Research Article

Application of Fuzzy-Based Hybrid Taguchi Method for Multiobjective Optimization of Product Form Design

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In today's competitive market, industrial product form design is moving towards being consumer centric. Affective responses relate to customers' affective needs and are receiving increasing attention. To design a product form that can appeal to consumers, designers should consider multiple affective responses (MARs). This paper proposes a robust design approach that uses a fuzzy-based hybrid Taguchi method to derive the optimal product form design concerning MARs. First, design analysis is used to identify design variables and MARs. According to the results, a Taguchi experiment is designed in which fuzzy sets are used to measure the MARs; then, signal-to-noise (S/N) ratios are calculated. Subsequently, a fuzzy questionnaire with multiple answers is employed to acquire consumers' preference weights for MARs, following which Vlsekriterijumska Optimizacija I Kompromisno Resenje (VIKOR) is adopted to transform the multiple S/N ratios into a multiperformance characteristic index (MPCI). On the basis of the MPCI, the effects of design variables are identified through analysis of variance and the response table and the response graph are obtained. Consequently, the optimal form design is achieved. A car profile design was used as an example to demonstrate the proposed approach. The results indicate that this approach can effectively improve consumers' affective response qualities and can be used as a robust design approach to optimize product form design.

1. Introduction

To survive in a highly competitive market, companies should design products that meet the needs of consumers. As a reflection of the affective needs of consumers on industrial product form, affective responses, which encompass consumers' psychological feelings as well as physiological issues, have received considerable attention from academia and industry [1]. Affective engineering, also called Kansei engineering, is a consumer centric technique for product design that aims to translate affective responses into design variables [2]. Many studies have been performed on optimizing product form design by using affective engineering [3–5]. In these studies, a questionnaire was commonly used to collect evaluation data, and only the mean scale rating was adopted [6]. On the basis of these data, the relationship

between design variables and affective responses can be constructed, and the optimal design can then be determined. Nevertheless, evaluations of affective responses are individualistic and subjective, and adopting a mean scale rating alone without considering variations in the evaluations is inappropriate.

A robust design focuses on reducing quality variation and bringing the mean closer to the desired target. The Taguchi method is a robust design approach that adopts many concepts from statistical experiments for optimizing the design of processes or products [7]. In the Taguchi method, “quality” refers to a product's ability to satisfy consumer requirements and expectations [8]. Related studies [9, 10] have suggested that the affective response quality significantly influences the desirability of a product and consumer satisfaction. Therefore, affective responses embody

an aspect of quality that must be considered in product form design [1, 11]. Several studies have addressed improving the quality of affective responses [6, 12].

The quality of affective responses has the features of fuzziness. When measuring affective responses, traditional methods such as semantic differential scales and Likert scales employ numerical values that do not exactly represent a perceptual interpretation because human perceptual interpretation of affective responses involves inherent imprecision or vagueness to a certain extent [13–16]. By contrast, fuzzy sets are a generalization of crisp sets for representing imprecision or vagueness in everyday life, which can serve as a means for modeling the vagueness underlying most natural linguistic terms [17]. Therefore, in many studies, researchers have employed fuzzy sets to subjectively evaluate decision-making processes [18–20]. However, little attention has been devoted to measuring affective responses by using fuzzy sets in the Taguchi method for product form optimization.

The affective responses of humans to products often have various facets. To acquire consumers' preference weights for multiple affective responses (MARs), numerous studies have used questionnaires with single answers [3, 4]. However, as fuzzy statistics scholars have indicated that human thinking cannot be measured or described with a single option [21]. A fuzzy questionnaire with multiple answers can reflect the variability and intricacy of human fuzzy thinking, and the robustness and consistency of the evaluation process can be enhanced by reducing the degree of evaluator subjectivity [22, 23]. From the results of such a fuzzy questionnaire, the final option and the fuzzy thinking of a participant can be determined from fuzzy data; that is, the participant's preferences are reflected more accurately in a fuzzy questionnaire [24]. However, to the best of our knowledge, very few studies have used a fuzzy questionnaire to measure consumers' MARs preferences.

To integrate the performance characteristics of MARs into one performance characteristic according to preference weights, a multicriteria decision-making (MCDM) method is usually required. Vlsekriterijumska Optimizacija I Kompromisno Resenje (VIKOR) was developed by Opricovic [25] for multicriteria optimization of complex systems. It determines a compromise ranking list, a compromise solution, and weight stability intervals for the preference stability of the compromise solution obtained using the initial weights. The obtained compromise solution is very satisfactory because it provides the minimum individual regret for the opponent and the maximum group utility for the majority [26]. Recently, owing to its characteristics and capabilities, the VIKOR method has been employed by many researchers to solve decision-making problems [27]. Thus far, however, few studies have used the VIKOR method in research related to affective responses.

