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The Application and Research on Multi-criteria Decision Making Oriented in Mechanical Manufacturing

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The mechanical manufacturing process is the whole process of transforming raw materials into the final products which can be directly used for customers, and of putting them into markets which is in that process involves many decision-making problems. In fact, decision-making is one of the basic activities existing in any aspects of life and production. This paper, aiming at material selection, process parameter optimization, and agile supply chain configuration in the product manufacturing process, implemented researches on the methods of multi criteria decision making. It has important theoretical and practical significances for improving the scientific, accuracy, and reliability of decision making in the product manufacturing process, and further for improving the economic benefits of any manufacturing enterprises and winning in the fierce marketplace.

1. Introduction

The mechanical manufacturing process decision parameters uncertainty, complexity, which correlation and decision knowledge limitations and making the manufacturing process decision mostly in multi criteria decision making problems related to environment (Stadtler, 2015). The traditional method is based on the experience of the decision maker that is to choose a certain scheme, which is lack of scientific basis. Multi criteria decision making as an important part of the expert system, which can carry through logical reasoning according to human knowledge and experience, and can capture the contained in human expert knowledge. The minds of human expert knowledge are a certain degree of dominance, procedures, and promote a scientific and reasonable decision. Research on the multi criteria decision making method for mechanical manufacturing process is build up the bridge between the mechanical manufacturing process and fuzzy multi criteria decision making. Fuzzy multi criteria decision making enriches and develops the application fields on the other hand, it also promotes a series of decision making and Optimization in the process of mechanical manufacturing, which is gradually transformed into the scientific decision-making. This paper starts with the research of enterprise, mainly studies the selection of engineering materials and the optimization of process parameters (Li et al, 2016; Wu et al, 2016).

2. Machining method based on fuzzy reasoning

2.1 The Fuzzy Inference System

The fuzzy inference system is composed of 3 parts: fuzzy module, approximate reasoning module and clear module. The process of mapping the input crisp value into a fuzzy subset and its membership degree is called fuzzy process. Although the number of fuzzy subsets in the domain Ud should be appropriate, the accuracy of the operation can be improved, but the number of fuzzy rules increases exponentially. $u_{\tilde{A}}: Ud \to [0,1]$, $x \to u_{\tilde{A}}(x) \in [0,1]$ is subset in Ud, $u_{\tilde{A}}(\bullet)$ is membership function in $\tilde{A}$, $u_{\tilde{A}}(x)$ is the degree of membership for x to $\tilde{A}$. If any two elements x and Y in the field are satisfied (Xu, 2012)

$$u_{\tilde{A}}\,(tx + (1-t)y) \geq \min\ \{u_{\tilde{A}}(x), u_{\tilde{A}}(y)\} \quad t \in [0,1]$$

$\tilde{A}$ is a fuzzy subset in convex fuzzy subset.

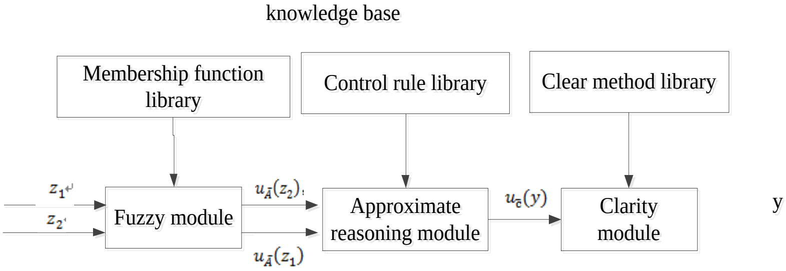

Figure 1: Illustrative diagram for Madman fuzzy inference with two dimensions

2.2 The approximate reasoning module

If A fuzzy control rules is Ru, Z is $\tilde{A}$, then y is $\tilde{B}$, then the fuzzy rule representation between $\tilde{A}$ and $\tilde{B}$ of the entailment relations, denoted as $\tilde{A}\rightarrow\tilde{B}$. Fuzzy implication is minimal operation in the application of fuzzy logic, fuzzy implication operation, fuzzy implication operation and fuzzy implication Boolean operation. We use the fuzzy implication minimal operation, Let Z and Y domain, $\tilde{A}\in P(Z)$,P(Z) is the set all subset of fuzzy Z ,which is called fuzzy power set of Z, $\tilde{B}\in P(Y)$ (Chen and Chen, 2015), $\frown$ is the small operation, which is membership function of the fuzzy control rules for Ru.

