

Design of Improved Algorithm and Model for Multi-constrained Fuzzy Predictive Analysis

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ABSTRACT

Complex system engineering often has high fuzziness and multiple constraints. In this case, it is difficult to achieve consistent results through predictive analysis. To solve the problem, this paper explores the key techniques and methods for predictive analysis on complex systems, and puts forward an improved strategy for multi-constrained fuzzy predictive analysis. The author explained the normalization, weighting, granularity setting and classic domain of the attributes of multiple constraints, introduced the calculation of the fuzzy distance and fuzzy closeness for the attributes of multiple constraints, and detailed the realization of our algorithm and model multi-constrained fuzzy predictive analysis. The effectiveness and feasibility of our algorithm and model were demonstrated through comparison with relevant data in the literature. The results show that the results of our approach agree with those of the literature. The proposed algorithm and model provide a good theoretical basis to predictive analysis of complex system engineering, especially that with multiple fuzzy constraints.

1. INTRODUCTION

The problem with multiple constraints (multi-constrained problem) is a difficulty in system engineering analysis. In many fields of engineering, multi-constrained problem calls for optimal design and analysis, especially for complex system engineering [1, 2]. To make matters worse, the presence of multi-constrained problem adds to the unpredictability in the development of complex systems. Thus, it is very difficult to predict the trend of complex systems in a scientific, accurate and reliable manner [3, 4]. To overcome the difficulty, the key lies in capturing the constraints, especially when they are fuzzy and uncertain, accurately, and using them to make effective predictions of the trend of complex systems. Doing so could provide powerful support to the design, maintenance and repair of complex systems, making them more applicable in engineering cases.

Currently, fruitful results have been achieved on the prediction and analysis of fuzzy systems. Some scholars predicted the trend of fuzzy systems based on the gray theory. Lu [5] discussed the multi-attribute prediction of complex systems based on grey relational analysis (GRA), and presented a grey prediction model for the implicit associations in complex systems. Through the GRA, Javed et al. [6] optimized the shape and analyzed the thermal properties of heat exchangers, providing an important reference for industrial thermal analysis and gray multi-objective optimization. Based on the gray model, Bezuglov and Comert [7] predicted the traffic parameters (e.g. speed, travel time and flow) in smart transport system in an accurate manner. Memon et al. [8] combined the gray system theory with the uncertainty theory to study the supplier selection problem with random uncertainty and identifiable uncertainty.

Some scholars predicted the trend of fuzzy systems based on neural networks (NNs). Vukovic et al. [9] analyzed a

Sharpe ratio prediction NN model, and proved that the NN can successfully forecast the nonlinear time lag sequences. Navas et al. [10] applied different artificial neural networks (ANNs) and empirical classification regression models to predict wind speed, and estimated the wind speed using the SPSS software. Using the growing and pruning method, Akyol [11] determined the ideal parameters (i.e. the optimal number of hidden layers, the optimal number of hidden layer neurons, and the activation function) of deep NNs and extreme learning machines, and verified the prediction ability of the designed model. Liu et al. [12] implemented the uncertain genetic neural network in the prediction of landslide risk, and achieved good engineering application effect.

Some scholars predicted the trend of fuzzy systems based on support vector machine (SVM). Wadkar et al. [13] adopted SVM-based technique to detect malwares. Hou et al. [14] developed a projection nonparallel SVM for pattern classification, and applied it to recognize and analyze the patterns of complex systems. Lukmanto et al. [15] integrated feature selection and fuzzy SVM for early detection and prediction of diabetes mellitus. Gangsar et al. [16] studied the fault diagnosis and prediction of induction motors based on the SVM.

Some scholars predicted the trend of fuzzy systems based on the genetic algorithm (GA), and applied the results in the combinatory optimization and decision-making of complex systems. Lee [17] reviewed the applications of the GA in operations management. Iyer et al. [18] applied the GA in the design and economic optimization of shell-and-tube heat exchanger. de Assis. et al. [19] identified Volterra systems with the aid of the GA. Tseng et al. [20] investigated disassembly sequence planning based on the GA.

