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Research Article

Design of Winding Parameters Based on Multiobjective Decision-Making and Fuzzy Optimization Theory

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The design tries to solve the problem of low pass rate of platinum wire production and the waste of platinum in company. The paper uses multiobjective decision system fuzzy optimization theory to analyze five parameters, which are tensile strength, ductility, fracture load, filling aperture, and resistance. Besides, MATLAB software is used to write programs and calculate. To sum up the above analysis, the weight vector of five parameters is obtained and that can be used to determine which parameter has the greatest influence on the pass rate of the wire winding process.

1. Foreword

The diameter of Pt wire, which is the raw material of the winding process, is 12.7 μm. The process is through hand and machine coordination. The final platinum wire is a spiral product with uniform spacing, no rebound and no deformation. The length of the spiral platinum wire after winding is required to be in the range of 305-356 μm. At the same time, each lap must be evenly spaced at 33 μm. Any rebound or uneven spacing will be considered nonconforming. Since wire winding is a standard machine process, the only difference is the characteristic of Pt which is used in the winding process. Therefore, if we test the characteristic parameters of platinum wire (tensile strength, extension value, fracture load, perfusion aperture, and resistance), we will find out the certain parameter which has the greatest influence on the pass rate. After that, the factory can control the parameters to improve the winding yield.

In the paper, we use multiobjective decision-making system fuzzy optimization theory and combine fuzzy optimal decision theory with dynamic programming optimization theory to solve the problem of complexity system, whose classic optimization technique cannot be done. On the one hand, we use the concept of relative continuous system of numbers to describe the relative membership degree of fuzzy phenomena, events and concept [1–4]. On the other hand, we establish a set of engineering fuzzy theory based on the concept of relative membership of dynamic changes. Finally, the theory of variable fuzzy sets is proposed again.

2. Multiobjective Fuzzy Decision Cycle Iterative Model

We suppose that the set of n samples that remain to clustering is $\{x_1, x_2, \ldots, x_n\}$, clustering samples with m indicator eigenvalue vectors $(x_{1j}, x_{2j}, \ldots, x_{nj})$, and obtained indicator eigenvalue matrix $X = (x_{ij})$, where x_{ij} is the eigenvalue of sample j and index i, $i = 1, 2, \ldots, n$. Since the physical dimensions of the m clustering indicator feature values are different, this requires us to normalize the index feature. That is to say, the index eigenvalue x_{ij} should be transformed into the relative membership degree r_{ij} of the index of clustering sample about fuzzy concept A [5–7]. There are usually three types of indicators in fuzzy clustering. The first is the positive indicator, which just means the lager the indicator feature value is, the higher the rank of the clustering category will be. Its normalization formula is shown in

$$r_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \tag{1}$$

The second is negative indicator, which just means the smaller the indicator feature value is, the higher the rank of the clustering category will be [8]. Its normalization formula is shown as

$$r_{ij} = \frac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}} \tag{2}$$

The last one is intermediate indicator, which just means the rank of the clustering will be higher when the indicator feature value is certain. Its normalization formula is shown as

$$r_{ij} = 1 - rij = 1 - \frac{\left|x_{ij} - \overline{\mathrm{x}}_{\mathrm{i}}\right|}{\max\left|\mathrm{x}_{\mathrm{ij}} - \overline{\mathrm{x}}_{\mathrm{i}}\right|} \tag{3}$$

We transform the index eigenvalue matrix into the relative membership matrix of the index pair fuzzy concept A and then obtain the index eigenvalue normalization matrix R, $R = (r_{ij})$, $0 \leqslant r_{ij} \leqslant 1$. N samples have been normalized according to m index feature values and cluster according to c levels. Its fuzzy clustering matrix is $U = (u_{hj})$, where u_{hj} is the relative membership of the sample j, $h = 1, 2, \ldots, c$; $j = 1, 2, \ldots, n$. At the same time, the conditions need to be met, formula (4) [9–11].

