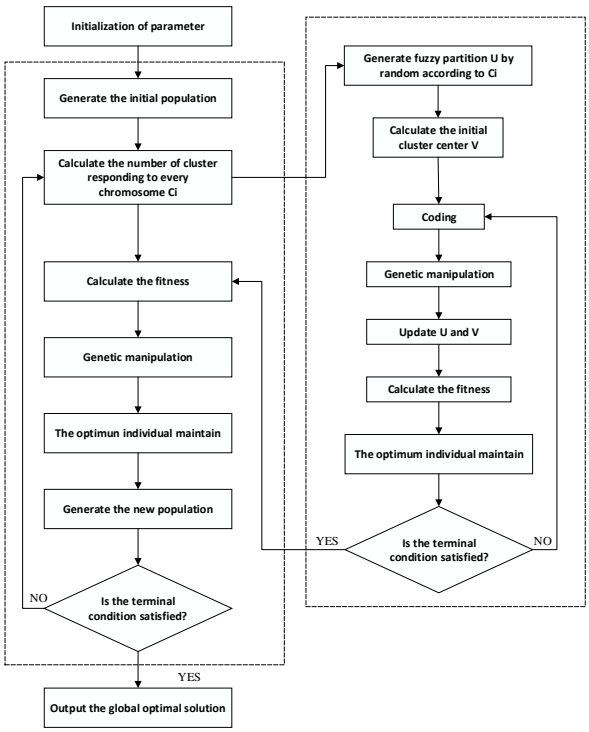


Fig. 1 Schematic representation of hybrid approach

In order to test the effectiveness of the algorithm, the set of manufacturing resources shown in Table 1 was divided according to the features that can be processed in the device. The relevant features considered in this paper are cylinders and tapers, planes, bevels, holes, surfaces and steps. The device is represented by a pattern vector. The length of the pattern vector is 8. The first six digits represent cylinders, tapers, planes, grooves, holes, surfaces and steps. The two diagrams on the left indicate the dimensions of the parts that can be machined with the machining equipment, and whether the machining equipment can be used for finishing. The mode vector consists of 0 and 1, which corresponds to a value of 1 if the machine can handle the feature and 0 otherwise, and 1 if the machine can machine large parts and 0 otherwise, and 1 if the machine can be used for finishing, and 0 otherwise. For example, vertical milling machine can handle plane slot, it can't handle large part and can be used to finish processing, so the vector is 01100001, lathe 2 can handle cylinder and cone, plane, slot and hole, it can't handle large part and can be used to finish processing, so the vector is 1110000, Figure 2 shows. The pattern vectors of 32 machining equipments are shown in Table 1, using the algorithm of this paper to these Equipment is grouped.

	Cylinder and taper	Plane	Groove	Hole	Curved surface	Step	Large-size part	Finish processing
Vertical milling machine	0	1	1	0	0	0	0	1
Lathe 2	1	1	1	1	0	0	0	0

Fig. 2 The vector representation of manufacturing resources

Table1 A set of manufacturing resources

Number	Device name	Features	Pattern vector
1	Vertical milling machine	Plane, groove, finish processing	011000 01
2	Drilling machine 1	Hole	000100 00
3	Drilling machine 2	Hole	000100 00
4	Drilling machine 3	Hole, large-size part	000100 10
5	Lathe 1	Cylinder and taper, hole	100100 00
6	Lathe 2	Cylinder and taper, plane, groove, hole	111100 00
7	Lathe 3	Cylinder and taper, plane, groove, hole, curved surface, step, finish processing	111111 01
8	Lathe 4	Cylinder and taper, hole, finish processing	100100 01
9	Lathe 5	Cylinder and taper, hole	100100 00
10	Lathe 6	Cylinder and taper, plane, groove, hole, large-size part, finish processing	111100 11
11	Drilling machine 4	Hole	000100 00
12	Milling and drilling machine	Plane and hole	010100 00
13	Drilling machine 5	Hole	000100 00
14	Boring-milling machine 1	Cylinder and taper, plane, hole, large-size part, finish processing	110100 11
15	Coordinate setting boring	Plane, groove, hole, large-size part, finish	011100 11