Some scholars predicted the trend of fuzzy systems based on the extension theory. Lu [21] designed a multilevel extension association forecast model under the influence of

multiple factors. Chao [22] combined the extension theory and traditional perturbation and observation method, and relied on the combined approach to design a maximum power tracker based on the particle swarm optimization (PSO). Drawing on the extension theory, Chao et al. [23] analyzed the maximum power point (MPP) tracking of photovoltaic (PV) systems.

To sum up, the above research results have been applied successfully in engineering. However, there is ample room for improvement in the following aspects due to the unknown nature of fuzzy information: the effective measurement of fuzzy information, and more refined and accurate prediction of information. Therefore, this paper carries out an in-depth analysis on multi-constrained fuzzy prediction of complex system engineering based on the fuzzy system theory [24-26]. The key contents include normalizing multi-constrained fuzzy information, fuzziness calculation, and the steps of fuzzy prediction. On this basis, the author developed an algorithm and model for improved multi-constrained fuzzy prediction.

The remainder of this paper is organized as follows: Section 2 introduces the basic concepts of multi-constrained fuzzy predictive analysis; Section 3 presents our algorithm and model for multi-constrained fuzzy prediction, explains the normalization, weighting, granularity setting and classic domain of the attributes of multiple constraints, and details the steps of multi-constrained fuzzy predictive analysis; Section 4 verified our algorithm and model for multi-constrained fuzzy prediction through comparative analysis; Section 5 puts forward the conclusions of this research.

2. BASIC CONCEPTS

2.1 Attribute set of multi-constrained fuzzy predictive analysis

The term multi-constrained has multiple meanings. First, the design goals for the design, analysis and optimization of complex systems are constrained by various factors. To achieve ideal design results, the relationship between design constraints and design goals must be handled well. Second, the design requirements and design goals for complex systems might be contradictory or incompatible. The relationship between the relevant influencing factors must be sorted out to solve the contradiction or incompatibility. Third, there are implicit or explicit correlations between the design attributes of complex systems, which may affect the system performance. To improve the design and predictive analysis of multi-constrained fuzzy systems, this paper attempts to extract the features and attributes of the multiple constraints, forming the attribute set of multi-constrained fuzzy predictive analysis. Let Q be the number of the extracted attributes of the multiple constraints and S be each extracted attribute. Then, the attribute set \mathcal{S} of multi-constrained fuzzy predictive analysis, a.k.a. the fuzzy set, can be expressed as:

$$\mathcal{S} = \{S_1, S_2, \dots, S_k, \dots, S_{Q-1}, S_Q\} \quad (1)$$

2.2 Fuzzy distance

In fuzzy system theory, the fuzzy distance is defined to reflect the closeness between the predictive analysis target and the fuzzy set \mathcal{S} . Let $v_k = [v_k(a), v_k(b)]$ be the fuzziness of the attribute k corresponding to the predictive analysis target,

and $v_k^S = [v_k^S(a), v_k^S(b)]$ be the fuzziness interval of attribute k . Then, the fuzzy distance between the target and the attribute can be defined as:

$$D_k = \sqrt[p]{\left(|v_k^S(a) - v_k(a)|^p + |v_k^S(b) - v_k(b)|^p\right) / 2} \quad (2)$$

If $P=1$, then:

$$D_k = \left(|v_k^S(a) - v_k(a)| + |v_k^S(b) - v_k(b)|\right) / 2 \quad (3)$$

In this case, the distance is the Hamming distance.

If $P=2$, then:

$$D_k = \sqrt{\left(|v_k^S(a) - v_k(a)|^2 + |v_k^S(b) - v_k(b)|^2\right) / 2} \quad (4)$$

In this case, the distance is the Euclidean distance.