$$u_{Ru}(z,y) = \tilde{A}\rightarrow\tilde{B} = \tilde{A}\times\tilde{B} = \frac{\int_{z\times y} u_{\tilde{A}}(z)\forall u_{\tilde{B}}(y)}{(z,y)}$$

For finite sets $\tilde{A}=\{u_{\tilde{A}}(z_1), u_{\tilde{A}}(z_2), \ldots, u_{\tilde{A}}(z_m)\}$, $\tilde{B}=\{u_{\tilde{B}}(y_1), u_{\tilde{B}}(y_2), \ldots, u_{\tilde{B}}(y_m)$, has $u_{Ru}(z,y) = \tilde{A}\rightarrow\tilde{B} = \tilde{A}^{T}\times$

$$\tilde{B} = \begin{bmatrix} u_{\tilde{A}}(z_1)\cap u_{\tilde{B}}(y_1) & \ldots & u_{\tilde{A}}(z_1)\cap u_{\tilde{B}}(y_n) \\ \vdots & \vdots & \vdots \\ u_{\tilde{A}}(z_m)\cap u_{\tilde{B}}(y_1) & \ldots & u_{\tilde{A}}(z_m)\cap u_{\tilde{B}}(y_n) \end{bmatrix}$$

If the fuzzy control rule Ru: if z_1 is $\tilde{A}$, then y is $\tilde{C}$. For a given $\widetilde{A^*}$, $\widetilde{A^*}\in P(z_1)$ known as $\tilde{A}\rightarrow\tilde{C}$is fuzzy implication relations Ru, will be launched $\widetilde{C^*}$,$\widetilde{C^*}=\widetilde{A^*}$•Ru, $\widetilde{C^*}$-related membership degree of an arbitrary element y in $\widetilde{C^*}$ is y is any of the elements $\widetilde{C^*}$ for membership $u_{\tilde{C}}(y)=u_{\widetilde{A^*}}(z_1)\bullet u_{Ru}(z,y)=\sup\{u_{\tilde{A}}(z_1)\forall[u_{\tilde{A}}(z_1)\forall u_{\tilde{C}}(y)\}$ The reasoning process is shown in Figure.2

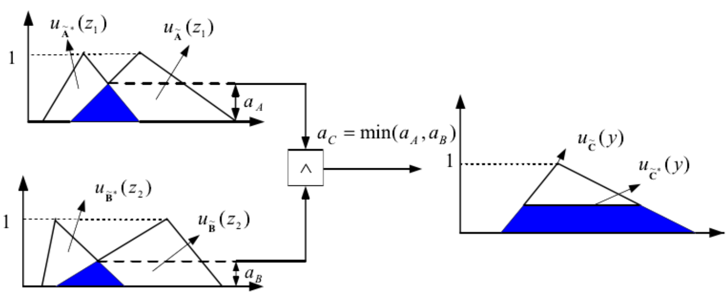

Figure 2: Mamdani fuzzy logic reasoning process with one input

3. Experiment design and output responses

3.1 Determination of control factors

The quality index of FDM process mainly from two aspects, namely efficiency and machining precision which molding to measure the indexes, so the optimization of process parameters for precision, the amount of warpage and processing time three. Dimensional accuracy and warpage are mainly used to measure the level of processing accuracy (Chen and Chen, 2015). The higher the value, the higher the accuracy. processing time is mainly used for the level of processing efficiency, the higher the value, the higher the processing efficiency, which temperature can easily lead to improper nozzle clogging, temperature of molding chamber changes that can easily lead to improper prototype separation and molding plate, so it is not the temperature as a control factor, and directly with the manufacturers recommended parameters. The replacement of