$$\begin{gathered}\sum_{\mathrm{h}=1}^{\mathrm{c}} U_{\mathrm{hj}} = 1 \\ \sum_{\mathrm{j}=1}^{\mathrm{n}} U_{\mathrm{hj}} > 0 \\ 0 \leq u_{ij} \leq 1\end{gathered} \tag{4}$$

The m norm eigenvalue normalization numbers of level h represent the h-level clustering features, which are often called the cluster center in fuzzy clustering. Then c-level clustering features can be represented by m×c-order fuzzy clustering feature matrix, just $S = (s_{ih})$, $0 \leq s_{ih} \leq 1$, in which s_{ih} is the clustering feature normalization number of the h-level indicator, $i = 1, 2, \ldots, m$ and $h = 1, 2, \ldots, c$. The difference between sample j and category is shown as formula (5).

$$d_{hj} = \left[\sum_{i=1}^{m} \left|r_{ij} - s_{ih}\right|^{p}\right]^{1/p} \tag{5}$$

In formula (5), p is a variable distance parameter, which can be taken as the Hamming distance: p = 1 and Euclidean distance: p = 2. We introduce the index weight vector since different indicators have different influences on clustering. $W = (w_1, w_2, \ldots, w_m) = (w_i)$ (wi). At the same time, formula (6) needs to be met.

$$\begin{gathered}\sum_{\mathrm{i}=1}^{\mathrm{m}} W_i = 1 \\ 0 \leq w_1 \leq 1\end{gathered} \tag{6}$$

The difference between the sample j and the h-level can be described by the generalized index weight distance (7).

$$d_{hj} = \left\{\sum_{i=1}^{m} \left[w_i \left|r_{ij} - s_{ih}\right|\right]^{p}\right\}^{1/p} \tag{7}$$

In order to obtain the optimal relative membership degree, the optimal clustering feature sih*, and optimal weight vector w*, we use weighted generalized index weight distance with relative membership degree uhj as weight. Finally, we get the weighted generalized distance $d_{hj} = u_{hj}$, where d_{hj} is the distance concept; it contains the variables u, s, w. An objective function is created which is shown in formula (8) [12–14].

$$\begin{aligned}\min F(u, s, w) &= \sum_{j=1}^{n} \sum_{h=1}^{c} {u_{hj}}^{2} {d_{hj}}^{\mathrm{a}} \\ &= \sum_{j=1}^{n} \sum_{h=1}^{c} {u_{hj}}^{2} \left\{\sum_{i=1}^{m} \left[w_i \left|r_{ij} - s_{ih}\right|\right]^{p}\right\}^{1/p}\end{aligned} \tag{8}$$

The formula satisfies the following constraints:

$$\begin{gathered}\sum_{\mathrm{h}=1}^{\mathrm{c}} u_{\mathrm{hj}} = 1 \\ 0 \leq u_{\mathrm{hj}} \leq 1 \\ \sum_{\mathrm{j}=1}^{\mathrm{n}} u_{\mathrm{hj}} > 0 \\ \sum_{\mathrm{i}=1}^{\mathrm{m}} w_i = 1 \\ 0 \leq w_i \leq 1\end{gathered} \tag{9}$$

In (8), a is a variable optimization criterion parameter; when a = 1, the meaning of the objective function (8) is the cluster sample set n's first-order power sum minimum to $u_{hj}d_{hj}$. When a = 2, the meaning of the objective function (8) is the cluster sample set n's second power sum minimum to $u_{hj}d_{hj,n}$. It is significant for the variable fuzzy sets theory to extend the least-absolute criteria and the least-squares criteria to $u_{hj}d_{hj}$'s sum minimum and d_{hj}'s sum of square minimum in the classic mathematics. Besides, it is also the basis of variable fuzzy clustering, pattern recognition, and optimum decision-making and evaluation model. In order to extend conditional extreme value problem to unconditional extreme value problem, we construct Lagrangian function, as shown in formula (10),

$$L\left(u_{hj}, s_{ih}, w_i, \lambda_u, \lambda_w\right) = \sum_{j=1}^{n}\sum_{h=1}^{c} {u_{hj}}^2 \left\{\sum_{i=1}^{m}\left[w_i\left|r_{ij}-s_{ih}\right|\right]^p\right\}^{1/p} - \lambda_u\left(\sum_{h-1}^{c} u_{hj}-1\right)-\lambda_w\left(\sum_{i=1}^{m} w_i-1\right) \tag{10}$$