	machine	processing	
16	Boring-milling machine 2	Plane, groove, hole, large-size part, finish processing	011100 11
17	Horizontal fine-boring machine	Hole, finish processing	000100 01
18	Milling machine 1	Plane, groove, finish processing	011000 01
19	Milling machine 2	Plane, curved surface, large-size part, finish processing	010010 11
20	Milling machine 3	Plane, groove, step, finish processing	011001 01
21	Milling machine 4	Plane, groove, curved surface, step, finish processing	011011 01
22	Milling machine 5	Plane, groove, hole, step, finish processing	011101 01
23	Milling machine 6	Plane, large-size part, finish processing	010000 11
24	Milling machine 7	Plane, large-size part, finish processing	010000 11
25	Milling machine 8	Plane, curved surface, large-size part, finish processing	010010 11
26	Boring-milling machine 3	Plane, hole, large-size part, finish processing	010100 11
27	Planning machine 1	Plane, groove	011000 00
28	Cylindrical grinder	Cylinder and taper, finish processing	100000 01
29	Internal grinding machine	Hole, finish processing	000100 01
30	Surface grinding machine	Plane, finish processing	010000 01
31	Planning machine 2	Plane, large-size part, finish processing	010000 11
32	Broaching machine	Plane, curved surface, finish processing	010010 01

The algorithm is implemented in C++. The population sizes of internal and external iterations are set to 40 and 20, respectively. The number of evolutionary generations of the hybrid algorithm is set to 100, and the crossover rate and variation rate are 0.8 and 0.1, respectively.

The variation of the fuzzy clustering objective function J_m and the mean distance D between cluster centers with respect to the number of clusters is shown in Fig. 3. J_m decreases monotonically with the increase in the number of clusters. D is monotonically increasing in the range (2, 10) (11, 12) and monotonically decreasing in the range (10, 11). The sum of J_m and D is minimal when the number of cluster is 6. The variation of the outer iterative fitness function is shown in Figure 4, and the maximum value of fitness is obtained when the number of clusters is 6. According to the optimal number of 6 of the proposed algorithm, the optimal classification is obtained according to the principle of maximum affiliation, and the optimal classification of manufacturing resources is shown in Table 2.

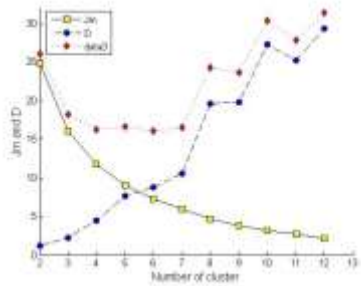


Fig. 3 Relationship between J_m, D and the number of cluster

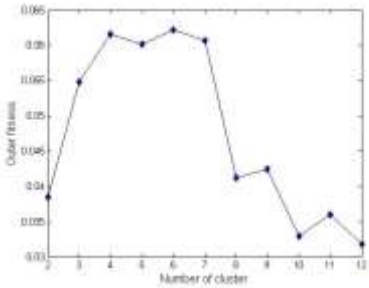


Fig. 4 Relationship between the outer fitness and the number of cluster

Table2 Classification result of manufacturing resources

Number of cluster	Machining equipment	Feature
1	Lathe 2, Lathe 3, Milling and drilling machine, Milling machine 5, Broaching machine	Cylinder and taper, plane, groove, hole, curved surface, step
6, 7, 12, 22, 32		
2	Drilling machine 1-5, Lathe 1, Lathe 5, Horizontal fine-boring machine, Cylindrical grinding machine,	Cylinder and taper, hole
2, 3, 4, 5, 9, 11, 13, 17, 29		
3	Vertical milling machine, Milling machine 1, Milling machine 3, Milling machine 4, Planning machine 1, Surface grinding machine	Plane, groove, step, finish processing
1, 18, 20, 21, 27, 30		
4	Milling machine 2, Milling machine 6-8, Planning machine 2	Plane, curved surface, large-size part, finish processing
19, 23, 24, 25, 31		
5	Lathe 4, Cylindrical grinder	Cylinder and taper, hole, finish processing
8, 28		
6	Lathe 6, Boring-milling machine 1-3, Coordinate setting boring machine	Cylinder and taper, plane, groove, hole, large-size part, finish processing
10, 14, 15, 16, 26		