different nozzle diameters will greatly increase the cost. We choose the four parameters of the line width compensation (x_1), extrusion velocity (x_2), filling velocity (x_3), and slice thickness (x_4) as the control factors:
(1) Line width compensation. The spinneret has certain width, which fill in the actual contour path beyond the theoretical contour, thus filling the contour path to compensate the theoretical contour. The compensation value is the width compensation, and the width of the spinneret is influenced by many factors, so it is not a fixed value in the process of piling up.
(2) Filling speed. The extrusion speed is the speed of the wire from the nozzle, the size of which is determined by the wire feeding speed and extrusion pressure. Filling speed is the nozzle moving speed. The filling speed is too low, and the processing efficiency is reduced, and the hot spray head is baked with the processed layer below, and the nodule is generated in a serious condition. The filling speed is too high, one hand may cause the nozzle to produce mechanical vibration, affecting the accuracy of parts; on the other hand, Silk is pulled into filaments, resulting in normal processing. Filling speed is constant with the increase of extrusion speed, wire width gradually expanded, section shape of filler wire from 1 to 2, the 3 expansions, when the extrusion wire speed increases to a certain extent. The outer cone surface of extruded filament adhered to the nozzle, which is resulting in normal processing. Therefore, the two kinds of speed should be reasonable matching, filling speed increases, the extrusion speed should be increased accordingly.
(3) Thickness of layer. Through the single factor experiment to determine the range of the four control factors were: $x_1 \in$[0.17,0.25]mm, $x_2 \in$ [20,30]mm, $x_3 \in$ [20,40]mm, $x_4 \in$ [0.15,0.30]mm (Bustince and Burillo, 2016)

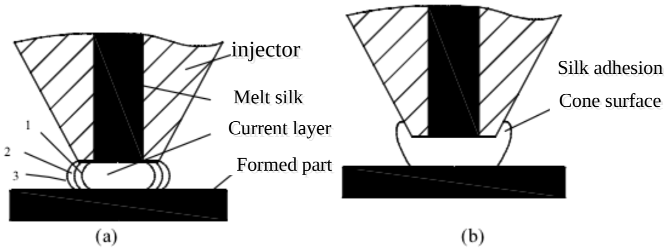

Figure 3: Influence of extrusion velocity on the shape of extruded filament

3.2 The experimental design

The experimental design is an analysis of experimental plan and statistics related to treatment plan, which is an important branch of mathematical statistics, and experimental design methods of comprehensive experiment, orthogonal design and uniform design.
(1) The comprehensive experimental design. A comprehensive experimental design is to match each level of each factor, which to find out the best production conditions. Assuming that the number of experimental factors in an experiment is m, each experimental factor takes n levels, the number of experiments required ism^n. The advantages of comprehensive experiment are the analysis results more carefully, more precise conclusion, but because of the number of experiments it needs more. Such as 4, a number of experimental factors of each experimental factor 5 levels[7], while the whole factor experiment method need the number of experiments is 5^4=625, the multi factor and multi-level situation is not desirable.
(2) The orthogonal experimental design. We are According to the theory of orthogonal design, using mathematical method, the orthogonal experiment and the optimal level of various factors in the collocation results compiled into tables that is called the set of standardized forms for orthogonal experimental design. The orthogonal table has two characteristics of balanced collocation and comprehensive comparison, so it can replace the comprehensive experiment with a small amount of experimental scheme. Balanced collocation is refers to many factors in all orthogonal experiments, the each level of each factor in the same variety, each of the two factors they are an equal number in all experiments. The integrated design of turn table than it is exactly the same in other factors, comparison each level of other factors, that Has the standard orthogonal table commonly used symbol $L_k(p^J)$, such as $L_8(2^7)$, its meaning is: L represents the orthogonal experimental program number K table; representative experiment; the P representatives to participate in the experimental factors; orthogonal table J represents the number of columns, up to a few experimental factors. the characteristics of orthogonal arrays can be obtained, the number of experiments is an integer multiple of the square of the number of factors, namely the K=n••p^2 level when the number increases, the number of experiments according to the square of the ratio increased, such as the level number increased from 9 to 10, the number of experiments at least to increase from 100 to 81. Therefore, the multi factor orthogonal experimental design level is not only suitable for too much, when the level number is large, the number of

experiments very much, for example, 11 levels of at least 11 experiments on 11^2=121times, 30 levels of at least 30 experiments to 30^2=900.

(3) uniform design, uniform experimental design by uniform design table, only considering the experimental point in the experimental range of uniform dispersion without considering the comparability, this method has been achieved in the missile design. Uniform design table $U_k(p^J)$, such as $U_{17}(17^{16})$ the meaning is: U represents uniform design; K represents the number of the level number; P representatives the time of the experiment; J represents the uniform table that can be arranged.