3. ALGORITHM AND MODEL OF MULTI-CONSTRAINED FUZZY PREDICTIVE ANALYSIS

3.1 Normalization of the attributes of multiple constraints

In predictive analysis, different indices may differ in dimensions. To make the analysis results more reliable, all the indices should have uniform metrics. Since the predictive analysis in this research is fuzzy, it is assumed that the value of each attribute in predictive analysis falls into a fuzzy interval, i.e. the initial value of index k corresponding to the predictive analysis target is $v_k = [v_k(a), v_k(b)]$. Let $u_k = [u_k(a), u_k(b)]$ be the normalized correlation, and $v_k^\ominus = [v_k^\ominus(a), v_k^\ominus(b)]$ be the threshold of index k . Then, the normalization of the cost-based index k can be described as:

$$\begin{cases} u_k = [u_k(a), u_k(b)] \\ u_k(a) = \frac{v_k^\ominus(b) - v_k(b)}{v_k^\ominus(b) - v_k^\ominus(a)} \\ u_k(b) = \frac{v_k^\ominus(b) - v_k(a)}{v_k^\ominus(b) - v_k^\ominus(a)} \end{cases} \quad (5)$$

The normalization of the benefit-based index k can be described as:

$$\begin{cases} u_k = [u_k(a), u_k(b)] \\ u_k(a) = \frac{v_k(a) - v_k^\ominus(a)}{v_k^\ominus(b) - v_k^\ominus(a)} \\ u_k(b) = \frac{v_k(b) - v_k^\ominus(a)}{v_k^\ominus(b) - v_k^\ominus(a)} \end{cases} \quad (6)$$

3.2 Weighing of the attributes of multiple constraints

The weights of the attributes of multiple constraints can be determined by various methods, such as the analytic hierarchy process (AHP), entropy weight method, comprehensive evaluation, the NN method and gray correlation method. Considering its simplicity, practicality and result reliability, the AHP was adopted for the weighting of attributes of multiple constraints.

Step 1. Create the attribute set of multi-constrained fuzzy predictive analysis.

Step 2. Perform expert scoring based on a nine-point scale, producing the judgement matrix \mathbf{A} :

$$\mathbf{A} = \{a_{ij}\}_{nm} = \begin{bmatrix} a_{11} & a_{12} & \cdots & \cdots \\ a_{21} & a_{22} & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & a_{mm} \end{bmatrix} \quad (7)$$

Step 3. Normalize the judgement matrix \mathbf{A} :

$$\bar{a}_j = \sum_{i=1}^n \left(a_{ij} / \sum_{i=1}^n a_{ij} \right) \quad (8)$$

Step 4. Obtain the maximum characteristic root of judgement matrix \mathbf{A} :

$$\lambda_{\max} = \sum_{j=1}^n \frac{(AW)_i}{nW_i} \quad (9)$$

Step 5. Check the consistency of judgement matrix \mathbf{A} :

$$\begin{cases} CI = \frac{\lambda_{\max} - n}{n - 1} \\ CR = CI / RI \end{cases} \quad (10)$$

If $CR \leq 0.1$, then judgement matrix \mathbf{A} has good consistency, and proceed with the next step; Otherwise, reestablish the judgement matrix.

Step 6. Acquire the weights:

$$w_j = \bar{a}_j / \sum_{j=1}^n \bar{a}_j \quad (11)$$

3.3 Granularity setting for the attributes of multiple constraints

The granularity setting for the attributes of multiple constraints refers to the division of the value interval of the attribute set for multi-constrained fuzzy predictive analysis. The granularity should be properly configured according to the actual condition of the predictive analysis target. If the granularity is too small, the attribute set will be divided into too many items. In extreme cases, each item is a reference object, making it impossible to predict the target. If the granularity is too large, the attribute set will be divided too coarsely. In this case, the range of the reference object is too broad, so is that of the prediction result. Then, it is also impossible to accurately predict the target.