Each manufacturing resource belongs to only one class, but each feature can belong to multiple classes. The second group and the fifth group all can process cylinder, taper and hole features for small and medium-sized parts, but the equipments in the fifth group can be used for finishing, so the two groups are divided into different groups. The first group and the sixth group all can handle cylindrical and conical, hole, plane and groove features, but the equipments in the sixth group can handle large parts of these features and is used for finish machining, these equipments are in different partition groups although they can handle the same features. The main component of manufacturability evaluation is to evaluate whether each feature of the part has the corresponding processing equipment. By classifying processing equipment in groups, only the group with the evaluated feature needs to be searched. Therefore, the search time and space for processing equipment corresponding to features is reduced, and the efficiency of manufacturability evaluation is improved.

After finding the processing equipment corresponding to the features, the information model of the equipment needs to be established and used to evaluate whether the processing capability of the equipment meets the design requirements. In this paper, an object-oriented approach is used to build the model.

5. Information modeling of manufacturing resources based on O-O method

5.1 The object-oriented method in manufacturing resource model

The basic principle of object-oriented approach (O-O approach) is the identification and definition of entities in the objective world. Object-oriented methods have effective structural features, including classification, encapsulation and inheritance, but there is a vague analytical model. Unlike the structural modeling approach, the object-oriented modeling approach emphasizes the relationships and states among the objects when measuring the system. The state of each object in the system is expressed through properties in the object-oriented modeling approach. Relationships and interactions between objects are measured through events and messages. The structure of the object model can be described by objects, attributes and associations [26].

5.2 Demands and structure of manufacturing resource model based on O-O method

Manufacturability evaluation needs to consider a few factors such as the manufacturing capacity of enterprise resource, processing materials, processing capability of processing of equipments (machining precision, working range, carrying capability of table and so on), etc. The manufacturability of part relates to not only the processing equipments but also the technological equipments such as cutting tool, fixture, measuring tool and so on. So the detailed information model of manufacturing resource which includes processing equipments and technological equipments should be built to evaluate the process capability of them. In the manufacturing resources model based on features, the manufacturing features are involved in this model too. Manufacturability evaluation not only assesses whether the part can be machined by the existing manufacturing resources but also selects the optimum processing equipments according to different demands of client efficiently. The selection of equipments needs a lot of information such as the state of equipments, processing cost, processing time, location, and so on. The information of the model is more detail, the result of evaluation is better. So the model should contain information as much as possible and can be changed whenever necessary.

In order to meet the demands of manufacturability evaluation, the information model of manufacturing resource should be dynamic, integrated and steady. The data of manufacturing resources model should be stored in a coherent and safe way and data structure of the model should be convenient for data processing. The object oriented class hierarchical structure model is constructed by taking advantage of the encapsulation and inheritance of the object oriented method to abstract manufacturing resource. Each class has its own subclasses.

According to the content of manufacturability evaluation, the manufacturing resources model consists of information model of manufacturing equipment class, technological equipment class and feature class. The information model of manufacturing equipment class includes processing equipments mainly. The processing equipments involve milling machine, grinding machine, lathe and so on. The grinding machine involves cylindrical grinding machine, internal grinding machine and surface grinding machine. The cylindrical grinding machine involves CNC cylindrical grinding machine, universal cylindrical grinding machine and so on. The information model of technological equipment class includes cutting

tools, measuring tools and fixture. The information model of feature class involves the features which can be processed by the equipments in this manufacturing resources model such as plane, hole, groove and so on. The diagrammatic sketch is shown in Fig. 5.

