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Research Article

Study on Hesitant Fuzzy Multiattribute Quality Evaluation Based on Surface Defect Information of Autobody Panels

Jia Mao [1], Qi Sun [1], and Kun Gui [1,2]

[1]*School of Transportation, Jilin University, Changchun 130025, China*
[2]*Festo Production Ltd., Jinan 250014, China*

Correspondence should be addressed to Jia Mao; maojia@jlu.edu.cn

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Surface defects of autobody panels have the greatest impact on the surface quality of the automobile body, but many enterprises lack a scientific and reasonable evaluation method of surface quality, relying solely on the subjective judgment of decision makers which will lead to an increase in the probability of misjudgment. In this paper, the subjective weight is determined by the genetic algorithm based on optimization, and the objective weight is determined by the improved deviation maximization method. Combining the hesitant fuzzy set theory, the hesitant fuzzy mixed weighted arithmetic average operator (HFHWA), and the score function, the surface defect information of the panel is quantified. On this basis, a complete set of hesitant fuzzy multiattribute evaluation model of surface defect information is proposed. Taking a batch of inner panels of the automobile door produced by A automobile enterprise as an example, five common defects including hidden pit, bump and scratch, rust, indentation pockmark, and ripple are selected as evaluation attributes to evaluate their surface quality, which verifies the validity and practicability of the model.

1. Introduction

Multiattribute decision-making as an important content of management science has profound theoretical basis and application background in the fields of logistics management, engineering construction, and military affairs, such as warehouse location, production prediction, grade ranking, and medical diagnosis [1, 2]. Multiattribute decision-making is to compare different attribute information of different schemes by using certain methods, which mainly includes three parts, respectively, as index data acquisition, operator aggregation, and result ranking.

After decades of development, the research and application of multiattribute decision-making theory have been mature, with its application field greatly expanded [3, 4]. As to the study of multiattribute decision-making, Saaty [5] firstly proposed analytic hierarchy process (AHP); thus, a new definition of hierarchical structure was proposed, the method of eigenvalue measurement was applied to AHP, and the validity of eigenvalue measurement and AHP was verified by an example. Hwang and Yoon [6] systematically reviewed and classified the literatures of multiattribute decision-making methods and their applications, introduced the basic theories of transformation of different types of attributes, the rules of fuzzy decision-making, and the method of weight determination and put forward a system for classifying 17 main MADM methods. Karacapilidis [7] proposed a comprehensive framework for multicriteria decision-making on the World Wide Web, where the involved agents use a fully implemented debating discourse system to pursue their standards and goals and then introduced a fuzzy similarity measurement to evaluate existing alternative solutions related to the required solutions.

The concept of fuzzy sets proposed by Zadeh [8] and studied by numerous scholars had diverged outward many branches, in which, fuzzy multiattribute decision-making as one of the branches recognized by scholars has been applied in many fields. Xu [9] studied three kinds of multiattribute decision-making methods based on different numerical forms and discussed weight determination, different types of operators, and preference effect. Cheng and Liu [10] proposed a new method of weight determination, with the consideration of the preferences of decision makers and relevant experts and verified by examples that this method is suitable for determining the weights of different types of attributes. Ma and Sun [11] conducted sensitivity analysis on attribute weights determined by the comparison method, which is helpful for decision makers to make more reliable decisions and has been verified by examples. Sun and Guan [12] proposed a multiattribute decision-making method based on grey correlation for the mixed multiattribute decision-making problems with real numbers, interval numbers, triangular fuzzy numbers, intuitionistic fuzzy numbers, and uncertain linguistic variables.

1.1. Problems and Related Work. Fuzzy multiattribute evaluation and traditional multiattribute evaluation will both consider weight, preference of the reviewer, normalization of attribute values, and aggregation operators, but their attribute values are expressed differently, that is, traditional multiattribute evaluation uses the deterministic number to represent attribute value, while fuzzy multiattribute evaluation, which has the color of uncertainty and is more suitable for the actual evaluation process, uses the fuzzy number to represent attribute value.

Many scholars had conducted deep research studies and practical application on hesitant fuzzy set theory firstly proposed by Torra [13]. Xia and Xu [14] firstly discussed the relationship between intuitionistic fuzzy sets and hesitant fuzzy sets and based on which, the operations of some fuzzy elements and set operators were given. Chao and Zhao [15] defined a new aggregation operator with the consideration of both intuitionistic and hesitant fuzzy sets and gave the corresponding accuracy function and score function. Josh [16]introduced a new biparametric exponential information measure based on intuitionistic fuzzy sets (IFSs) for intuitionistic fuzzy sets and also produced a new multicriteria decision-making method based on the proposed intuitionistic fuzzy (IF) measure and weighted correlation coefficients. Zhu et al. [17] combined the hesitant fuzzy number and the TOPSIS method to calculate the approach degree between each scheme and ideal solution and based on which, the prioritization was conducted. Liang and Liu [18] introduced fuzzy sets into rough sets of decision theory and proposed a new model of rough sets of fuzzy decision theory. Wang [19] constructed aggregation operators of picture fuzzy sets and studied their properties and applications. Joshi [20] introduced an information measure defined on PFSs called R-norm picture fuzzy information measure and proposed a new set of axioms as criteria for picture fuzzy entropy. Liu et al. [21] proposed a multiobjective optimization model to determine the optimal weight. Liu [22] put forward the hesitant fuzzy symmetric mean operator, introduced its four good properties, and applied this model to the selection of cloud service providers. Li and Liu [23] proposed a new distance measure formula for hesitant fuzzy sets, which is very convenient with the advantage that it does not need to add fuzzy elements to shorter fuzzy sets.