In this paper, the authors propose a fuzzy-based hybrid Taguchi method for optimizing product form design concerning affective responses. In this approach, fuzzy sets are used to measure the affective responses of consumers to a product, and a fuzzy questionnaire is used to collect consumers' preference weights for MARs. Furthermore, the proposed approach uses VIKOR to convert the signal-to-noise

(S/N) ratios of MARs into a single index called the multiperformance characteristic index (MPCI). Product form design is then optimized on the basis of the MPCI. The remainder of this paper is organized as follows. Section 2 presents the relevant theoretical research background. Section 3 describes the proposed approach. Section 4 presents a case study, the results of which are discussed in Section 5. Finally, Section 6 provides a few concluding remarks.

2. Theoretical Background

2.1. Taguchi Method. The Taguchi method is a simple, efficient, and systematic quality improvement method that has been used to achieve robustness in many fields, including materials science [28], mechanical engineering [29], and usability engineering [30]. It can be used to derive optimal processes and products, as well as to identify the control factors that significantly influence a particular quality characteristic [31]. The Taguchi method involves two major tools: the orthogonal array (OA) and S/N ratio [32].

The OA is a fractional factorial matrix that can balance any factor and interactions among the factors, and it forms the basis of experimental design. For product form design by using classical experimental methods, numerous experimental samples must be considered when the number of design variables is high. To solve this problem, the Taguchi method employs the OA to study the entire design variable space by using only a few experimental samples. The S/N ratio is used as a quality characteristic that can be analyzed using analysis of variance (ANOVA) to ascertain both the effects of the design variables and the contribution percentage of each design variable. In addition, on the basis of S/N ratios, a response table and a response graph can be derived and, then, the optimal design can be determined.

The original Taguchi method was designed to optimize a single performance characteristic, and it has successfully been applied in various fields. However, it fails to optimize multiple performance characteristics [33]. Therefore, a hybrid approach is required to solve multiobjective optimization problems [10]. Affective responses of humans to products have multiple aspects and, thus, optimizing the quality of affective responses is a multiobjective problem. In this study, the authors propose a fuzzy-based hybrid Taguchi method to optimize product form design, and this method employs VIKOR as an MCDM method to integrate the S/N ratios of MARs into one quality characteristic for single-objective optimization.

2.2. Fuzzy Set Theory. Fuzzy set theory, developed by Zadeh [34], is a powerful tool for managing concepts and rules that involve uncertainty, imprecision, and nonlinearity. This theory is based on the premise that the key points of human thinking are not numbers but linguistic terms or labels of fuzzy sets. In fuzzy set theory, fuzzy numbers can be used to efficiently represent knowledge and to measure affective responses by using linguistic terms [13]. There are many types of fuzzy numbers, such as triangular, trapezoidal, sigmoid, and Gaussian. Triangular fuzzy numbers are intuitive, simple to calculate, and easy to understand and can well express

multiple linguistic variables [35]; therefore, in this study, triangular fuzzy numbers were used to measure affective responses.

One of the most important concepts of fuzzy set theory is the alpha cut. The alpha cut of a fuzzy set $\tilde{A}$ of the universal set X can be defined as [36]

$$\tilde{A}(\alpha) = \{x \in X \mid \mu_{\tilde{A}}(x) \geq \alpha\}, \quad \forall \alpha \in [0, 1]. \quad (1)$$

Clearly, the alpha cut of a fuzzy set $\tilde{A}$ is the crisp set that contains all elements of the universal set X whose membership grades in $\tilde{A}$ are greater than or equal to the specified alpha value [37].

In this study, fuzzy sets have been used to measure consumers' MARs preferences, and the alpha cut has been used to calculate the S/N ratios. In addition, a fuzzy questionnaire with multiple answers has been employed to acquire consumers' MARs preferences.

2.3. VIKOR. The VIKOR method focuses on ranking and sorting a set of alternatives against various, possibly conflicting, criteria. The method employs a ranking index based on a particular measure of "closeness" to the "ideal" solution [36]. Given that each alternative is evaluated according to each criterion, compromise ranking of an alternative can be performed by comparing its measure of closeness to the ideal alternative. The multicriteria measure for compromise ranking is developed from the L_p metric. For an alternative a_i , the rating of the j th criterion is denoted by f_{ij} and the L_p metric can be defined as follows:

$$L_{p,i} = \left\{ \sum_{j=1}^n \left[\frac{w_j (f_j^* - f_{ij})}{(f_j^* - f_j^-)} \right]^p \right\}^{1/p}, \quad (2)$$

where $1 \leq p \leq \infty$ and $i = 1, 2, \dots, m$.