In formula (10), $\partial L/\partial u_{hj} = 0$, $\partial L/\partial w_i = 0$, $\partial L/\partial \lambda_1 = 0$, $\partial L/\partial \lambda_2 = 0$, $\partial L/\partial \mathrm{u}_{\mathrm{hj}} = 0$, $\partial L/\partial s_{\mathrm{ih}} = 0$, $\partial L/\partial \mathrm{w}_{\mathrm{i}} = 0$, $\partial L/\partial \lambda_{\mathrm{u}} = 0$, $\partial L/\partial \lambda_{\mathrm{w}} = 0$. During this way it can get formulae (11), (12), and (13).

$$u_{hj} = \left\{\sum_{\mathrm{k}=1}^{\mathrm{c}}\left[\frac{\sum_{i=1}^{m}\left[w_i\left|r_{ij}-s_{ih}\right|\right]^p}{\sum_{i=1}^{m}\left[w_i\left|r_{ij}-s_{ik}\right|\right]^p}\right]^{\alpha/p}\right\}^{-1} \tag{11}$$

$$s_{ih} = \frac{\sum_{\mathrm{j}=1}^{n} {u_{hj}}^{2/(p-1)} r_{ij}}{\sum_{\mathrm{j}=1}^{n} {u_{hj}}^{2/(p-1)}} \tag{12}$$

$$w_i = \left\{\sum_{\mathrm{k}=1}^{\mathrm{m}}\left[\frac{\sum_{j=1}^{n}\sum_{h=1}^{c}\left[{u_{hj}}^2\left|r_{ij}-s_{ih}\right|\right]^p}{\sum_{j=1}^{n}\sum_{h=1}^{c}\left[{u_{hj}}^2\left|r_{kj}-s_{kh}\right|\right]^p}\right]^{1/(p-1)}\right\}^{-1} \tag{13}$$

As for the aspect of being purely mathematical, formula (11), formula (12), and formula (13) are too complicated to be solved with gradient descent method. However, the index weight vector w is a variable parameter according to the practical problems in the variable fuzzy set theory.

3. Multiobjective Fuzzy Decision Optimization Theory

The flow chart of multiobjective fuzzy decision method is shown in Figure 1. We choose 25 suitable schemes in multiobjective decision-making system and judge them by five target eigenvalues; the formula is shown as (14). In formula (14), x_{ij} is the special value for the target i and the scheme j, $\mathrm{i} = 1, 2, \ldots, \mathrm{m}$; $\mathrm{j} = 1, 2, \ldots, \mathrm{n}$. In this scheme, five target eigenvalues are divided into 5 levels according to superiority down to inferiority.

$$\mathrm{X} = \begin{bmatrix} \mathrm{x}_{11} & \mathrm{x}_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \mathrm{x}_{\mathrm{m}1} & \mathrm{x}_{\mathrm{m}2} & \cdots & x_{mn} \end{bmatrix} = \begin{bmatrix} 119000 & 121000 & \cdots & 125000 \\ 0.9 & 0.8 & \cdots & 0.9 \\ \cdots & \cdots & \cdots & \cdots \\ 489.5 & 485.7 & \cdots & 474.8 \end{bmatrix} = \mathrm{X}_{\mathrm{ij}} \tag{14}$$

