Research on the Cost Control Model of Power Grid Maintenance Based on Fuzzy Pattern Recognition Theory

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Abstract. The power grid lines and equipment maintenance of power enterprises is a complicated construction process, the cost of which is affected by meteorological and geographical factors, and the influence mode is uncertain. Using fuzzy clustering method and the threshold intervals of the objective function in clusters, this paper builds a predictive control model to control the project cost. This model uses relative fuzzy operator to build fuzzy matrix, construct correlation between factors, and describe the factors’ effect. Extracting the cluster’s eigenfunction, and defining the boundaries of various clusters, we determined the type of the predicted points and the range of the objective function. When the actual cost of the maintenance project is within the range calculated by the cost model, then it is normal. If the actual cost exceeds this range, then further analysis of all the aspects of the cost is needed to find out the reason.

Keywords: Cost management; predictive control; fuzzy clustering; control interval.

1. Introduction
Cost management is one of the main tasks of enterprise management, an important source of corporate profit, and a guarantee of the enterprise’s development. In regard of an engineering project, cost management ensures that projects are finished within the required time with both quality and quantity guaranteed, and controls and supervises all kinds of expenses, the measures taken, and the entire process of the project. Through long-term practices, a standard oversight process is developed, including resource planning, cost estimation, expense budget and cost control[1]. Due to the different emphasis of cost management, different administration method is formed. Enterprise-oriented cost management includes methods such as standard cost[2] and average cost; customer-oriented cost management includes methods such as quality cost, value engineering, life cycle cost etc.[3]; future-oriented cost management includes methods such as strategic cost management, and learning curve[4][5]. Regarding the methods of cost management, on the one hand, they base on the qualitative analysis and set up a scientific management system, in order to control the cost within the reasonable range. On the other hand they set up a standard for cost management, in order to test and supervise the effect of it.

Grid system is the main equipment of transmission system. Its maintenance accounts for more than 70% of the power enterprises’ productive task[6]. With the marketization of the power industry, maintenance and overhaul’s business mode is diversifying. Thus the control of the cost components is relatively weakened at the micro level, and the importance of the integral control of maintenance cost is highlighted. For a long time, due to the monopolistic nature of power industry and the complexity of the environment, there was no mature cost management method for the maintenance cost both domestic and abroad. The major control methods are standard cost methods and prediction control methods. The frequently-used prediction control methods include multiple regression method[7] and artificial neural networks[8]. This paper uses interval prediction method to control the maintenance cost of the power
grid’s complex equipment failures, and to achieve real-time control with the help of operating center’s data-mining.

2. Fuzzy Clustering and Pattern Recognition

In the process of data analysis, cluster analysis is an important method. Jain believes that data clustering analysis process has three important goals, (1) Data structure analysis, which means to divide the data into several different-featured types by using cluster analysis; (2) Analyze the level of similarity between various natural groups of data. (3) Classify and combine the data using the given cluster center[9]. Clustering method’s flexibility allows it to adapt to various objectives, and its application are more and more extensive. It is widely used in areas such as data mining, image processing, and biological science. The introduction of fuzzy sets enables the classification of data to better describe the uncertainty of it[10]. Comparing to hard clustering method, fuzzy clustering has better adaptability. Commonly used fuzzy clustering method is transitive closure method based on fuzzy equivalent relation[11], and clustering algorithm based on fuzzy relation and similarity relation. In order to achieve data dimensionality reduction and data clustering, typical matrix’s clustering properties and methods are promoted, and the definition of objective function is presented based on the data’s compactness[12]. Proposed by E. Ruspini and promoted to fuzzy clustering by J. C. Dunn, Fuzzy c-Mean(FCM) has become the most completed and widely used theory of algorithms[13]. The existence of eigenvalue and eigenfunctions not only optimizes the clustering process and reveals the differences between categories, but also can easily and accurately identify the type of predicted points[14]. According to the clustering result’s projection on the prediction axis, the characterization of various types can be extracted, and then construct eigenfunctions[15]. Using the range of the projection on the prediction axis as controlled interval, control models can be built.