3.4 Classic fields for the attributes of multiple constraints

Based on the granularity set in the preceding subsection, the attributes of multiple constraints can be divided into H classic fields. Then, the interval of the reference object h in each classic field of the attribute set can be expressed as $Z_h = [Z_h(a), Z_h(b)]$. The size of this interval determines the reference objects in the corresponding historical records. Suppose there are N reference objects. Then, the classic field Ω_k^h of the reference object h formed by these reference object relative to index k can be expressed as:

$$\begin{cases} \Omega_k^h = [\Omega_k^h(a), \Omega_k^h(b)] \\ \Omega_k^h(a) \leq \min_{1 \leq i \leq N} (u_k = [u_k^i(a), u_k^i(b)]) \\ \Omega_k^h(b) \geq \max_{1 \leq i \leq N} (u_k = [u_k^i(a), u_k^i(b)]) \end{cases} \quad (12)$$

To ensure the reliability and accuracy of prediction results, the following values are selected to make the predicted range wider:

$$\begin{cases} \Omega_k^h(a) < \min_{1 \leq i \leq N} u_k^i(a) \\ \Omega_k^h(b) > \max_{1 \leq i \leq N} u_k^i(b) \end{cases} \quad (13)$$

3.5 Fuzzy closeness for the attributes of multiple constraints

Let $u_k = [u_k(a), u_k(b)]$ be the value of predictive analysis targets relative to index k . Then, the fuzzy distance D_k^h between $u_k = [u_k(a), u_k(b)]$ and the reference object h can be computed by:

$$D_k^h = \sqrt[p]{\left(\left| \Omega_k^h(a) - u_k(a) \right|^p + \left| \Omega_k^h(b) - u_k(b) \right|^p \right) / 2} \quad (14)$$

In particular, if the value of the predictive analysis target relative to index k is an exact value, i.e. $u_k = u_k(a) = u_k(b)$, then:

$$D_k^h = \sqrt[p]{\left(\left| \Omega_k^h(a) - u_k \right|^p + \left| \Omega_k^h(b) - u_k \right|^p \right) / 2} \quad (15)$$

The fuzzy distance D_k^h is negatively correlated with the closeness between the two factors. Hence, the fuzzy closeness Φ_k^h can be introduced:

$$\Phi_k^h = 1 - D_k^h \quad (16)$$

Considering the weight of each attribute of the multiple constraints, the integrated weighted fuzzy closeness Φ_k^h can be described as:

$$\Phi^h = \sum_{k=1}^K \left(w_k * (1 - D_k^h) \right) \quad (17)$$

The integrated weighted fuzzy closeness Φ_k^h has a negative

correlation with the closeness between the predictive analysis target and the reference object.

3.6 Realization of multi-constrained fuzzy predictive analysis

Based on the integrated weighted fuzzy closeness Φ_k^h , the classic field of the reference object h corresponding to the predictive analysis target can be obtained as $Z_h =$

$[Z_h(a), Z_h(b)]$. Then, the fuzzy prediction Z^* of the predictive analysis target must satisfy:

$$Z^* \in Z_h = [Z_h(a), Z_h(b)] \tag{18}$$

Therefore, the algorithm of multi-constrained fuzzy predictive analysis can be established. The workflow of the established algorithm is shown in Figure 1.