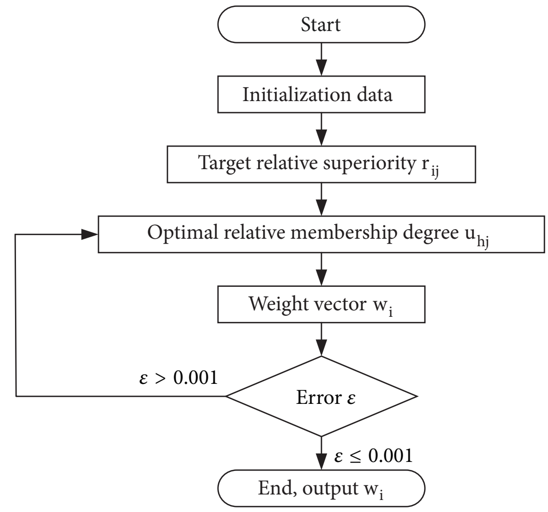

Figure 1: Flow chart of multiobjective fuzzy decision method.

Obviously, the relative superiority can be specified as 1, and the inferior relative superiority can be set to zero, the superiority is 1-level, and the inferior level is c-level for any target parameter. During the fuzzy theory, superiority shows a gradual change in the intermediate transition period; therefore, it can be considered that the process of relative superiority from 1-level to c-level is equivalent to a linear increment process of 0 to 1. It can be concluded that the relative superiority decrement difference of two adjacent levels should meet $\triangle = 1/(\mathrm{c}\text{-}1)$; for any target parameter, the relative superiority standard value vector for each level from 1-level to c-level should be shown as formula (15).

$$\mathrm{S} = \left[1, \frac{(\mathrm{c}-2)}{(\mathrm{c}-1)}, \frac{(\mathrm{c}-3)}{(\mathrm{c}-1)}, \ldots, 0\right] = [1, 0.75, 0.5, 0.25, 0] = \left(\mathrm{S}_{\mathrm{h}}\right) \tag{15}$$

In formula (15), $\mathrm{h} = 1, 2, \ldots, \mathrm{c}$. The target parameter of multiobjective decision system is composed of five parameters: tensile strength, extension value, breaking load, perfusion aperture, and resistance, which can be divided into three types, just the positive indicator, negative indicator, and intermediate indicator. We select the relative membership degree of objectives according to the different conditions of target eigenvalue x_{ij} and the formulas shown as (16), (17), and (18). If the system is good because the feature value is small, we use formula (16). If the system is good because the feature value is bigger, we use formula (17). If the system is good because the feature value is in the middle, we use formula (18)

Table 1: Production data.

T-V	E-V	B-L	C-D	R	Verification	Rate
119000	0.8	9.6	35	489.5	Pass	89.41%
121000	0.9	10.1	32	485.7	Pass	87.46%
122285	1.7	10.9	30	483.5	Pass	82.93%
124000	1.1	11.1	35	481	Pass	87.78%
127079	1.9	11.1	30	467.8	Pass	72.00%
138000	1.1	11	30	486.4	Pass	89.14%
128806	1.5	11.4	32	479.2	Pass	40.00%
129000	1.2	11	35	475.7	Pass	89.91%
130000	1.6	12.2	33	483.3	Pass	82.75%
132000	1.1	11.7	32	477.7	Pass	86.64%
133000	1.2	10.5	35	488.1	Pass	89.00%
134000	0.8	12	30	474.2	Pass	79.46%
135000	1.3	10.7	30	472.5	Pass	87.62%
135616	1.4	10.6	30	489	Pass	58.62%
136000	1.3	11.6	32	476.8	Pass	85.61%
138000	1.1	9.2	30	469.1	Pass	79.79%
138000	1.1	11	30	486.4	Pass	89.52%
139757	1.5	12	30	472	Pass	39.56%
141000	0.9	11.2	35	473.7	Pass	67.08%
141000	0.9	11.2	35	473.7	Pass	79.46%
141000	1.3	11.2	32	482.3	Pass	82.32%
141000	1.3	11.2	32	482.3	Pass	83.89%
119000	0.8	9.6	35	485.5	Pass	88.57%
128000	0.9	10.2	35	470.6	Pass	88.57%
125000	0.9	10.5	35	474.8	Pass	90.20%

Table 2: Parameter data.