At the same time, hesitant fuzzy operators have also been greatly developed. He et al. [24] defined the *i*-order polymerization-degree function, proposed a new ranking method to further compare different hesitant fuzzy sets, and used new aggregation operators to give a fuzzy method for fuzzy multiattribute group decision-making. Liang et al. [25] extended the application of decision theory rough set to the indecisive fuzzy information system in view of the new evaluation format of the fuzzy set. Lin et al. [26] discussed the use of product preference relations to deal with the consistency of probabilistic hesitant product preference relations (PHMPRs); thus, a complete group decision-making model based on PHMPRs was proposed, whose validity was verified by an example. Gao et al. [27] proposed a Hamacher prioritized aggregation operator for fusing dual hesitant bipolar fuzzy information and developed some methods for solving the problem of dual hesitant bipolar fuzzy multiattribute decision-making. It is proven that the feature of hesitant fuzzy sets (HFSs) to assign membership degrees in the form of a set has made them very useful for solving the multiple attribute decision-making (MADM) problem. Joshi and Kumar [28] introduced a new exponential hesitant fuzzy entropy based on well-known exponential entropy, which is then used for solving the MADM problem. Liao [29] comprehensively introduced the theories of intuitionistic fuzziness, hesitant fuzziness, and hesitant linguistic fuzziness in detail and put forward some new aggregation operators on the basis of various operators. These research documents provide a solid theoretical support for this paper.

1.2. Research Contents. Based on the basic theories of supply management, quality management, fuzzy mathematics, operations research, and metal technology, this paper makes a thorough study on the multiattribute evaluation of panel surface quality with the reference of research ideas and methods of relevant scholars:

(1) With full consideration of the close relationship between fuzzy evaluation and actual production, attribute values are given in the form of hesitant fuzzy numbers. The characteristic of hesitant fuzzy numbers is that there is no limit on the number of attribute index values. When the opinions of decision makers are not uniform, all attribute values can be added to the fuzzy set.

(2) A new method for measuring hesitant fuzzy distance is introduced, while it is not necessary to add fuzzy elements to a shorter fuzzy set, so the calculation is simpler. An improved deviation maximization method is used to solve objective weights, and a genetic algorithm based on optimization is used to solve subjective weights.

(3) The HFHWA operator used in this paper aggregates data information, whose advantage is to weigh the fuzzy information itself and its position at the same time.

(4) Based on the hesitation fuzzy score function, the hierarchical partition function of surface quality is defined by combining related criteria.

1.3. Research Framework. The contents of rest of the article are as follows: Section 2 presents the evaluation model of panel surface quality; Section 3 introduces relevant algorithms. Section 4 validates the model and algorithm with examples. Section 5 analyses the results of the examples. Section 6 is the summary of the whole paper.

2. Model

Suppose the numbering set of the autobody panel is $\delta = \{\delta_1, \delta_2, \ldots, \delta_m\}$, attribute set is $\alpha_i = \{\alpha_1, \alpha_2, \ldots, \alpha_n\}$, subjective weight of each evaluation attribute is $\lambda_j = (\lambda_1, \lambda_2, \ldots, \lambda_n)^T$, objective weight is $\gamma_j = (\gamma_1, \gamma_2, \ldots, \gamma_n)^T$, and combination weight is $\omega_j = (\omega_1, \omega_2, \ldots, \omega_n)^T$, in which the corresponding attribute α_{ij} of each scheme δ_i is given in the form of hesitant fuzzy number, namely, $\alpha_{ij} = (\tau_x)$, $x = 1, 2, \ldots, n$, and τ_x denotes the possible membership given by the evaluator. With $0 \le \tau_x \le 1$, all the values of $\alpha_{ij} = (\tau_x), x = 1, 2, \ldots, n$, constitute a preliminary matrix of hesitant fuzzy evaluation:

$$B = \begin{bmatrix} \alpha_{11} & \alpha_{12} & \cdots & \alpha_{1n} \\ \alpha_{21} & \alpha_{22} & \cdots & \alpha_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ \alpha_{m1} & \alpha_{m2} & \cdots & \alpha_{mn} \end{bmatrix} \quad (1)$$

2.1. Definition of Parameters and Variables

λ_j: subjective weight of the j-th attribute, $j = 1, 2, \ldots, n$

γ_j: objective weight of the j-th attribute, $j = 1, 2, \ldots, n$

ω_j: combination weight of the j-th attribute, $j = 1, 2, \ldots, n$

α_j: evaluation attribute set of each scheme, $j = 1, 2, \ldots, n$

h_j: evaluation attribute set of each scheme after normalization, $j = 1, 2, \ldots, n$

μ_{ij}: membership of the i-th evaluation scheme to the j-th attribute, $i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$

ν_{ij}: nonmembership of the i-th evaluation scheme to the j-th attribute, $i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$

π_{ij}: hesitancy degree of the i-th evaluation scheme to the j-th attribute, $i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$

$\varepsilon_{(j)}$: a sort, namely, $\{1, 2, \ldots, n\} \longrightarrow \{1, 2, \ldots, n\}$, making α_j as the $\varepsilon_{(j)}$-th great element in the intuitionistic fuzzy sequence $\alpha_j (j = 1, 2, \ldots, n)$

$s(h)$: score function for the comparison of the two intuitionistic fuzzy numbers

$G(x)$: hierarchical partition function, while hierarchical partition is conducted according to the final results of each scheme

2.2. Normalization of Evaluation Index. The evaluation attributes of surface quality of autobody panels belong to cost attributes. The larger the membership degree, the more serious the defect of this attribute and the more affected the surface quality. Therefore, it is necessary to normalize the attribute indexes and transform the hesitant fuzzy preliminary matrix $B = (\alpha_{ij})_{m\times n}$ into a normalized matrix $H = (h_{ij})_{m\times n}$, in which

$$h_{ij} = \begin{cases} \alpha_{ij}, & \text{income attribute}, \\ \alpha_{ij}^c, & \text{cost attribute}, \\ i = 1, 2, \ldots, m; \; j = 1, 2, \ldots, n. \end{cases} \quad (2)$$