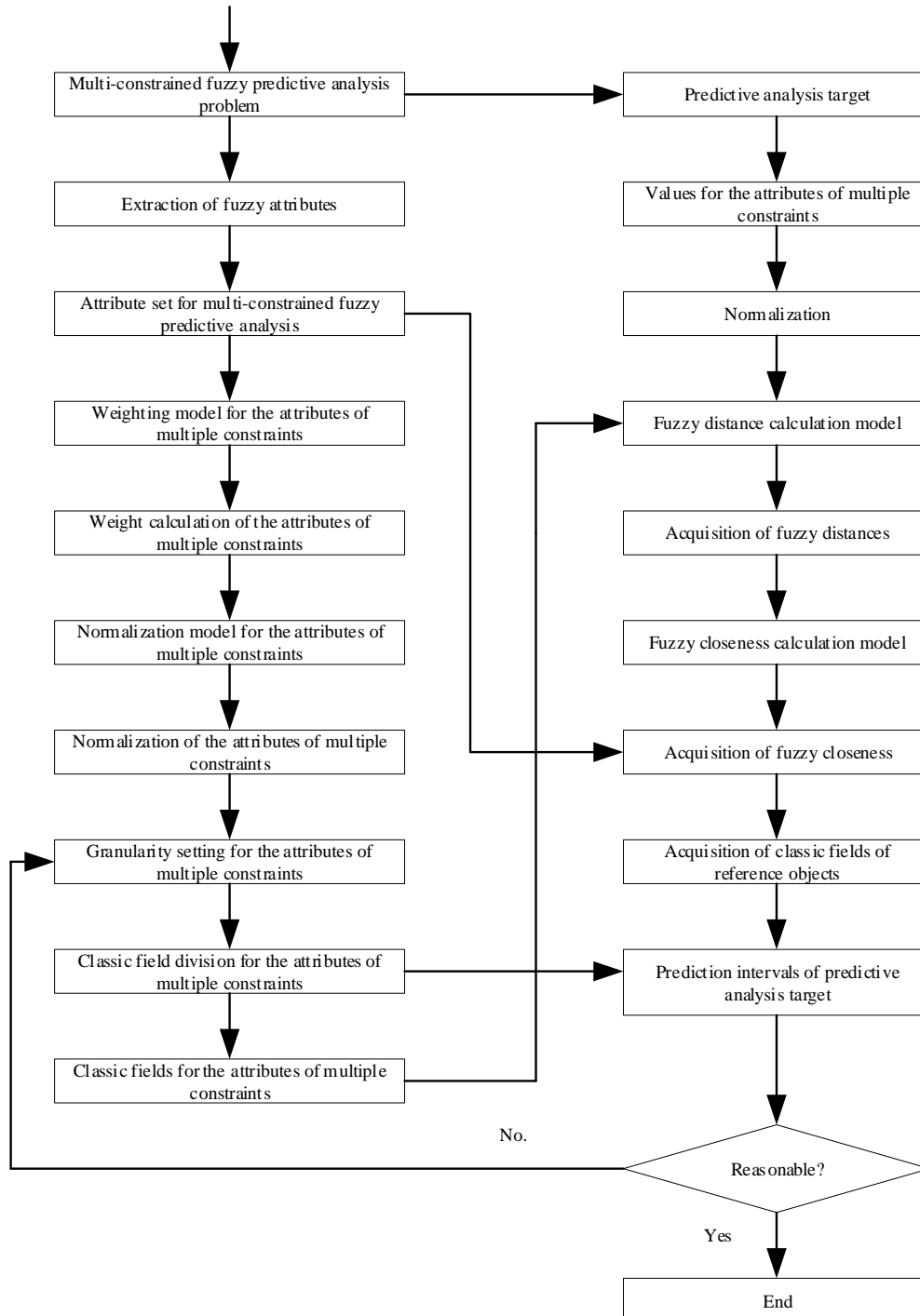


Figure 1. Workflow of multi-constrained fuzzy predictive analysis algorithm

4. COMPARATIVE ANALYSIS

This section aims to verify the feasibility and effectiveness of the proposed algorithm and model for multi-constrained

fuzzy predictive analysis, and explain the realization of our algorithm and model. As mentioned before, the fuzzy distance is measured by Euclidean distance. The predictive analysis results of our algorithm and model were compared with the

data in the research of Lu [5]. The initial data are compared in Table 1 below.

The fuzzy distance and fuzzy closeness were computed by the corresponding formulas in our algorithm, and compared with those in Lu Hui’s research (Tables 2 and 3).