Parameter	max	min	$\overline{x}$
Tensile Value (N/mm^2)	141000	119000	128000
Elongation Value	1.9	0.8	1.4
Breaking Load (N)	12.4	9.2	
Cast Diameter (μm)	35	30	33
Resistance (N)	489.5	467.8	474.6

$$r_{ij} = \frac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}} \tag{16}$$

$$r_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \tag{17}$$

$$r_{ij} = 1 - \frac{\left|x_{ij} - \overline{x_i}\right|}{\max\left|x_{ij} - \overline{x_i}\right|} \tag{18}$$

In a word, r_{ij} is the relative superiority for the scheme j and target i, max x_{ij} is the upper bound of the target eigenvalue I, and min x_{ij} is the lower bound. $\overline{x}$ is the intermediate optimal value of target i. By analyzing the data given in Table 1, we can get some conclusions just as shown in Table 2. As shown in Table 1, T-V represents tensile value, E-V represents elongation value, B-L represents breaking load, C-D represents cast diameter, and R represents resistance.

The target eigenvalue matrix x can be transformed into a target affinity matrix by using formulae (16), (17), and (18) and then getting a new formula, as shown in formula (19).

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} = \begin{bmatrix} 0.3077 & 0.4615 & \cdots & 0.7692 \\ 0 & 0.1667 & \cdots & 0.1667 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0.2550 & \cdots & 0.9866 \end{bmatrix} = i_{rj} \tag{19}$$

The next step is to determine the initial solution of the target weight vector and the target weights w_i or u_{hj} which are both unknown at this moment. The solution process requires using formula (20).

$$d_{hj} = u_{hj} \left\{ \sum_{i=1}^{m} \left[w_{ij} \left(r_{ij} - s_h \right) \right]^2 \right\}^{1/2} \tag{20}$$

We can use the sum of squares for generalized weighted distances to express the differences between the scheme j and 1-level to c-level. The formula is shown as

$$f_j \left[u_j^{\overline{w}}, w^{\overline{w}} \right] = \sum_{h=1}^{c} \left\{ u_{hj} \sqrt{\sum_{i=1}^{m} \left[w_i \left(r_{ij} - s_h \right) \right]^2} \right\}^2 \tag{21}$$

Calculation formula for program set x can use formula (22).

$$f \left[u^{\overline{w}}, w^{\overline{w}} \right] = \left[f_a \left[u_a^{\overline{w}}, w^{\overline{w}} \right] \right] \tag{22}$$

In formula (22), $a = 1, 2, \ldots, n$. It is clear that the larger the $f_j[u_j^{\overline{w}}, w^{\overline{w}}]$ is, the greater the difference for scheme j to h-level will be, which becomes large too. In other words, it is more difficult to identify the h-level. Therefore, it is necessary to establish a number of multiobjective decision-making optimization programs. The objective function $\min\{f[u^{\overline{w}}, w]\}$ needs to satisfy formula (23).

$$\begin{gathered} \sum_{h=1}^{c} u_{hj} = 1 \\ \sum_{i=1}^{m} w_i = 1 \end{gathered} \tag{23}$$

In the program set, there is a fair competition among all programs. So the objective function $\min\{f[u^{\overline{w}}, w]\}$ can transform the multiobjective decision optimization problem into a single-objective optimization problem by equal linear weighted average method. Finally formula (24) can be obtained.

$$\min \left\{ f \left[u^{\overline{w}}, w \right] \right\} = \sum_{j=1}^{n} f_j \left[u_j^{\overline{w}}, w^{\overline{w}} \right] \tag{24}$$

Formula (24) satisfies conditional formula (25).

$$\begin{gathered} \sum_{h=1}^{c} u_{hj} = 1 \\ \sum_{i=1}^{m} w_i = 1 \end{gathered} \tag{25}$$