2.3. Solving Model of Subjective Weight. The eigenvector method was proposed by Satty [30] in 1980. The decision maker can make a comparison between two attributes, which can be either a definite value or a fuzzy language, as shown in Table 1. If it is the fuzzy language, it needs to be transformed into a real number interval [31]; thus, the preliminary judgment matrix E can be obtained:

$$E = \begin{bmatrix} 1 & \dfrac{1}{x(1)} & \dfrac{1}{x(2)} & \dfrac{1}{x(4)} & \dfrac{1}{x(7)} \\ x(1) & 1 & \dfrac{1}{x(3)} & \dfrac{1}{x(5)} & \dfrac{1}{x(8)} \\ x(2) & x(3) & 1 & \dfrac{1}{x(6)} & \dfrac{1}{x(9)} \\ x(4) & x(5) & x(6) & 1 & \dfrac{1}{x(10)} \\ x(7) & x(8) & x(9) & x(10) & 1 \end{bmatrix}. \quad (3)$$

With reciprocal of maximum eigenvalue $\lambda_{\max}$ as fitness function, genetic algorithm based on optimization is used to solve the optimal solution of each element in the matrix. The specific algorithm is as follows:

Step 1: linguistic scales for the importance comparisons between the five attributes of hidden pit, bump and scratch, rust, indentation pockmark, and ripple are given by the decision maker, and the value interval of each element in the judgment matrix is obtained according to the corresponding table of the linguistic scale.

Step 2: according to the value interval, ten variables are conducted with real-number coding.

Step 3: the initial population and fitness function are determined, while with reciprocal of maximum eigenvalue $\lambda_{\max}$ as fitness function, the greater $F(x)$, the stronger the adaptability of the individual and the greater the probability of being inherited to the offspring.

Step 4: selection, crossover, and mutation operations are carried out on the feasible solution population, thus making the population evolve forward and keep approaching the optimal value.

Step 5: when the number of cycles of the algorithm does not meet the required maximum number of cycles, go back to Step 3 and continue the following calculation. The final result is not the output until the termination condition is met.

Table 1: Language definition and scale value.

Scale value	Language definition
1.0	Attribute i is as important as attribute j
2.0–3.0	Attribute i is slightly more important than attribute j
4.0–5.0	Attribute i is more important than attribute j
6.0–7.0	Attribute i is extremely more important than attribute j
8.5–9.9	Attribute i is absolutely more important than attribute j
1.0–2.0; 3.0–4.0; 5.0–6.0; 7.0–8.5	The importance ratio of attribute i to attribute j is between the above two
Reciprocal	Ratio of attribute j to attribute i

The preliminary judgment matrix is determined according to the optimal solution, and then the subjective weight $\lambda_j = (\lambda_1, \lambda_2, \ldots, \lambda_n)^T$ is obtained.

2.4. Solving Model of Objective Weight. The deviation maximization method reflects the importance of attributes by the difference between the data of each attribute set. In the fuzzy evaluation, the difference is reflected by the fuzzy distance, while due to the characteristics of hesitant fuzzy numbers, the length of evaluating the fuzzy set of each attribute corresponding to each evaluated object is different. Li Chuncheng has proposed a new distance measurement method.

Suppose hesitant fuzzy set is $H = \{X\colon X \in [0,1], X \notin \varnothing\}$, $|X|$ refers to the number of elements in X, $N_n = \{1, 2 \ldots, n\}$, and $H^{(m)} = \{Z \in H\colon |Z| = m\}$.

Definition 1. When $X \in H$, the mapping is $\sigma_x\colon N_{|X|} \longrightarrow X$, resulting in $i \in N_{|X|-1}, \sigma_X(i) \le \sigma_X(i+1)$.

Definition 2. When $X, Y \in H^{(m)}$, there is $X \le_{H^{(m)}} Y$ only when $\forall i \in N_m, \sigma_X(i) \le \sigma_Y(i)$.

Definition 3. When $X \in H, k \in N, 1 \le i_1 < i_2 < \cdots < i_k \le |X|$,

$$\begin{aligned} X^{(i_1, i_2, \ldots, i_k)} &= \{\sigma_X(i_1), \sigma_X(i_2), \ldots, \sigma_X(i_k),\}, \\ X^{[k]} &= \left\{X^{(i_1, i_2, \ldots, i_k)}\colon 1 \le i_1 < i_2 < \cdots < i_k \le |X|\right\}. \end{aligned} \tag{4}$$

Suppose $n = \max\{|X|, |Y|\}, m = \min\{|X|, |Y|\}$; then, the distance between hesitant fuzzy sets X and Y is

$$d_h(S, T) = \left(\frac{1}{n!/m!} \sum_{\substack{Y^* \in Y[m] \\ X^* \in X[m]}} \frac{1}{m} \sum_{i=1}^{m} \left|\sigma_{X^*}(i) - \sigma_{Y^*}(i)\right|^{\lambda}\right)^{1/\lambda}. \tag{5}$$

The above formula does not need to add fuzzy elements in a short fuzzy set to make the length consistent and can guarantee the originality of the attribute information. The improvement is conducted on the basis of the traditional deviation maximization method in combination with formula (2); thus, a new formula for solving objective weights of attributes based on hesitant fuzzy numbers is proposed:

$$\gamma_j = \frac{\sum_{i=1}^{n} \sum_{k=1}^{n} d\left(r_{ij}, r_{kj}\right)}{\sum_{j=1}^{m} \sum_{i=1}^{n} \sum_{k=1}^{n} d\left(r_{ij}, r_{kj}\right)}, \quad \text{s.t.} \begin{cases} \sum_{j=1}^{m} \gamma_j = 1 \\ \gamma_j \ge 0, \quad j = 1, 2, \ldots \infty, m. \end{cases} \tag{6}$$

2.5. Solving Model of Combination Weight. In order to combine the advantages of subjective weight and objective weight, the linear weighting method is used to add variable β to formula (5) to reflect the preference degree of decision makers and obtain the combination weight ω_j:

$$\omega_j = \beta\lambda_j + (1-\beta)\gamma_j, \quad \text{s.t.} \begin{cases} \sum_{j=1}^{m} \omega_j = 1 \\ \omega_j \ge 0, \quad j = 1, 2, \ldots, m, \end{cases} \tag{7}$$

where β is the coefficient given by the evaluator and $0 \le \beta \le 1$. If the decision maker pays more attention to the subjective classification in the evaluation work, β will be bestowed with a larger value, while on the contrary, if the decision maker pays more attention to objective classification, β will be bestowed with a smaller value.