| Table 1. Process of Cost Control. |
|-----------------------------------|
| Step1 | Input the original data matrix and build fuzzy matrix. |
| Step2 | Fuzzy causality clustering. Use the transitive closure $T(R) = R^2$ based on fuzzy equivalence relation, and calculate the optimal clustering. |
| Step3 | Set up a characteristic, project $U_i$ on the factor axis, construct a triangular fuzzy number using $(Y_0, 3\delta_i)$ as parameter, get $I(x)$ and eigenmatrix $I_i$. Work out each cluster’s eigenfunction $P_i$. |
| Step4 | Predictive control. Apply the Maximum Subordination Principle, calculate the eigenfunction, determine the type of predicted points, and identify the control interval. |

3. Select the Variables and Set up a Data Matrix

The goal of establishing a cost control system is not only to gradually reduce the cost of lines and equipment maintenance, but also to provide a standard price for the outsourcing business. Therefore when choosing variables, material costs, labor costs, machine-shift costs and other direct costs should be selected.

Given $n$ variables $X_1, X_2, \cdots, X_n$, and $m$ sets of observed data, build $m \times n$ matrix

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{1}$$
In this matrix, $x_{ij}$ is the $i$th observed value of $j$th variable.

There are many ways to select variables, and Delphi method is a simple and convenient one\cite{16}. But the defect is that the factors’ determination depends on the experts’ subjective judgement and lacks supporting data. It is normally used in the early stage of the system when there is less collected data. Set-valued statistic method is adapted when a certain amount of raw data is collected\cite{17}. This method is objective for it is supported by data, but the defect is that the original variables in the set value may be different from the variables that the model requires, and if they are different from each other, some factors will be omitted, which will affect the credibility and validity of the model. After years of hard working and learning, the State Grid Corporation of China had established monitoring indicators for grid operations, in order to roundly reflect the situation of the transmission network’s design, construction, maintenance, and operation, etc. The units can select which one to use according to their needs, and provide production and scientific research services. It is common to use correlation test in statistical analysis, or by examining the significance of each factor $i$’s impact on $y$, to further screen the factors and then get the result. Since electrical equipment’s maintenance can be influenced by many factors, here we abstract some of which that have relatively bigger impact to build the control model. There are mainly thirteen influencing factors, and they are divided into four types, which are process, transportation, weather and field, as shown in table 1 below.

Table 2. Index system of maintenance engineering.

| Serial Number | Criterion Layer     | Index Level                  | Symbol |
|---------------|---------------------|------------------------------|--------|
| 1             | Total costs         |                               | $x_0$  |
| 2             | Voltage level       |                               | $x_1$  |
| 3             | Maintenance level   |                               | $x_2$  |
| 4             | Maintenance time    |                               | $x_3$  |
| 5             | The distance to the site |                         | $x_4$  |
| 6             | The complexity to reach the site |                    | $x_5$  |
| 7             | The level of required vehicle |                | $x_6$  |
| 8             | The type of the device |                           | $x_7$  |
| 9             | Air temperature     |                               | $x_8$  |
| 10            | Air humidity        |                               | $x_9$  |
| 11            | Staff composition   |                               | $x_{10}$ |
| 12            | Fixation material   |                               | $x_{11}$ |
| 13            | The length of replaced material |                   | $x_{12}$ |
| 14            | The weight of replaced material |                | $x_{13}$ |

The variable value mostly adopts the same categories used by the State Grid Corporation of China, such as the voltage level has 10kV, 35kV, 220kV and 500kV, and the job types are classified into overhaul, repair, urgent repair, test and so on, labeled according to the cost and complexity of projects, and therefore forms a raw data matrix both qualitative and quantitative.
4. Construct Fuzzy Matrix

4.1. Data Preprocessing
In order to make sure the data’s variation range is the same between factors and controlled variables, centralized and standardized methods are used to preprocess the raw data.