Then building the Lagrange function, the formula is shown as

$$\begin{aligned} L \left[w^{\overline{w}}, w^{\overline{w}}, \lambda_1, \lambda_2 \right] &= \sum_{j=1}^{n} f_j \left[u_j^{\overline{w}}, w^{\overline{w}} \right] \\ \lambda_1 \left[\sum_{h=1}^{c} u_{hj} - 1 \right] - \lambda_2 \left[\sum_{i=2}^{m} w_i - 1 \right] & \\ &= \sum_{i=1}^{n} \sum_{h=1}^{c} \left\{ u_{hj}^{\ 2} \sum_{i=1}^{m} \left[w_i \left(r_{ij} - s_h \right) \right]^2 \right\} \\ &\quad - \lambda_1 \left(\sum_{h=1}^{c} u_{hj} - 1 \right) - \lambda_2 \left(\sum_{i=1}^{m} w_i - 1 \right) \end{aligned} \tag{26}$$

In formula (26), when meeting conditions $\partial L / \partial u_{hj} = 0$, $\partial L / \partial w_i = 0$, $\partial L / \partial \lambda = 0$, $\partial L / \partial \lambda_2 = 0$, formulae (27) and (28) can be obtained.

$$u_{hj} = \frac{1}{\sum_{k=1}^{c} \left(\left(\sum_{i=1}^{m} \left[w_i \left(r_{ij} - s_h \right) \right]^2 \right) / \left(\sum_{i=1}^{m} \left[w_i \left(r_{ij} - s_{\mathrm{k}} \right) \right]^2 \right) \right)} \tag{27}$$

$$w_i = \frac{1}{\sum_{\mathrm{l}=1}^{m} \left(\left(\sum_{j=1}^{n} \sum_{h=1}^{c} \left[u_{hj} \left(r_{ij} - s_h \right) \right]^2 \right) / \left(\sum_{j=1}^{n} \sum_{h=1}^{c} \left[u_{hj} \left(r_{\mathrm{l}j} - s_h \right) \right]^2 \right) \right)} \tag{28}$$

Formulae (27) and (28) are the iterative model to solve the target weights, among them $i = 1, 2, \ldots, m$, $j = 1, 2, \ldots, n$, $h = 1, 2, \ldots, c$. Firstly, we assume that the initial target weight vector is $w_i^{\ c} = [1/5, 1/5, 1/5, 1/5, 1/5]$, $\varepsilon = 0.001$. Secondly, we substitute $w_i^{\ c}$ into formulae (27) and (28) for iteration until $\max |w_i^k - w_i^{k-1}| \leq \varepsilon = 0.001$. Finally we get the final weight vector Wi^k which represents the importance of the parameter throughout the analysis process, which just means when the value is larger, the influence will be bigger.

4. Results and Analysis

We use MATLAB to substitute the data from Table 1. Therefore, the target feature value X can be obtained, and the target feature value X is shown in

$$X = \begin{bmatrix} \mathrm{x}_{11} & \mathrm{x}_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \mathrm{x}_{\mathrm{m}1} & \mathrm{x}_{\mathrm{m}2} & \cdots & x_{mn} \end{bmatrix}$$

Table 3: Relative preference.

Tensile value	Elongation value	Breaking load	Cast diameter	Resistance
0.3077	0	0.8750	0.3333	0
0.4615	0.1667	0.7188	0.6667	0.2550
0.5604	0.5000	0.4687	0	0.4027
0.6923	0.5000	0.4663	0.3333	0.5705
0.9292	0.1667	0.4063	0	0.5436
0.2308	0.5000	0.4375	0	0.2081
0.9380	0.8333	0.3125	0.6667	0.6913
0.9231	0.6667	0.4375	0.333	0.9262
0.8462	0.6667	0.0625	1	0.4161
0.6923	0.5000	0.2188	0.6667	0.7919
0.6154	0.6667	0.5937	0.3333	0.0940
0.5385	0	0.1250	0	0.9732
0.4615	0.8333	0.5313	0	0.8591
0.4142	1	0.5625	0	0.0336
0.3846	0.8333	0.2500	0.6667	0.8523
0.2308	0.5000	1	0	0.6309
0.2308	0.5000	0.4375	0	0.2081
0.0956	0.8333	0.1250	0	0.8255
0	0.1667	0.3750	0.3333	0.9396
0	0.1667	0.3750	0.3333	0.9396
0	0.8333	0.3750	0.6667	0.4832
0	0.8333	0.3750	0.6667	0.4832
0.3077	0	0.8750	0.3333	0.2685
1	0.1667	0.6875	0.3333	0.7315
0.7692	0.1667	0.5937	0.3333	0.9866