2.6. HFHWA Operator Aggregation Model. After determining the weight, the normalized attribute indexes will be weighted through special operators to obtain a hesitant fuzzy set that can be used for comparison and ranking. HFHWA operator is used for aggregation in this paper, and at the same time, the information of the evaluation attribute index itself and its position can be weighted:

$$\mathrm{HFHWA}_{\lambda,\omega}(h_1, h_2, \ldots, h_n) = \frac{\oplus_{n}^{j=1} \lambda_j \omega_{\varepsilon(j)} h_j}{\sum_{j=1}^{n} \lambda_j \omega_{\varepsilon(j)}} = \cup_{\tau_1 \in h_1, \tau_2 \in h_2, \ldots, \tau_n \in h_n} \left\{1 - \prod_{j=1}^{n} \left(1 - \tau_j\right)^{\frac{\lambda_j \omega_{\varepsilon(j)}}{\sum_{j=1}^{n} \lambda_j \omega_{\varepsilon(j)}}}\right\}. \tag{8}$$

2.7. Score Function and Hierarchical Partition Function Models. The content of this paper is to evaluate whether the surface quality of autobody panels in the same batch is up to the standard, without involving ranking, which only needs to use the score function to get the score value of each evaluation object.

$$s(h) = \frac{1}{l_h} \sum_{\tau \in h} \tau. \tag{9}$$

In the relevant standards, there are no quantitative rules for the hierarchical partition of surface quality, most of which are qualitative fuzzy language descriptions. According to experts' opinions and evaluation experience, the formula of the hierarchical partition function is defined as follows:

$$G(s(h)) = \begin{cases} \text{advanced finishing surface}, & 0.8 \le s(h) \le 1, \\ \text{higher finishing surface}, & 0.6 \le s(h) < 0.8, \\ \text{ordinary surface}, & 0.5 \le s(h) < 0.6, \\ \text{unqualified surface}, & 0 \le s(h) < 0.5. \end{cases} \tag{10}$$

3. Algorithm

There are many evaluation attributes of panel surface quality, in which five factors with great impact on surface quality are selected as the evaluation attribute. The index value of each attribute is given by the evaluator in the form of hesitant fuzzy numbers, and HFHWA operators are used to process the information of each part. Then, the final score value of the aggregated structure is calculated according to the score function of hesitant fuzzy sets, with ranking and hierarchical partition conducted according to score value. The algorithm is as follows:

Step 1: the optimal maximum eigenvalues $\lambda_{\max}$ and the values of 10 variables are obtained by using the algorithm in Section 4.2. Resubstituting the values of 10 variables into the judgment matrix can obtain the eigenvectors, whose values are normalized to obtain the subjective weight λ_j of each attribute.

Step 2: according to the hesitant fuzzy value given by the evaluator to the attribute set of each door inner panel, the hesitant fuzzy distance between two parts of each attribute is calculated, and then the objective weight γ_j of each attribute is calculated by using the new deviation maximization method.

Step 3: the combination weight ω_j of each attribute is calculated by using the simple linear weighting method, in which the combination weight coefficient β is given by the decision maker according to the preference degree.

Step 4: after solving all kinds of weights, the score value $s(h_{ij})$ of the j-th attribute of the i-th door inner panel is calculated by using the score function formula.

Step 5: the attributes of each part are conducted with ranking, and the higher the score value, the higher the ranking, while ranking is denoted by $\varepsilon_{(j)}$.

Step 6: by combining the idea of mixed weighting, the weight value $\lambda_{(j)}\omega_{\varepsilon_{(ij)}}$ of the j-th attribute of the i-th part is calculated and normalized, namely, $(\lambda_j\omega_{\varepsilon_{(ij)}}/\sum_{j=1}^{n}\lambda_j\omega_{\varepsilon_{(ij)}})$.

Step 7: the HFHWA operator is used to aggregate each attribute information of each part, thus obtaining the set of hesitant fuzzy numbers for each part.

Step 8: the final score value of each part is calculated by using the score function again, with the ranking conducted according to their scores, and the higher the score value, the better the surface quality of the part.

Step 9: according to the hierarchical partition function, the surface quality of each part is conducted with hierarchical partition, and the unqualified rate of the whole batch of parts is calculated according to this piecewise function.

After running the above algorithm, the score value of surface quality of parts and the qualified rate of this batch of parts can be obtained.

4. Case Analysis

4.1. Numerical Example Description. Five pieces of door inner panels are selected from the same batch of 100 inner panels stocked by the A automobile enterprise, as shown in Figure 1. Then, the decision maker evaluates the obtained defect information to obtain preliminary matrix B of fuzzy evaluation, as shown in Table 2 and 3.