Let \( \bar{y} = \frac{1}{T} \sum_{t=1}^{T} y_t \); \( \bar{x}_i = \frac{1}{T} \sum_{t=1}^{T} x_{it} \)

Standard deviation \( s_y = \left[ \frac{1}{T} \sum_{t=1}^{T} (y_t - \bar{y})^2 \right]^{\frac{1}{2}} \)

\( s_{x_i} = \left[ \frac{1}{T} \sum_{t=1}^{T} (x_{it} - \bar{x}_i)^2 \right]^{\frac{1}{2}} \)

Standardized transformation:

\( y'_t = \frac{y_t - \bar{y}}{s_y} \)

\( x'_{it} = \frac{x_{it} - \bar{x}_i}{s_{x_i}} \), \( i = 1, 2, \ldots, m \)  \hspace{1cm} (2)

Central standardization and the data it processed has better statistical properties and it is widely applied

|   | \( x_0 \) | \( x_1 \) | \( x_2 \) | \( x_3 \) | \( x_4 \) | \( x_5 \) | \( x_6 \) | \( x_7 \) | \( x_8 \) | \( x_9 \) | \( x_{10} \) | \( x_{11} \) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 70196 | 35 | 3 | 38 | 77.9 | 3 | 2 | 10 | 3 | 4.01 | 112 | 1.5 |
| 2 | 64122 | 22 | 1 | 22 | 56.3 | 5 | 1 | 4 | 4 | 2.96 | 0 | 2.9 |
| 3 | 70666 | 35 | 5 | 46 | 28.2 | 5 | 4 | 9 | 4 | 4.64 | 523 | 9 |
| 4 | 75368 | 35 | 5 | 63 | 54.5 | 4 | 4 | 9 | 3 | 5.95 | 3 | 471 |
| 5 | 72216 | 10 | 2 | 77 | 68.3 | 3 | 1 | 6 | 5 | 7.93 | 0 | 3.0 |
| 6 | 80464 | 22 | 2 | 84 | 77.1 | 7 | 3 | 4 | 6 | 7.09 | 0 | 3.5 |
| 7 | 91210 | 50 | 3 | 86 | 58.4 | 5 | 4 | 8 | 3 | 6.51 | 0 | 476 |
| 8 | 57000 | 10 | 4 | 81 | 69.7 | 3 | 4 | 5 | 4 | 3.04 | 0 | 488 |
| 9 | 82750 | 10 | 4 | 79 | 61.9 | 2 | 7 | 12 | 5 | 5.65 | 0 | 497 |
| 10 | 97743 | 22 | 5 | 85 | 8.5 | 7 | 7 | 3 | 7 | 7.77 | 0 | 2.3 |
| 11 | 110500 | 50 | 3 | 86 | 30.2 | 7 | 2 | 9 | 2 | 6.75 | 0 | 2.2 |
| 12 | 113768 | 22 | 4 | 81 | 15.1 | 6 | 2 | 10 | 1 | 6.69 | 1 | 476 |
| 13 | 106580 | 10 | 1 | 79 | 8.0 | 5 | 1 | 6 | 4 | 3.70 | 0 | 6.6 |
| 14 | 95277 | 35 | 5 | 91 | 3.0 | 7 | 7 | 6 | 5 | 9.80 | 0 | 415 |

Table 3. Maintenance Cost and Influencing Parameters.
in the engineering field. The processed data can be either positive or negative, but it doesn’t affect the result of the calculation. For convenience, we continue to record the processed data as 

\[ z'_t = (x_{i1}, x_{i2}, \ldots, x_{in}, y'_t), \quad t = 1, 2, \ldots, T \]