As shown in the data below, the prediction by our algorithm should fall into the target interval for 0.937, i.e. 0.230-0.300. The result agrees with the data in Lu Hui’s research. However, the predictive analysis target was closer to target interval 1 for attribute 1, and closer to target interval 2 for attribute 2 than that in Lu Hui’s research. There is no significant difference in

this respective for attribute 3. Since attribute 2 has the greatest weight, the final results were not obviously different.

Similarly, the prediction by our algorithm was compared with that of Kemal Akyol’s research [11] (Tables 4-6).

The fuzzy distance and fuzzy closeness were computed by the corresponding formulas in our algorithm, and compared with those in Kemal Akyol’s research (Tables 5 and 6).

It can be seen from Tables 5 and 6 that prediction by our algorithm should fall into the target interval for 0.939, i.e. 0.180-0.280. The result is consistent with the data in Kemal Akyol’s research.

Table 1. The initial data of our algorithm and Lu Hui’s research

	Classic field			Target interval
	Attribute 1	Attribute 2	Attribute 3	
1	0-0.070	0.135-0.195	0.120-0.180	0.070-0.150
2	0.070-0.180	0.080-0.270	0.110-0.200	0.150-0.230
3	0.130-0.340	0.200-0.260	0.340-0.400	0.230-0.300
Predictive analysis target	0.247	0.216	0.309	TBD
Weight	0.300	0.400	0.300	

Table 2. The fuzzy distances of our algorithm and Lu Hui’s research

	Classic field		
	Attribute 1	Attribute 2	Attribute 3
1	0.215	0.059	0.162
2	0.134	0.103	0.160
3	0.106	0.033	0.068

Table 3. The fuzzy closeness values of our algorithm and Lu Hui’s research

	Classic field			Weighted fuzzy closeness
	Attribute 1	Attribute 2	Attribute 3	
1	0.785	0.942	0.838	0.864
2	0.866	0.897	0.840	0.870
3	0.894	0.967	0.932	0.937

Table 4. The initial data of our algorithm and Kemal Akyol’s research

	Classic field				Target interval
	Attribute 1	Attribute 2	Attribute 3	Attribute 4	
1	0.069-0.158	0.085-0.327	0.146-0.196	0.077-0.162	0.080-0.180
2	0.083-0.181	0.172-0.265	0.127-0.275	0.106-0.216	0.180-0.280
3	0.187-0.327	0.256-0.284	0.292-0.332	0.209-0.301	0.280-0.400
Predictive analysis target	0.195	0.202	0.227	0.183	TBD
Weight	0.154	0.477	0.288	0.081	

Table 5. The fuzzy distances of our algorithm and Kemal Akyol’s research

	Classic field			
	Attribute 1	Attribute 2	Attribute 3	Attribute 4
1	0.093	0.121	0.061	0.076
2	0.080	0.049	0.078	0.059
3	0.094	0.069	0.087	0.085

Table 6. The fuzzy closeness values of our algorithm and Kemal Akyol’s research

	Classic field				Weighted fuzzy closeness
	Attribute 1	Attribute 2	Attribute 3	Attribute 4	
1	0.907	0.879	0.939	0.924	0.903
2	0.920	0.951	0.922	0.941	0.939
3	0.906	0.931	0.913	0.915	0.920

5. CONCLUSIONS

The presence of fuzzy information has complicated the predictive analysis of complex systems under multiple constraints. For engineering applications, it is very meaningful to develop a predictive analysis method facing multiple fuzzy constraints. This paper puts forward an improved multi-constrained fuzzy predictive analysis algorithm. The author explained the normalization, weighting, granularity setting and classic domain of the attributes of multiple constraints, introduced the calculation of the fuzzy distance and fuzzy closeness for the attributes of multiple constraints, and detailed the realization of our algorithm and model multi-constrained fuzzy predictive analysis. The effectiveness and feasibility of our algorithm and model were demonstrated through comparison with relevant data in the literature. The results show that the results of our approach agree with those of the literature. The proposed algorithm and model provide a new solution and support to multi-constrained fuzzy predictive analysis.

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