4.2. Numerical Example Solution

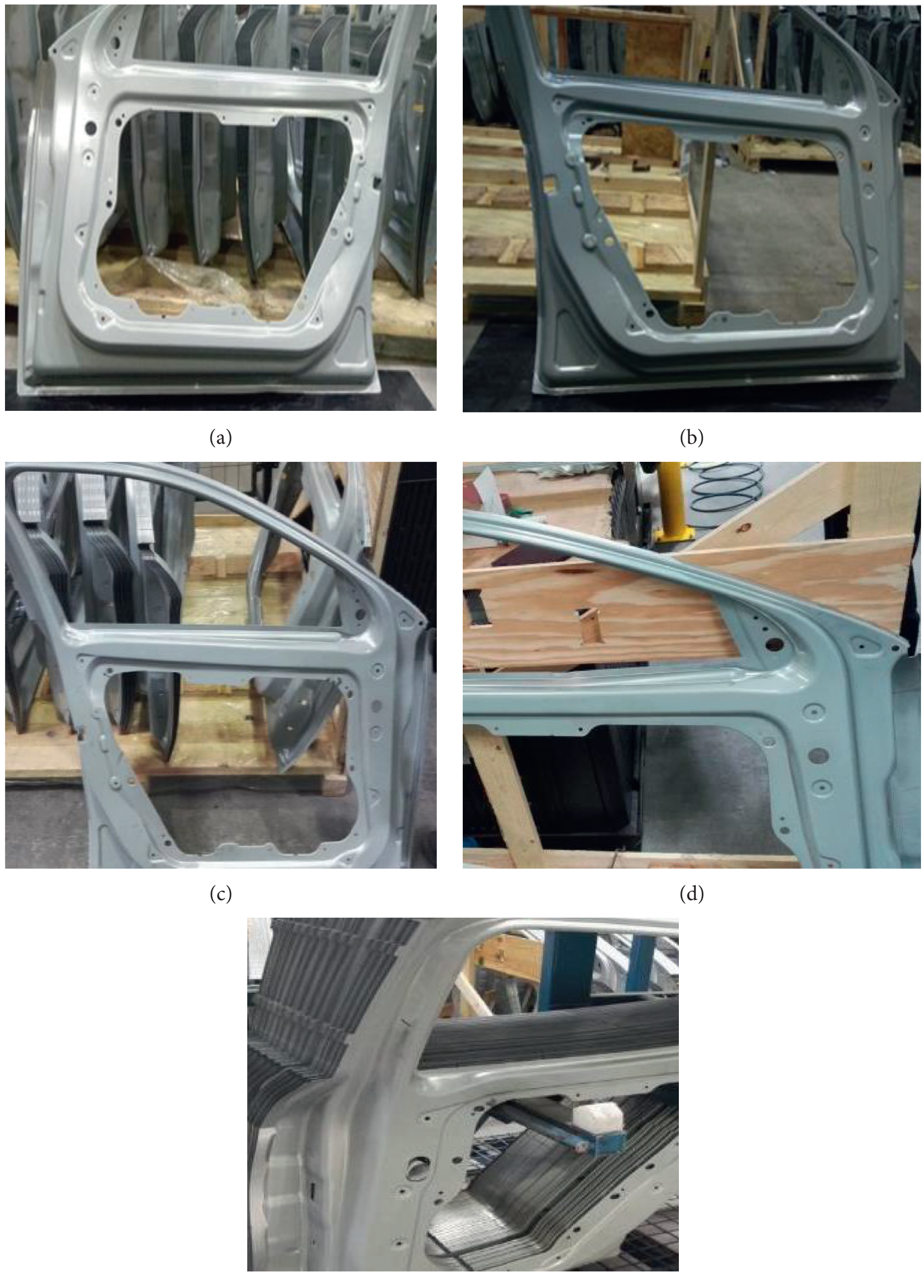
4.2.1. Subjective Weight Solution. Based on experts' opinions, the value ranges of the ten variables $x(1)$~$x(10)$ are determined by the paired comparison method, as shown in Table 4.

The value of each variable is input into the program; thus, the obtained optimal solution of objective function is $\lambda_{\max} = 5.0932$, with $x(1) - x(10) = \{6.6816, 9.7170, 2.4522, 2.0148, 0.2361, 0.1462, 4.0428, 0.2430, 0.2211, 2.0316\}$, and the convergent image of the algorithm is shown in Figure 2. The calculated eigenvector corresponding to the maximum eigenvalue of the judgment matrix is (0.0638, 0.4926, 0.8391, 0.1120, 0.1917), so the subjective weights of the five attributes are 0.04, 0.29, 0.49, 0.07, and 0.11.

4.2.2. Objective Weight Solution. Formula (5) is used to calculate the distance between the two schemes, as shown in Table 5.

By substituting formula (6), the obtained objective weight is $(0.15, 0.17, 0.4, 0.11, 0.18)$.

4.2.3. Combination Weight Solution. By taking the coefficient $\beta = 0.5$, the obtained combination weight is $(0.10, 0.23, 0.45, 0.09, 0.15)$.



(a) (b) (c) (d) (e)

Figure 1: Parts display drawing. (a) Part 1. (b) Part 2. (c) Part 3. (d) Part 4. (e) Part 5.

Table 2: Preliminary judgment matrix B. It is transformed into standard matrix H according to formula (2), as shown in Table 3.

	Hidden pit	Bumping and scratching	Rust	Indentation and pitting	Corrugation
Part 1	(0.2, 0.3)	(0.1, 0.2, 0.3)	(0.1, 0.2)	(0.2, 0.3)	(0.2, 0.4)
Part 2	(0.1, 0.2, 0.4)	(0.2, 0.4)	(0.2, 0.5)	(0.4, 0.6)	(0.3, 0.4)
Part 3	(0.4, 0.6)	(0.5, 0.7)	(0.6, 0.7, 0.8)	(0.4, 0.5, 0.6, 0.7)	(0.5, 0.6)
Part 4	(0.1, 0.2, 0.3)	(0.3, 0.4, 0.5)	(0.2, 0.5)	(0.2, 0.4)	(0.3, 0.6)
Part 5	(0.3, 0.5)	(0.3, 0.4)	(0.5, 0.6)	(0.3, 0.5)	(0.1, 0.2)

4.3. Result of the Numerical Example. HFHWA operator is used for data aggregation, and data integration information of parts is shown in Tables 6–10.

According to the calculation results of each part, the hesitant fuzzy sets of each part are obtained by using operator aggregation:

Table 3: Standardized matrix H.

	Hidden pit	Bumping and scratching	Rust	Indentation and pitting	Corrugation
Part 1	(0.8, 0.7)	(0.9, 0.8, 0.7)	(0.9, 0.8)	(0.8, 0.7)	(0.8, 0.6)
Part 2	(0.9, 0.8, 0.6)	(0.8, 0.6)	(0.8, 0.5)	(0.6, 0.4)	(0.7, 0.6)
Part 3	(0.6, 0.4)	(0.5, 0.3)	(0.4, 0.3, 0.2)	(0.6, 0.5, 0.4, 0.3)	(0.5, 0.4)
Part 4	(0.9, 0.8, 0.7)	(0.7, 0.6, 0.5)	(0.8, 0.5)	(0.8, 0.6)	(0.7, 0.4)
Part 5	(0.7, 0.5)	(0.7, 0.6)	(0.5, 0.4)	(0.7, 0.5)	(0.9, 0.8)

Table 4: Corresponding intervals of judgment matrix variables.