Within the VIKOR method, the utility function is an aggregate of $L_{1,i}$ and $L_{\infty,i}$. $L_{1,i}$ is interpreted as "concordance," and it can provide decision-makers with information about the maximum "group utility" or "majority." $L_{\infty,i}$ is interpreted as "discordance," and it provides decision-makers with information about the minimum individual regret of the "opponent."

The VIKOR method has the following unique characteristics [38]. (1) The best alternatives determined using the VIKOR method are the closest to the ideal solution and the farthest from the negative ideal solution. (2) The best alternative determined using the VIKOR method ensures the maximum group utility and the least regret from the viewpoint of decision-makers. (3) The VIKOR method considers two distance measurements, $L_{1,i}$ and $L_{\infty,i}$, based on the L_p metric to provide information about utility and regret. (4) The VIKOR method considers two weights in decision-making—one pertaining to the criteria and the other pertaining to the maximum group utility. Owing to these characteristics, the VIKOR method can be effectively used as a synthetic index for MCDM. Thus, VIKOR has been used to integrate multiple quality characteristics into one quality characteristic.

3. Proposed Approach

The authors propose a structured, generic approach that integrates the Taguchi method with fuzzy set theory and VIKOR to optimize product form design in terms of MARs. This approach comprises four stages: (1) design analysis, (2) Taguchi experiment, (3) transformation of S/N ratios, and (4) optimization design. Figure 1 illustrates a systematic flowchart of the proposed approach.

3.1. Design Analysis. The first stage is design analysis, and it involves product form analysis and affective response analysis. Product form analysis aims to clarify the character of form to ascertain design variables that are usually discrete, such as the type of design components [1, 9]. In the analysis of affective responses, adjectives are used to describe one's affective responses to a product [2], and factor analysis is then used to identify the affective factors underlying these adjectives.

3.2. Taguchi Experiment. After ascertaining the design variables and affective responses, the Taguchi experiment is designed, where the design variables are considered as control factors and the affective factors are considered as quality characteristics. On the basis of the design variables and their levels, the total degrees of freedom (DOFs) can be calculated. Subsequently, an OA is selected carefully to fit the specific task. The DOFs of the OA should be not less than those of the design variables [32].

The quality characteristics can be classified into three types, namely, larger-the-better (LTB), smaller-the-better (STB), and nominal-the-better (NTB), and their S/N ratios can be calculated by using (3), (4), and (5), respectively,

$$\left(\frac{S}{N} \right)_{LTB} = -10 \log_{10} \left(\frac{1}{n} \sum_{i=1}^n \frac{1}{y_i^2} \right), \quad (3)$$

$$\left(\frac{S}{N} \right)_{STB} = -10 \log_{10} \left(\frac{1}{n} \sum_{i=1}^n y_i^2 \right), \quad (4)$$

$$\left(\frac{S}{N} \right)_{NTB} = 10 \log_{10} \left(\frac{\bar{y}^2}{S_d^2} \right), \quad (5)$$

where y_i is the measured property that refers to affective responses in this study, n is the number of tests for one experimental sample, $\bar{y}$ is the mean of the measured property, and S_d is the standard deviation.

To measure the quality performance of the affective responses, a triangular fuzzy number $\tilde{A} = (a_1, a_2, a_3)$ is used, and it is defined as follows:

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < a_1 \\ \frac{(x - a_1)}{(a_2 - a_1)}, & a_1 \leq x \leq a_2 \\ \frac{(a_3 - x)}{(a_3 - a_2)}, & a_2 \leq x \leq a_3 \\ 0, & x > a_3, \end{cases} \quad (6)$$

FIGURE 1: Framework of proposed approach.

FIGURE 2: Illustration of alpha cut for triangular fuzzy numbers.

where $\mu_{\tilde{A}}$ is the membership function; x is a variable; and a_1 , a_2 , and a_3 are parameters. Computing the S/N ratios by using fuzzy numbers may involve the arithmetic operations of multiplication and division. Because the results of the arithmetic addition and subtraction of triangular fuzzy numbers are triangular fuzzy numbers as well, whereas those of arithmetic

multiplication and division of triangular fuzzy numbers may not be triangular fuzzy numbers [18, 37], alpha cuts were used to calculate the S/N ratios of different alpha levels. The alpha cut of a triangular fuzzy number is illustrated in Figure 2 and calculated according to

$$\tilde{A}_\alpha = [a_1 + (a_2 - a_1)\alpha, a_3 - (a_3 - a_2)\alpha]. \quad (7)$$

To derive the crisp output of the S/N ratio, defuzzification is necessary, and it can be performed using a few methods, including center of gravity (COG), center of area, and mean of maxima. Among these methods, COG, which has a distinct geometrical meaning, is the most precise and widely used method [39]. Therefore, in the present study, the COG method has been adopted for defuzzification, and it is expressed as follows:

$$SN = \frac{\sum SN_i \times [\mu(SN_i)]}{\sum [\mu(SN_i)]}, \quad (8)$$

where SN is the crisp value of S/N ratios, $\mu(SN_i)$ is the i th alpha level, and SN_i is the S/N ratio of the i th alpha level.