4.2. Calibrate Fuzzy Matrix

We are going to apply fuzzy clustering analysis on a fuzzy equivalent matrix \( R^* \), which is symmetric. First transform the standardized data into fuzzy matrix, that is to calibrate the data. As for domain \( U \), give a figure within the range [0,1] to represent the relationship between the element \( x_{ij} \), which is called a similarity coefficient. The numerical value represents the level of their similarity. Assume \( U = \{u_1, u_2, \ldots, u_n\} \) is all the things waiting to be classified, and \( u_i = \{x_{i1}, x_{i2}, \ldots, x_{in}\} \), \( x_{mi} \) is the characterization data of \( u_i \). Use \( r_{ij} \) to stand for the level of similarity between element \( u_i \) and \( u_j \), and \( 0 \leq r_{ij} \leq 1 \) \((i, j = 1, 2, \ldots, T)\). If \( r_{ij} = 0 \), then element \( u_i \) and \( u_j \) has no relationship or no similarity at all; if \( r_{ij} = 1 \), then element \( u_i \) and element \( u_j \) are the same.

Here we use dot product method to transform the fuzzy matrix, that is, 

\[
 r_{ij} = \begin{cases} 
 1 & i = j \\
 \frac{1}{M} \sum_{k=1}^{T} x_{ik} x_{jk} & i \neq j 
\end{cases}
\]

(3)

And \( M = \max \left\{ \sum_{k=1}^{T} x_{ik} x_{jk} \right\} \), \((i \neq j)\)

Get the fuzzy matrix

\[
 R = \begin{bmatrix} 
 1 & 0.83 & 0.72 & 0.67 & 0.75 & 0.46 & 0.49 & 0.78 & 0.62 & 0.37 & 0.35 & 0.16 & 0.20 & 0.08 \\
 1 & 0.79 & 0.55 & 0.29 & 0.49 & 0.78 & 0.41 & 0.37 & 0.68 & 0.28 & 0.23 & 0.24 & 0.31 \\
 1 & 0.35 & 0.45 & 0.52 & 0.48 & 0.58 & 0.41 & 0.36 & 0.45 & 0.71 & 0.44 & 0.30 & 0.30 \\
 1 & 0.52 & 0.43 & 0.38 & 0.65 & 0.54 & 0.37 & 0.45 & 0.42 & 0.47 & 0.35 & 0.32 & 0.28 \\
 1 & 0.54 & 0.53 & 0.78 & 0.65 & 0.51 & 0.42 & 0.26 & 0.36 & 0.26 & 0.32 & 0.35 & 0.34 \\
 1 & 0.76 & 0.51 & 0.71 & 0.32 & 0.38 & 0.35 & 0.48 & 0.73 & 0.51 & 0.34 & 0.35 & 0.35 \\
 1 & 0.63 & 0.65 & 0.36 & 0.13 & 0.24 & 0.35 & 0.85 & 0.53 & 0.24 & 0.35 & 0.35 & 0.35 \\
 1 & 0.54 & 0.56 & 0.47 & 0.25 & 0.39 & 0.58 & 0.51 & 0.34 & 0.35 & 0.35 & 0.35 & 0.35 \\
 1 & 0.53 & 0.48 & 0.30 & 0.46 & 0.79 & 0.51 & 0.34 & 0.35 & 0.35 & 0.35 & 0.35 & 0.35 \\
 1 & 0.65 & 0.58 & 0.57 & 0.35 & 0.51 & 0.34 & 0.35 & 0.35 & 0.35 & 0.35 & 0.35 & 0.35 \\
 1 & 0.53 & 0.55 & 0.61 & 0.34 & 0.34 & 0.35 & 0.35 & 0.35 & 0.35 & 0.35 & 0.35 & 0.35 \\
 1 & 0.79 & 0.53 & 0.31 & 0.31 & 0.31 & 0.31 & 0.31 & 0.31 & 0.31 & 0.31 & 0.31 & 0.31 \\
 1 & \end{bmatrix}
\]

(4)