Variable	Range of values
$x(1)$	(6, 7)
$x(2)$	(8.5, 9.9)
$x(3)$	(2, 3)
$x(4)$	(2, 3)
$x(5)$	(1/5, 1/4)
$x(6)$	(1/7, 1/6)
$x(7)$	(4, 5)
$x(8)$	(1/5, 1/4)
$x(9)$	(1/5, 1/4)
$x(10)$	(2, 3)

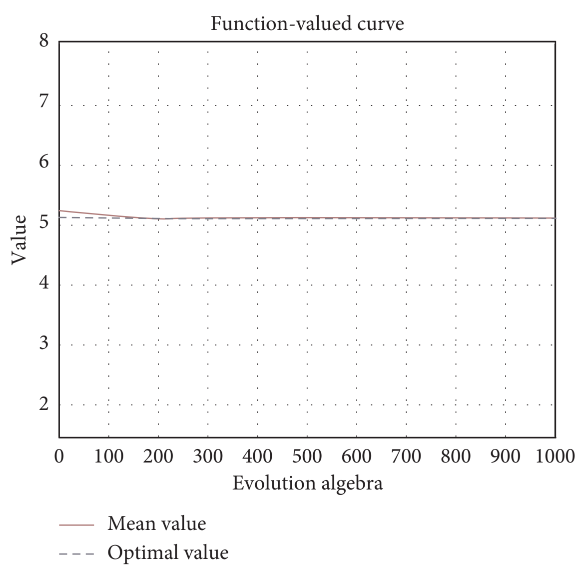


Figure 2: Convergence image of algorithms.

Table 5: Fuzzy distance between two attributes.

	b_1	b_2	b_3	b_4	b_5
d_{11}	0	0	0	0	0
d_{12}	0.08	0.10	0.20	0.25	0.05
d_{13}	0.25	0.40	0.55	0.15	0.25
d_{14}	0.05	0.20	0.20	0.05	0.15
d_{15}	0.15	0.15	0.40	0.10	0.15
d_{22}	0	0	0	0	0
d_{23}	0.27	0.30	2.10	0.03	0.20
d_{24}	0.03	0.10	0.00	0.20	0.10
d_{25}	0.17	0.05	0.20	0.10	0.20
d_{33}	0	0	0	0	0
d_{34}	0.30	0.20	0.35	0.13	0.10
d_{35}	0.10	0.25	0.15	0.08	0.40
d_{44}	0	0	0	0	0
d_{45}	0.20	0.05	0.20	0.10	0.30

Table 6: Calculation results of part 1.

h_{1j}	h_{11}	h_{12}	h_{13}	h_{14}	h_{15}
$s(h_{1j})$	0.75	0.8	0.85	0.75	0.7
$\varepsilon_{(1j)}$	3	2	1	4	5
$\lambda_{(j)}$	0.04	0.29	0.49	0.07	0.11
$\omega_{(j)}$	0.10	0.23	0.45	0.09	0.15
$\lambda_{(j)}\omega_{\varepsilon_{(1j)}}$	0.018	0.0667	0.049	0.0063	0.0165
$\lambda_j\omega_{\varepsilon_{(1j)}}/\sum_{j=1}^{n}\lambda_j\omega_{\varepsilon_{(1j)}}$	0.12	0.43	0.31	0.04	0.11

Table 7: Calculation results of part 2.

h_{2j}	h_{21}	h_{22}	h_{23}	h_{24}	h_{25}
$s(h_{2j})$	0.7667	0.7	0.65	0.5	0.65
$\varepsilon_{(2j)}$	1	2	3	5	4
$\lambda_{(j)}$	0.04	0.29	0.49	0.07	0.11
$\omega_{(j)}$	0.10	0.23	0.45	0.09	0.15
$\lambda_{(j)}\omega_{\varepsilon_{(2j)}}$	0.004	0.0667	0.2205	0.0105	0.0099
$\lambda_j\omega_{\varepsilon_{(2j)}}/\sum_{j=1}^{n}\lambda_j\omega_{\varepsilon_{(2j)}}$	0.01	0.21	0.71	0.03	0.03

Table 8: Calculation results of part 3.

h_{3j}	h_{31}	h_{32}	h_{33}	h_{34}	h_{35}
$s(h_{3j})$	0.5	0.4	0.3	0.45	0.45
$\varepsilon_{(3j)}$	1	4	5	2	3
$\lambda_{(j)}$	0.04	0.29	0.49	0.07	0.11
$\omega_{(j)}$	0.10	0.23	0.45	0.09	0.15
$\lambda_{(j)}\omega_{\varepsilon_{(3j)}}$	0.004	0.0261	0.0735	0.0161	0.0495
$\lambda_j\omega_{\varepsilon_{(3j)}}/\sum_{j=1}^{n}\lambda_j\omega_{\varepsilon_{(3j)}}$	0.02	0.15	0.43	0.10	0.29

Table 9: Calculation results of part 4.

h_{4j}	h_{41}	h_{42}	h_{43}	h_{44}	h_{45}
$s(h_{4j})$	0.8	0.6	0.65	0.7	0.55
$\varepsilon_{(4j)}$	1	4	3	2	5
$\lambda_{(j)}$	0.04	0.29	0.49	0.07	0.11
$\omega_{(j)}$	0.10	0.23	0.45	0.09	0.15
$\lambda_{(j)}\omega_{\varepsilon_{(4j)}}$	0.004	0.0261	0.2205	0.0161	0.0165
$\lambda_j\omega_{\varepsilon_{(4j)}}/\sum_{j=1}^{n}\lambda_j\omega_{\varepsilon_{(4j)}}$	0.01	0.09	0.78	0.06	0.06