$$= \begin{bmatrix} 119000 & 121000 & \cdots & 125000 \\ 0.9 & 0.8 & \cdots & 0.9 \\ \cdots & \cdots & \cdots & \cdots \\ 489.5 & 485.7 & \cdots & 474.8 \end{bmatrix} = X_{ij} \tag{29}$$

According to formula (29), the relative superiority R can be obtained, and the results are shown in Table 3.

Then the relative optimal subordinate degree matrix R can be obtained, as shown in formula (30).

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix}$$
$$= \begin{bmatrix} 0.3077 & 0.4615 & \cdots & 0.7692 \\ 0 & 0.1667 & \cdots & 0.1667 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0.2550 & \cdots & 0.9866 \end{bmatrix} = r_{ij} \tag{30}$$

Firstly, we choose the initial value and the tensile strength, elongation value, breaking load, cast diameter, and resistance which are 12800, 1.4, 9.2, 33, and 474.6. Secondly, we analyze the data. Tensile strength is intermediate, and the system will be optimal when $\overline{x} = 128000$. When $x_{1j} = \overline{x} = 128000$, $r_{1j} = 1$, and when $x_{1j} = \max x_{1j} = 141000$, $r_{1j} = 0$, which conforms with the characteristics of relative superiority degree. So, Ra = 1-abs(A-128000)/(141000-128000). Elongation value is intermediate, and the system will be optimal when $\overline{x} = 1.4$. When $x_{2j} = \overline{x} = 1.4$, $r_{2j} = 1$, and when $x_{2j} = \min x_{2j} = 0.8$, $x_{2j} = 0$, which conforms with the characteristics of relative superiority degree. So, Rb = 1- abs(B-1.4)/(1.4-0.8). The system is better when the eigenvalue is smaller for the parametric of breaking load. When $x_{3j} = \max x_{3j} = 12.4$, $r_{3j} = 0$. And when $x_{3j} = \min x_{3j} = 9.2$, $r_{3j} = 1$, which conforms with the characteristics of relative superiority degree. So, Rc = (C-12.4)/(12.4-9.2). Cast diameter is intermediate, and the system will be optimal when $\overline{x} = 33$. When $x_{2j} = \overline{x} = 33$, $r_{4j} = 1$, and when $x_{4j} = \min x_{4j} = 30$. There are $x_{4j} = 0$, which accord with the characteristics of relative superiority degree. So, Rd = 1 - abs(D-33)/(33-30). Resistance is intermediate, and the system will be optimal when $\overline{x} = 474.6$. When $x_{5j} = \overline{x} = 474.6$, there are $r_{5j} = 1$, and when $x_{5j} = \max x_{5j} = 489.5$, there are $x_{4j} = 0$, which conforms with the characteristics of relative superiority degree. So, Re = 1 - abs(E-474.6)/(489.5-474.6). About all, the relative optimal subordinate degree matrix R is established.

Substituting the subordinate degree matrix into the iterative formula for iteration, when $\max |w_i^k - w_i^{k-1}| < \varepsilon =$

Table 4: Relative membership degree for u_{hj} of each level.