The experimental result. There are three operations were performed under each experimental condition in this experiment. Teach molding with Vernier caliper respectively in the length direction and the width direction distant position of two measurements, each measurement value is the size of the error value minus theory, and calculated the 12 dimension error of the average value by z_{1j}(j=1,2,…,17), the warpage of each edge of the work piece was measured respectively, and the average value of the warpage of the was calculated by z_{2j} (j=1,2,…,17), the average value of the three processing time of each experimental scheme by z_{3j}(j=1,2,…,17). The experimental result is shown in Table.1.

Table 1: Uniform experiment design and output responses

No.	Control factor				experimental result		
	1(x1)	10(x2)	14(x3)	15(x4)	z1:DA (μm)	z2:WD (μm)	z3:BT (min)
1	1 (0.1700)	10 (25.620)	14 (36.25)	15 (0.2816)	2.02	5.24	25.11
2	2 (0.1750)	3 (21.250)	11 (32.50)	13 (0.2628)	2.31	6.70	29.18
3	3 (0.1800)	13 (27.500)	8 (28.75)	11 (0.2440)	2.00	9.28	33.27
4	4 (0.1850)	6 (23.125)	5 (25.00)	9 (0.2252)	4.60	10.30	33.51
5	5 (0.1900)	16 (29.375)	2 (21.25)	7 (0.2064)	1.58	11.10	34.41
6	6 (0.1950)	9 (25.000)	16 (38.75)	5 (0.1876)	2.81	12.67	29.89
7	7 (0.2000)	2 (20.625)	13 (35.00)	3 (0.1688)	6.29	11.08	33.21
8	8(0.2050)	12 (26.875)	10 (31.25)	1 (0.1500)	1.85	13.46	32.17
9	9 (0.2100)	5 (22.500)	7 (27.50)	16 (0.2910)	8.21	5.38	31.78
10	10 (0.2150)	15 (28.750)	4 (23.75)	14 (0.2722)	9.03	6.75	34.87
11	11 (0.2200)	8 (24.375)	1 (20.00)	12 (0.2534)	10.38	6.82	33.78

3.3 The Deburring

Fuzzy inference system interface show fuzzy reasoning after the comprehensive performance value (Comprehensive response, CR).the left 3 column is the input value, the right of the 1 column is the output value of CR. 1lin represents 1 fuzzy rules, 1 rows show only the membership functions of the fuzzy rules corresponding, such as first fuzzy rules is "If DE is S, WD is S, and BT is S then CR is EG", the membership function is first line followed by S, S, EG, and other membership function is not displayed. The vertical line on the left of the 3 column corresponds to the size of the current input value. Every of 1 line represents the membership function of each fuzzy rule corresponding to the output. The last 1 line represent all fuzzy rules output membership functions from the operation results of the membership function, the red thick lines show the membership function to clear the value after fuzzy. The fuzzy membership function is show in Figure 4.

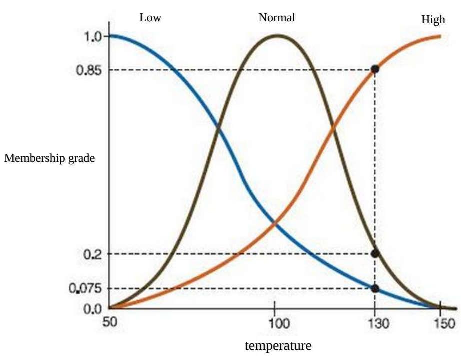

Figure 4: Fuzzy membership function

3.4 The parameter optimization

The traditional optimization methods are single point search, the point to point search method, the multi peak distribution of the search space is often trapped in a single peak of the local extremism. The genetic algorithm is used to deal with multiple individuals in the same time that is space to evaluate multiple solutions, which makes the genetic algorithm, which has a good global search performance. The global optimal solution can be found in a large probability even, if the fitness function is not continuous, irregular or noisy. There is no general method to deal with all kinds of constraint conditions, which are according to the specific problems can choose the following three methods, namely the search space is defined, the feasible solution transformation method and penalty function method.

$$\eta(\mathbf{x}) = -\hat{y}_{rsm}(\mathbf{x}) + M\sum_{i=1}^{8}\{\max[0, g_i(\mathbf{x})]\}^2$$

The penalty function is used to deal with the constraint condition, and the basic idea of penalty function is to combine the objective function with the original objective function to form a new objective function. The penalty function method is divided into interior point penalty function method and exterior point penalty function method and mixed penalty function method. This paper has the penalty function method is used to construct the exterior penalty function. M is the penalty factor, using the gradient descent method in the process of optimization, the penalty factor is from small to ∝, which is using genetic algorithm, can be directly to bring it to a large value, such as M=1010. The penalty form shows that when the iterative point is not feasible in X domain, the great value of penalty, the penalty function τ (x) could not obtain the minimum value; only when the iteration point is x in the feasible region, the penalty value is equal to zero, then it may reach the minimum penalty function this is the minimum value$-\widehat{y_{rsm}}(x)$. Exterior penalty function is show in Figure 5.