Table 10: Calculation results of part 5.

h_{5j}	h_{51}	h_{52}	h_{53}	h_{54}	h_{55}
$s(h_{5j})$	0.6	0.65	0.45	0.6	0.85
$\varepsilon_{(5j)}$	3	2	5	4	1
$\lambda_{(j)}$	0.04	0.29	0.49	0.07	0.11
$\omega_{(j)}$	0.10	0.23	0.45	0.09	0.15
$\lambda_{(j)}\omega_{\varepsilon_{(5j)}}$	0.006	0.0667	0.049	0.0063	0.011
$\lambda_j\omega_{\varepsilon_{(5j)}}/\sum_{j=1}^{n}\lambda_j\omega_{\varepsilon_{(5j)}}$	0.04	0.48	0.35	0.05	0.08

$$h_1 = \text{HFHWA}\left(h_{11}, h_{12}, h_{13}, h_{14,} h_{15}\right)$$
$$= \bigcup_{\tau_{11}\in h_{11,}\tau_{12}\in h_{12,}\tau_{13}\in h_{13,}\tau_{14}\in h_{14,}\tau_{15}\in h_{15,}} \left\{1-\left(1-\tau_{11}\right)^{0.12}\times\left(1-\tau_{12}\right)^{0.43}\times\left(1-\tau_{13}\right)^{0.31}\times\left(1-\tau_{14}\right)^{0.04}\times\left(1-\tau_{15}\right)^{0.11}\right\}$$
$$= \left\{\begin{array}{c} 0.8822, 0.8728, 0.8802, 0.8707, 0.8539, 0.8423, 0.8515, 0.8398, \\ 0.8412, 0.8287, 0.8387, 0.8259, 0.8032, 0.7876, 0.8000, 0.7841, \\ 0.8110, 0.7960, 0.8079, 0.7927, 0.7657, 0.7471, 0.7619, 0.7430, \\ 0.8763, 0.8665, 0.8743, 0.8643, 0.8466, 0.8345, .8441, 0.8318, \\ 0.8333, 0.8201, 0.8306, 0.8172, 0.7934, 0.7770, 0.7900, 0.7734, \\ 0.8016, 0.7859, 0.7983, 0.7824, 0.7540, 0.7345, 0.7500, 0.7302 \end{array}\right\},$$

$$h_2 = \text{HFHWA}\left(h_{21}, h_{22}, h_{23}, h_{24,} h_{25}\right)$$
$$= \bigcup_{\tau_{21}\in h_{21,}\tau_{22}\in h_{22,}\tau_{23}\in h_{23,}\tau_{24}\in h_{24,}\tau_{25}\in h_{25,}} \left\{1-\left(1-\tau_{21}\right)^{0.01}\times\left(1-\tau_{22}\right)^{0.21}\times\left(1-\tau_{23}\right)^{0.71}\times\left(1-\tau_{24}\right)^{0.03}\times\left(1-\tau_{25}\right)^{0.03}\right\}$$
$$= \left\{\begin{array}{c} 0.7914, 0.7896, 0.7888, 0.7870, 0.6002, 0.5967, 0.5953, 0.5918, \\ 0.7587, 0.7566, 0.7558, 0.7536, 0.5375, 0.5335, 0.5319, 0.5278, \\ 0.7899, 0.7881, 0.7874, 0.7855, 0.5974, 0.5939, 0.5925, 0.5889, \\ 0.7570, 0.7549, 0.7541, 0.7519, 0.5343, 0.5303, 0.5286, 0.5245, \\ 0.7885, 0.7867, 0.7859, 0.7840, 0.5946, 0.5911, 0.5896, 0.5861, \\ 0.7553, 0.7532, 0.7523, 0.7502, 0.5311, 0.5270, 0.5253, 0.5212 \end{array}\right\},$$

$$h_3 = \text{HFHWA}\left(h_{31}, h_{32}, h_{33}, h_{34,} h_{35}\right)$$
$$= \bigcup_{\tau_{31}\in h_{31,}\tau_{32}\in h_{32,}\tau_{33}\in h_{33,}\tau_{34}\in h_{34,}\tau_{35}\in h_{35,}} \left\{1-\left(1-\tau_{31}\right)^{0.02}\times\left(1-\tau_{32}\right)^{0.15}\times\left(1-\tau_{33}\right)^{0.43}\times\left(1-\tau_{34}\right)^{0.10}\times\left(1-\tau_{35}\right)^{0.29}\right\}$$
$$= \left\{\begin{array}{c} 0.4698, 0.4411, 0.4579, 0.4285, 0.4479, 0.4179, 0.4393, 0.4089, \\ 0.4335, 0.4028, 0.4207, 0.3893, 0.4101, 0.3780, 0.4009, 0.3684, \\ 0.4000, 0.3675, 0.3865, 0.3532, 0.3752, 0.3413, 0.3655, 0.3311, \\ 0.4424, 0.4121, 0.4298, 0.3989, 0.4193, 0.3878, 0.4103, 0.3783, \\ 0.4042, 0.3718, 0.3907, 0.3577, 0.3795, 0.3459, 0.3699, 0.3357, \\ 0.3690, 0.3347, 0.3547, 0.3197, 0.3429, 0.3072, 0.3327, 0.2964, \\ 0.4655, 0.4365, 0.4535, 0.4238, 0.4434, 0.4132, 0.4348, 0.4041, \\ 0.4289, 0.3979, 0.4160, 0.3843, 0.4053, 0.3730, 0.3960, 0.3632, \\ 0.3952, 0.3623, 0.3815, 0.3479, 0.3701, 0.3359, 0.3603, 0.3256, \\ 0.4379, 0.4073, 0.4252, 0.3940, 0.4146, 0.3828, 0.4055, 0.3732, \\ 0.3993, 0.3667, 0.3858, 0.3524, 0.3745, 0.3405, 0.3648, 0.3303, \\ 0.3638, 0.3293, 0.3495, 0.3142, 0.3375, 0.3015, 0.3272, 0.2907 \end{array}\right\}, \quad (11)$$