Tensile value	Elongation value	Breaking load	Cast diameter	Resistance
0.0767	0.1556	0.3151	0.3045	0.1480
0.0663	0.1868	0.4864	0.1928	0.0678
0.0501	0.1293	0.4457	0.2874	0.0874
0.0473	0.1640	0.6181	0.1296	0.0410
0.1062	0.2178	0.3410	0.2252	0.1097
0.0287	0.0634	0.2101	0.5535	0.1444
0.1641	0.4051	0.2766	0.1049	0.0494
0.1527	0.3882	0.2958	0.1116	0.0518
0.1414	0.2754	0.3165	0.1768	0.0899
0.0853	0.2475	0.4472	0.1585	0.0615
0.0643	0.1913	0.5101	0.1740	0.0603
0.0679	0.1327	0.2775	0.3408	0.1810
0.0899	0.2175	0.3996	0.2068	0.0862
0.0817	0.1721	0.3413	0.2774	0.1276
0.0816	0.2137	0.4388	0.1949	0.0760
0.1084	0.2137	0.3285	0.2317	0.1177
0.0287	0.0634	0.2101	0.5535	0.1444
0.0619	0.1179	0.2485	0.3604	0.2113
0.0550	0.1095	0.2545	0.3857	0.1953
0.0550	0.1095	0.2545	0.3857	0.1953
0.0550	0.1095	0.2545	0.3857	0.1953
0.0697	0.1459	0.3208	0.3189	0.1447
0.0697	0.1459	0.3208	0.3189	0.1447
0.0764	0.1646	0.3475	0.2856	0.1259
0.1677	0.3525	0.2892	0.1278	0.0627
0.1192	0.3086	0.3639	0.1447	0.0636

Table 5: The weight vector of ${w_i}^k$, ${w_i}^{k-1}$, and ε.

	Tensile value	Elongation value	Breaking load	Cast diameter	Resistance
${w_i}^k$	0.2587	0.1678	0.2351	0.1799	0.1585
${w_i}^{k-1}$	0.2578	0.1683	0.2349	0.1803	0.1587
ε	9.0038e-04	4.7868e-04	1.5723e-04	4.0426e-04	1.7467e-04

0.001, jump out of the while loop and end the iteration. The membership matrix u_{hj} of all the schemes at each level is shown in Table 4 and it suffices that $\sum_{h=1}^{c} u_{hj} = 1,\ 0 \leqslant u_{hj} \leqslant 1,\ \sum_{j=1}^{n} u_{hj} > 0$. It can be proved that the relative membership matrix u_{hj} of each level of the program set is correct.

The weight vectors ${w_i}^k$, ${w_i}^{k-1}$, and ${w_i}^k - w_i^{k-1}$ are shown in Table 5. At the same time, ${w_i}^k$, ${w_i}^{k-1}$ meet formula (31) and their difference is less than the error ε, and ε equals ${w_i}^k - w_i^{k-1}$.

$$\sum_{i=1}^{m} w_i = 1 \qquad 0 \leq w_i \leq 1 \tag{31}$$

According to Table 5, it can be seen that the weight of tensile strength is the largest. In other words, tensile strength is the most important factor for the qualified rate during wire winding process. Selecting two groups of platinum wire, in which one is superior products and the other is the defective products, the data are as shown in Table 6. Group 1 is the superior products; group 2 is the defective product.

According to Table 6, it can be seen that the hardness of the first group of platinum wires is high and the data are close, while the hardness of the second group of platinum wires is low and the data distribution is uneven. So the actual data in Table 6 coincide with the theoretical deduction. In summary, it is considered that the tensile strength has the greatest influence on the pass rate during the wire winding technology.

5. Summary

We use multiobjective decision system fuzzy optimization theory to analyze the parameters in the wire winding process, which are tensile value, elongation value, breaking load, cast

Table 6: Comparative data.

Sample number	Nanoindentation hardness/(GPa)					Average value
1#	3.18	3.28	3.58	3.72	3.10	3.37
2#	2.84	1.94	4.22	1.90	2.56	2.69

diameter, and resistance. Besides, MATLAB software is used to write programs and calculate. Finally, the weight vector of five parameters is obtained, respectively. It is concluded that the tensile strength parameter has the greatest influence on the pass rate of the wire winding process. Our design is to solve the problem that the platinum wire pass rate is low at present. So the factory can improve the production yield of platinum wire by modifying the production parameters in the platinum wire winding process.

Data Availability

The [DATA TYPE] data used to support the findings of this study have been deposited in the [NAME] repository ([DOI or OTHER PERSISTENT IDENTIFIER]).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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