5. Fuzzy Clustering Analysis

5.1. Fuzzy Classification

Since the fuzzy similar matrix \( R \) may not be transitive, we need to use transitive closure method to substitute matrix \( T(R) \) for matrix \( R \) and transfer closure \( T(R) = R^2 \). The final result is when the transfer deviation is the minimum. The correlation matrix is denoted by \( R = (r_{ij})_{T \times T} \), given \( A_1^*, A_2^* \) as
the confidence interval, and then select the best clustering.

\[ R^* = \begin{bmatrix}
1 & 0.72 & 0.72 & 0.55 & 0.72 & 0.46 & 0.43 & 0.72 & 0.57 & 0.21 & 0.21 & 0.08 & 0.20 & 0.21 \\
1 & 0.72 & 0.55 & 0.32 & 0.30 & 0.70 & 0.48 & 0.47 & 0.45 & 0.71 & 0.44 & 0.32 \\
1 & 0.42 & 0.43 & 0.40 & 0.43 & 0.51 & 0.21 & 0.45 & 0.38 & 0.47 & 0.21 \\
1 & 0.49 & 0.40 & 0.72 & 0.57 & 0.34 & 0.45 & 0.38 & 0.36 & 0.25 \\
1 & 0.70 & 0.47 & 0.71 & 0.34 & 0.34 & 0.38 & 0.48 & 0.71 \\
1 & 0.47 & 0.57 & 0.34 & 0.08 & 0.31 & 0.35 & 0.72 \\
1 & 0.51 & 0.47 & 0.34 & 0.31 & 0.39 & 0.47 \\
1 & 0.47 & 0.34 & 0.31 & 0.46 & 0.72 \\
1 & 0.57 & 0.57 & 0.57 & 0.45 \\
1 & 0.57 & 0.55 & 0.57 \\
1 & 0.72 & 0.57 \\
1 & 0.42 \\
1 
\end{bmatrix} \]

By optimizing the clusters, get the optimal cluster: \( \hat{\lambda} = 0.7 \). Divide it into 5 categories, denoted by \( U_1, U_2, \ldots, U_m \).

| Category | Factors |
|----------|---------|
| I        | \( x_1, x_2, x_3, x_4, x_5, x_6, x_8 \) |
| II       | \( x_6, x_7, x_9, x_{14} \) |
| III      | \( x_{10}, x_{12}, x_{13} \) |
| IV       | \( x_4 \) |
| V        | \( x_{11} \) |

5.2. Extract Eigenvalue

To all the clusters \( U_j \), project them on the factor axis \( X = X_1 \times X_2 \times \cdots \times X_m \), and get \( V_1, V_2, \ldots, V_m \). Corresponding to \( V_i \) (\( i = 1, 2, \ldots, m \)), build a fuzzy set \( A \in F(X) \) to reveal its character.

To any \( V_i \), let \( V_i = (x_{i1}, x_{i2}, \ldots, x_{in}) \)

\[
\bar{x}_j = \frac{1}{ki} \sum_{i=1}^{ki} x_{is}, \quad (i = 1, 2, \ldots, m) \tag{5}
\]

\[
\delta_{ij}^2 = \frac{1}{ki} \sum_{s=1}^{ki} (x_{ij} - \bar{x}_j)^2, \quad (j = 1, 2, \ldots, n) \tag{6}
\]

The eigenfunction of \( x = (x_1, x_2, \ldots, x_n) \in X \) is

\[
P_i(x) = \sum_{j=1}^{n} e^{-\frac{(x_j - \bar{x}_j)^2}{2\delta_{ij}^2}}, \quad (i = 1, 2, \ldots, m) \tag{7}
\]
Assume \( W_i = (y_{i1}, y_{i2}, \cdots, y_{im}) \), \( (i = 1, 2, \cdots, m) \) is \( U_i \)'s projection on the prediction axis, so \((x_{is}, y_{is}) = z_i \in U_i, (s = 1, 2, \cdots, ki) \). Calculate,

\[
\bar{y}_i = \frac{1}{ki} \sum_{s=1}^{ki} y_{is}
\]

\[
\delta_i = \max_{1 \leq s \leq ki} |y_{is} - \bar{y}_i|
\]