$$h_4 = \text{HFHWA}\left(h_{41}, h_{42}, h_{43}, h_{44,} h_{45}\right)$$
$$= \bigcup_{\tau_{41}\in h_{41,}\tau_{42}\in h_{42,}\tau_{43}\in h_{43,}\tau_{44}\in h_{44,}\tau_{45}\in h_{45,}} \left\{1-\left(1-\tau_{41}\right)^{0.01}\times\left(1-\tau_{42}\right)^{0.09}\times\left(1-\tau_{43}\right)^{0.78}\times\left(1-\tau_{44}\right)^{0.06}\times\left(1-\tau_{45}\right)^{0.06}\right\}$$
$$= \left\{\begin{array}{c} 0.7889, 0.7800, 0.7800, 0.7706, 0.5687, 0.5503, 0.5503, 0.5312, \\ 0.7834, 0.7742, 0.7742, 0.7646, 0.5573, 0.5385, 0.5385, 0.5189, \\ 0.7790, 0.7696, 0.7696, 0.7598, 0.5484, 0.5292, 0.5292, 0.5092, \\ 0.7875, 0.7784, 0.7784, 0.7690, 0.5657, 0.5472, 0.5472, 0.5280, \\ 0.7819, 0.7726, 0.7726, 0.7630, 0.5543, 0.5353, 0.5353, 0.5156, \\ 0.7775, 0.7680, 0.7680, 0.7582, 0.5452, 0.5259, 0.5259, 0.5058, \\ 0.7866, 0.7775, 0.7775, 0.7681, 0.5639, 0.5454, 0.5454, 0.5261, \\ 0.7810, 0.7717, 0.7717, 0.7620, 0.5524, 0.5334, 0.5334, 0.5136, \\ 0.7766, 0.7671, 0.7671, 0.7572, 0.5434, 0.5240, 0.5240, 0.5038 \end{array}\right\},$$

$$h_5 = \text{HFHWA}\left(h_{51}, h_{52}, h_{53}, h_{54,} h_{55}\right)$$
$$= \bigcup_{\tau_{51}\in h_{51,}\tau_{52}\in h_{52,}\tau_{53}\in h_{53,}\tau_{54}\in h_{54,}\tau_{55}\in h_{55,}} \left\{1-\left(1-\tau_{51}\right)^{0.04}\times\left(1-\tau_{52}\right)^{0.48}\times\left(1-\tau_{53}\right)^{0.35}\times\left(1-\tau_{54}\right)^{0.05}\times\left(1-\tau_{55}\right)^{0.08}\right\}$$
$$= \left\{\begin{array}{c} 0.6715, 0.6527, 0.6630, 0.6437, 0.6498, 0.6298, 0.6407, 0.6203, \\ 0.6228, 0.6013, 0.6130, 0.5910, 0.5979, 0.5750, 0.5875, 0.5640, \\ 0.6647, 0.6456, 0.6560, 0.6364, 0.6426, 0.6222, 0.6333, 0.6124, \\ 0.6150, 0.5931, 0.6051, 0.5825, 0.5896, 0.5663, 0.5790, 0.5550 \end{array}\right\}.$$

Table 11: Part comprehensive score.

$s(h_1)$	$s(h_2)$	$s(h_3)$	$s(h_4)$	$s(h_5)$
0.8133	0.6662	0.3835	0.6548	0.6163

Table 12: SN calculation result.

$\overline{y}$	S_m	V_e	$\widetilde{\vartheta}$
0.6268	1.9645	0.0241	0.6548

The comprehensive score of each part can be obtained through score function formula (9), as shown in Table 11.

5. Result Analysis

5.1. Signal-to-Noise Ratio (SN) Analysis of Numerical Results. SN proposed by Dr. Taguchi of Japan is an index to measure the stability of product quality, which can be divided into the SN with nominal-the-best (NTB), small-the-best (STB), and large-the-best (LTB) characteristics according to the different optimal values. The SN with NTB characteristics means that the closer the SN is to the target value, the better the stability of product quality. The optimal score of surface quality of the door inner panel is 1, so the result is analyzed by the SN with NTB characteristics. Assume that the quality characteristics of the research problems all conform to the normal distribution $N(\mu, \sigma^2)$; thus, the formula of SN is as follows:

$$\widetilde{\vartheta} = 10lg\frac{(1/n)(S_m - V_e)}{V_e}, \qquad (12)$$

where $S_m = (1/n)(\sum_{i=1}^{n} y_i)^2$ and $V_e = (1/n-1)\sum_{i=1}^{n}(y_i - \overline{y})^2$. By substituting the comprehensive score value of the parts in Table 11 into formula 12, the SN with NTB characteristics of surface quality of this batch of parts can be obtained, with the calculation results shown in Table 12.

As shown in Table 12, the final calculation result of the SN with NTB of the five door inner panel is $\vartheta = 12.069$, which is far away from the optimal value 1; thus, it can be seen that the surface quality of this batch of parts is very unstable.

5.2. Overall Situation of Surface Quality of the Door Inner Panel. Part 1 with the highest score belongs to the advanced finishing surface; part 2, part 4, and part 5 belong to the higher finishing surface; and part 3 with the lowest score belongs to unqualified parts. Using the method of estimating population by samples, it can be judged that the overall unqualified rate of these 100 parts is 20%, in which the advanced finishing surface in all parts accounts for 20% of the total, the higher finishing surface accounts for 60%, and the unqualified rate is high, so comprehensive inspection and repairs are required.

6. Conclusion

Based on the fuzzy theory, a complete set of surface quality evaluation model for panels is established in this paper by combining the analytic hierarchy process with the multi-attribute evaluation. Two new methods are proposed to solve the subjective weight and objective weight, and HFHWA operators are used for information aggregation to give the algorithm. A hierarchical partition function of panel surface quality is defined by combining with relevant standards. Finally, taking the door inner panel as an example, the surface defect information is analyzed and solved, which validates the effectiveness and practicability of the model and algorithm.

Data Availability

The numerical example data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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