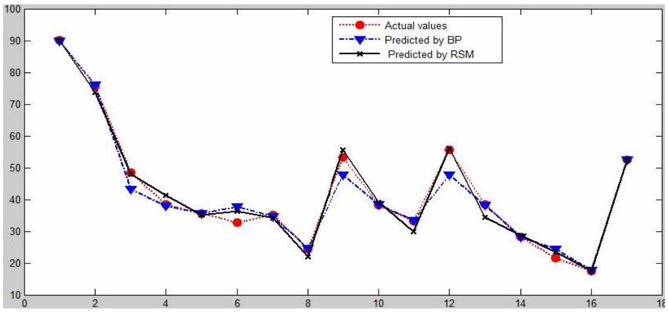

Figure 5: Illustrative comparisons between actual values and predicted values by BP and RSM

3.5 The confirmation tests and discussions

We are In order to test the correctness of the conclusion, under same conditions, which obtained by genetic algorithm of optimal parameters in MEM-300 that rapid prototyping machine manufacture and experiment in front of the same parts, which are making three times respectively to measure the index value, and the average values are listed in table 1.we are In order to facilitate comparison, which take table 1 lists the experimental value to deal the serial number of the index number of 1. The Confirmation Tests and Discussions is show in Figure 6.

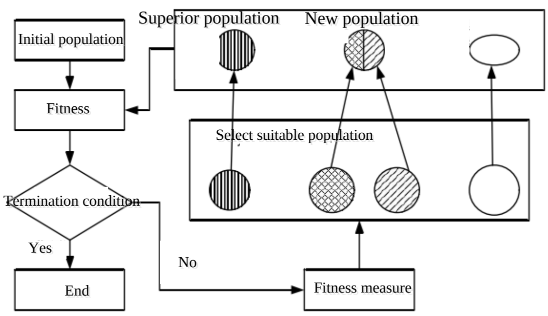

Figure 6: Flow chart for GA

Overall, the overall performance is improved. The large thickness and low filling speed, it is reasonable to reduce the warpage. The processing time mainly depends on the thickness and scanning speed, although the optimal process parameters of middle thick, but because the scanning speed is very low, so the processing time has been extended is reasonable. if the scanning speed is large, it is easy to appear the phenomenon of drawing, so the optimal process parameters obtained in the lower scanning speed is reasonable. Optimization iterative process in GA is show in Figure 7.

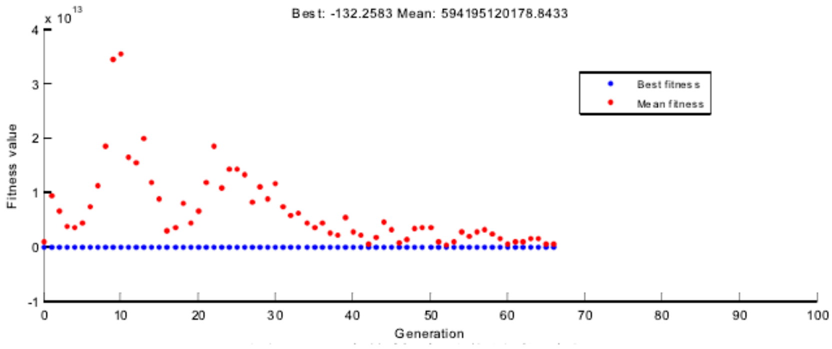

Figure 7: Optimization iterative process in GA

4. Conclusions

This paper describes the necessity of applying fuzzy multi-criteria decision making related to the concept of fuzzy multi criteria decision making and machinery manufacturing process, a comprehensive analysis of the uncertainty in machinery manufacturing process and its application research situation, which carry out the fuzzy multi criteria decision making, and material selection in mechanical manufacturing process parameter optimization, so the optimal partner selection in the study, the primary task allocation.

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