Construct a triangular fuzzy numbers (orthostate fuzzy numbers) using \((\bar{y}_i, 3\delta_i)\) as the parameter.

\[
I(x) = \begin{cases} 
\frac{x + \sigma - \alpha}{\sigma} & \alpha - \sigma \leq x \leq \alpha \\
\frac{-x + \sigma - \alpha}{\sigma} & \alpha \leq x \leq \alpha + \sigma 
\end{cases}
\]

\[
\alpha, \sigma \text{ are real numbers, and so become triangular fuzzy numbers, denoted by } t(\alpha, \sigma).
\]

Corresponding to the category \((U_1, U_2, \cdots, U_m)\), we have

\[
\begin{bmatrix}
P_1 & P_2 & \cdots & P_m \\
I_1 & I_2 & \cdots & I_m
\end{bmatrix}
\]

Put the data into steps (5), (6), (7), then get the eigenfunctions of each clusters. We only take \( P_1, P_2, \) and \( P_3 \) for in other categories \( \sigma_i \approx 0 \), it’s meaningless and therefore can be ignored.

\[
P_1 = e^{\frac{(x_1-108332)^2}{9x_{1286617187}}} + e^{\frac{(x_2-3.420)^2}{9x_{8.352}}} + e^{\frac{(x_3-1.1433)^2}{9x_{3.6512}}} + e^{\frac{(x_4-81.214)^2}{9x_{84.576}}} + e^{\frac{(x_5-71.6712)^2}{9x_{8.563}}} + e^{\frac{(x_6-5.1264)^2}{9x_{4.536}}}
\]

\[
+ e^{\frac{(x_7-5.3200)^2}{9x_{2.354}}} + e^{\frac{(x_8-8.3254)^2}{9x_{3.1261}}} + e^{\frac{(x_9-5.8035)^2}{9x_{1.124}}} + e^{\frac{(x_{10}-5.3241)^2}{9x_{1.204}}} + e^{\frac{(x_{11}-4.735)^2}{9x_{13.141}}} + e^{\frac{(x_{12}-5.8306)^2}{9x_{8.3153}}} \tag{11}
\]

\[
P_2 = e^{\frac{(x_1-97475)^2}{9x_{8076582}}} + e^{\frac{(x_2-3.6132)^2}{9x_{8.352}}} + e^{\frac{(x_3-2.7441)^2}{9x_{2.9672}}} + e^{\frac{(x_4-71.423)^2}{9x_{79.823}}} + e^{\frac{(x_5-60.782)^2}{9x_{6.7163}}} + e^{\frac{(x_6-4.23465)^2}{9x_{9.26481}}}
\]

\[
+ e^{\frac{(x_7-3.9328)^2}{9x_{2.144}}} + e^{\frac{(x_8-6.2361)^2}{9x_{2.7427}}} + e^{\frac{(x_9-4.1332)^2}{9x_{1.2135}}} + e^{\frac{(x_{10}-4.2334)^2}{9x_{1.1876}}} + e^{\frac{(x_{11}-3.824)^2}{9x_{97.84}}} + e^{\frac{(x_{12}-4.7523)^2}{9x_{3.5023}}} \tag{12}
\]

\[
P_3 = e^{\frac{(x_1-71347)^2}{9x_{7817184}}} + e^{\frac{(x_2-3.2573)^2}{9x_{2.7427}}} + e^{\frac{(x_3-2.1364)^2}{9x_{1.2135}}} + e^{\frac{(x_4-63.397)^2}{9x_{1.1876}}} + e^{\frac{(x_5-53.6712)^2}{9x_{73.536}}} + e^{\frac{(x_6-4.1735)^2}{9x_{6.5326}}}
\]

\[
+ e^{\frac{(x_7-3.4354)^2}{9x_{8.362}}} + e^{\frac{(x_8-6.1222)^2}{9x_{27.740}}} + e^{\frac{(x_9-3.0365)^2}{9x_{1.1523}}} + e^{\frac{(x_{10}-3.73264)^2}{9x_{1.1258}}} + e^{\frac{(x_{11}-4.368)^2}{9x_{84.532}}} + e^{\frac{(x_{12}-4.1735)^2}{9x_{3.1537}}} \tag{13}
\]