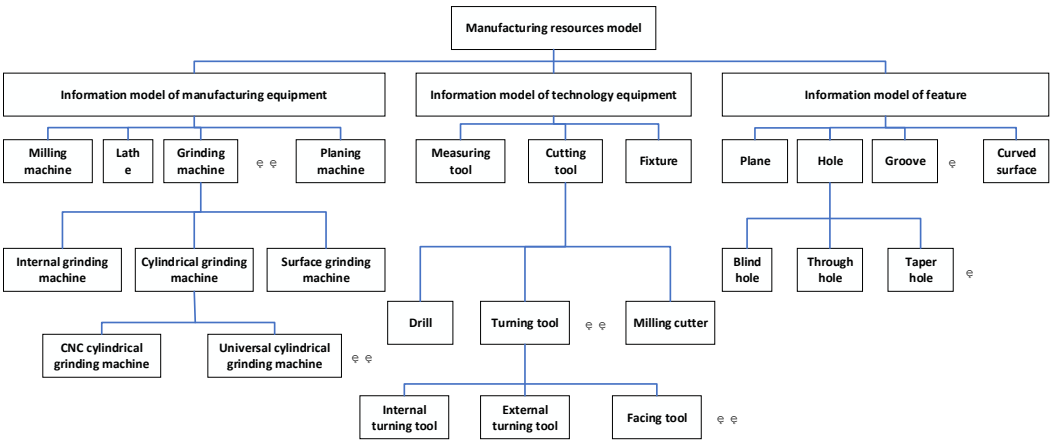
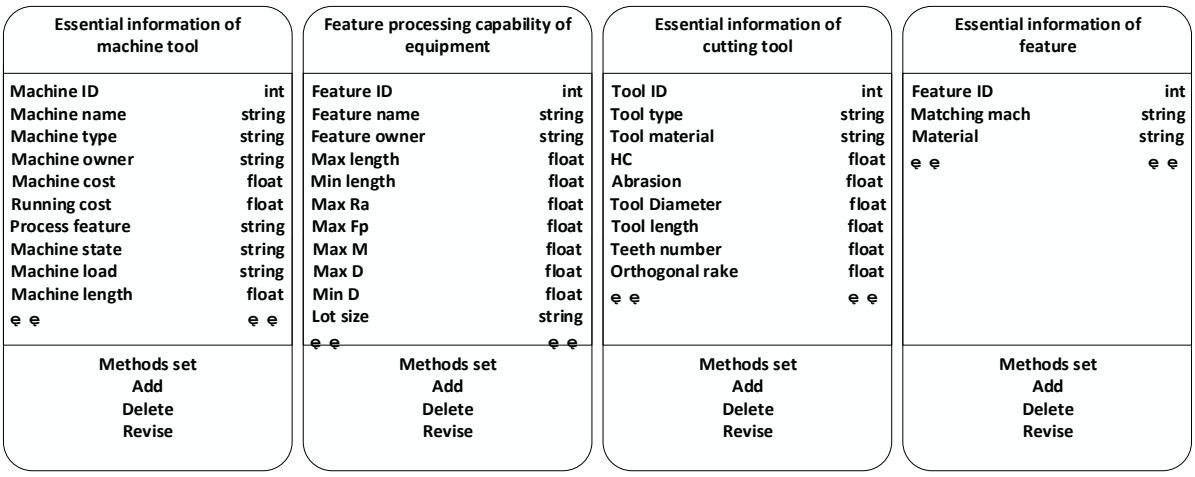


Fig. 5 Model of manufacturing resources

The object-oriented information model of processing equipments contains two sections: the essential information model of specific processing equipments and processing capability information of processing equipments. The essential information model describes the public information which is not related to processing. The information includes machine ID, machine name, machine type, machine owner, machine cost, machine load, and so on. It should assign a value to these attributes when the specific machine tools object of machine tools class is built. The essential information model of the machine tools is defined as Fig. 6(a). The processing capability model describes the capability of generating manufacturing features. The information includes feature ID, feature name, feature owner, max length (max length machined), min length (min length machined), max Ra (max roughness), max Fp (max form and position accuracy), max D (max diameter machined), min D (min diameter machined), lot size and so on. The feature processing capability model of equipment is defined as Fig. 6(b).

The essential information model of cutting and feature is defined as Fig. 6(c) and 6(d).



a b c d

Fig. 6 The object-oriented information model

a Essential information of machine tool; b Feature processing capability of equipment;

c Essential information of cutting tool; d Essential information of feature

5.3 Manufacturability evaluation based on the manufacturing resources constraints

The manufacturability of a part is the adapt degree of design to the manufacturing resource, which involves machining cost, machining time, machining technology, assembly process and so on[27]. The manufacturing resource model based on the object-oriented method has been built. An important content of manufacturability evaluation based on the manufacturing resource constraints is to test whether the part and design feature can satisfy the constraints and be machined by the existing manufacturing resources. The manufacturability evaluation is also based on feature and evaluation process is shown as Fig. 7.