Build triangular fuzzy numbers according to (8), (9), (10)

\[
I_1 = \begin{cases} 
\frac{y}{653} - 26.43 & 83567 \leq y \leq 98564 \\
\frac{y}{653} + 32.47 & 98564 \leq y \leq 121362 
\end{cases}
\]

\[
I_2 = \begin{cases} 
\frac{y}{218} - 79.51 & 71815 \leq y \leq 75743 \\
\frac{y}{96} + 182.54 & 75743 \leq y \leq 87529
\end{cases}
\]
Therefore, the corresponding eigenfunctions and fuzzy numbers of categories $U_1$, $U_2$, and $U_3$ are
\[
\begin{align*}
I_1 &= \begin{cases} 
\frac{y}{653} - 26.43 & 56331 \leq y \leq 66294 \\
\frac{y}{653} + 32.47 & 66294 \leq y \leq 76256
\end{cases} \\
I_2 &= \begin{cases} 
32.47 & 66294 \leq y \leq 76256
\end{cases} \\
I_3 &= \begin{cases} 
-26.43 & 56331 \leq y \leq 66294 \\
32.47 & 66294 \leq y \leq 76256
\end{cases}
\end{align*}
\]
(16)

Therefore, the corresponding eigenfunctions and fuzzy numbers of categories $U_1$, $U_2$, and $U_3$ are
\[
\begin{align*}
P_1 &= 0.56; \\
P_2 &= 0.73; \\
P_3 &= 0.61.
\end{align*}
\]

6. Confirm the Maintenance Cost’s Control Interval
For each cluster $U_i$, $y$’s variation range is $(y_i', 3\delta_i')$, which is the confidence interval of cost control.
Now we have a maintenance project that will start soon,

Table 5. The maintenance projects to be controlled.

| $x_0$ | $x_1$ | $x_2$ | $x_3$ | $x_4$ | $x_5$ | $x_6$ | $x_7$ | $x_8$ | $x_9$ | $x_{10}$ | $x_{11}$ |
|-------|------|------|------|------|------|------|------|------|------|--------|--------|
| Yuan | kV   | h    | km   | Degr |       |      |      |      |      |        |        |
| 1     | 35   | 2    | 47   | 58   | 3     | 4    | 11   | 3    | 4.0   | 162    | 3.5    |

According to (11) (12) (13), we have $P_1 = 0.56; P_2 = 0.73, P_3 = 0.61$. In accordance with the maximum membership principle, the project belongs to $U_2$, the control range of the cost is interval $(71815, 87529)$. After the construction, if the actual cost falls into this range, the project cost is normal. If it exceeds the range, the cost analysis meeting is needed to find out the reason of this abnormality.

7. Conclusion
Power enterprises’ power supply network is distributed in many complex regions, therefore the maintenance is affected not only by the equipment’s intricacy and the condition of the malfunction, but also by geographical and meteorological factors. Because of uncertainties during the maintenance, it is needed to us the fuzzy clustering method to overcome these difficulties and have obtained satisfactory result. Fuzzy clustering and pattern recognition methods are also insensitive to the initialization and undemanding of the sample’s quantity and distribution, which increases the model’s adaptation. By extracting and judging the eigenvalue in the model, the clusters are more evident, and the classification of the sample data from the forecast period are much easier. This model can adapt to the characteristics of the projects’ cost, and make sure the cost’s control interval is within a reasonable range.

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