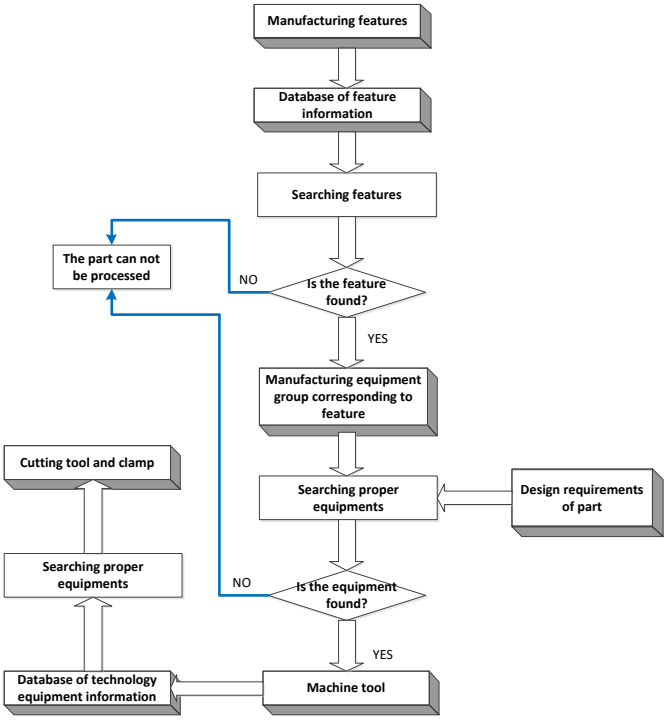


Fig. 7 Manufacturability evaluation based on manufacturing resource constraints

Step1. The manufacturing feature is defined as input. Searching the database of feature information, if the feature is found, the part can be processed; otherwise the part can not be processed.

Setp2. Searching machining tool group corresponding to feature according to design requirements of the part, if the equipments which can process the feature are found, the part can be processed; otherwise the part can not be processed by the limited manufacturing resource.

Setp3. Searching the database of technology equipment information, if the proper cutting tools and fixtures are found according to design requirements the part can be processed in the existing manufacturing environment; otherwise the part can not be processed.

There are two meanings of manufacturability evaluation: one is to test whether the part can be processed by the existing manufacturing resource, and the other is to decide how to process the part at lower cost effectively. The first meaning of manufacturability evaluation based on manufacturing resources is only concerned. The next step is to find the optimal way to process the part according to different demands.

6. Conclusions

This study has developed a hybrid algorithm of genetic algorithm and fuzzy c-means to group the processing equipments according to the manufacturing and geometric features which can be processed by the equipments. The fuzzy rules employed can cope with the problem of the difference between processing capability of modern processing equipments. The algorithm has been tested with applications. The mathematical model of this algorithm was constructed in the above sample and the algorithm was tested with each of the 32 processing machines. The results show that the search space and search time of the processing equipment are successfully reduced by using the hybrid algorithm, indicating that the hybrid algorithm is reasonably effective and insensitive to the initial values.

The information model of manufacturing resources is built by using the object-oriented method based on features and the features are also involved in this model. This model can provide information which is needed in the development of product to manufacturability evaluation to determine whether the product can be processed by the existing manufacturing resource. The information model also can provide information to computer aided process planning and make the manufacturing resources convenient for managing. The framework of manufacturability evaluation based on the constraints of the proposed manufacturing resources model is defined. By this means, the time of evaluation also can be decreased. The model of manufacturing resources is useful in enhancing the whole performance of an enterprise and in making the management decisions more effectively and feasibility. This model can be further refined, the information is more detailed the manufacturability evaluation and decisions are making more effectively and feasibility.

Data availability

All data generated or analyzed during this study are included in this published article.

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Author contribution

Z.CL.、M.C.、Z.HF. propose research methods and theoretical models. All authors performed data analyses, wrote, and reviewed the manuscript.

Competing interests

The authors declare no competing interests.