3.3. Transformation of S/N Ratios. The S/N ratio of one affective response is inappropriate for optimizing MARs because a high S/N ratio for one affective response can lead to low S/N ratio for another affective response, and vice versa. Thus, the authors have presented a method that combines a fuzzy affective response questionnaire and VIKOR to transform the multiobjective optimization problem relevant to MARs into an equivalent single-objective optimization problem.

3.3.1. Expressing MARs Preferences by Using Fuzzy Questionnaire. To represent the values of MARs preferences, the authors have used a fuzzy questionnaire with multiple answers that can help consumers express their preferences accurately. When analyzing the fuzzy questionnaire, the fuzzy sample mean is required, and it is defined as follows [21].

Let U be the universal set, $L = \{L_1, L_2, \dots, L_k\}$ be a set of k -linguistic variables in U , and $\{Fx_i = m_{i1}/L_1 + m_{i2}/L_2 + \dots + m_{ik}/L_k, i = 1, 2, \dots, n\}$ be a sequence of random fuzzy samples in U . m_{ij} is the membership with respect to L_j , and $\sum_{j=1}^k m_{ij} = 1$. Then, the fuzzy sample mean can be expressed as

$$F\bar{x} = \frac{(1/n) \sum_{i=1}^n m_{i1}}{L_1} + \frac{(1/n) \sum_{i=1}^n m_{i2}}{L_2} + \dots + \frac{(1/n) \sum_{i=1}^n m_{ik}}{L_k}. \quad (9)$$

To derive consumers' preference weights for MARs, the fuzzy relative weight (FRW) is employed, and it is defined as follows [24].

Consider the universe of discourse $S = \{S_1, S_2, \dots, S_K\}$, utility sequence $r = \{r_1, r_2, \dots, r_f\}$, and $\mu_{S_i, f}$ as the membership function of r_j in S_i . Then, the fuzzy relative weight $FRW = (FRW_{S_1}, FRW_{S_2}, \dots, FRW_{S_K})$ can be calculated as

$$FRW_{S_i} = \frac{\sum_{l=1}^f l \cdot \mu_{S_i, l}}{\sum_{i=1}^K \sum_{l=1}^f l \cdot \mu_{S_i, l}}, \quad (10)$$

where $r_1 < r_2 < \dots < r_f$ (usually $r_1 = 1, r_2 = 2, \dots, r_f = f$) and $i = 1, 2, \dots, m$.

3.3.2. Obtaining MPCl by Using VIKOR. The VIKOR method has been employed to convert the S/N ratios into an MPCl value through the following steps [26].

Step 1. Normalize the decision matrix of S/N ratios.

The S/N ratio of an experimental sample is normalized as follows:

$$f_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}}, \quad (11)$$

where x_{ij} is the S/N ratio of experimental sample A_i with respect to the j th performance characteristic; f_{ij} is the normalized S/N ratio; $i = 1, 2, \dots, m$; and $j = 1, 2, \dots, n$. Then, the normalized decision matrix can be represented as follows:

$$F = [f_{ij}]_{m \times n}. \quad (12)$$

Step 2. Determine the ideal and negative ideal solutions.

The ideal solution A^* and the negative ideal solution A^- are determined as follows:

$$A^* = \left\{ \left(\max f_{ij} \mid j \in J \right) \text{ or } \left(\min f_{ij} \mid j \in J' \right) \mid i = 1, 2, \dots, m \right\} = \{f_1^*, f_2^*, \dots, f_n^*\}, \quad (13)$$

$$A^- = \left\{ \left(\min f_{ij} \mid j \in J \right) \text{ or } \left(\max f_{ij} \mid j \in J' \right) \mid i = 1, 2, \dots, m \right\} = \{f_1^-, f_2^-, \dots, f_n^-\}, \quad (14)$$

where $J = \{j = 1, 2, \dots, n \mid f_{ij}, \text{ a large response is desired}\}$ and $J' = \{j = 1, 2, \dots, n \mid f_{ij}, \text{ a small response is desired}\}$.

Step 3. Compute the utility measure and the regret measure.

The utility measure and the regret measure for each alternative are computed as follows:

$$S_i = \sum_{j=1}^n w_j \frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)}, \quad (15)$$

$$R_i = \max_j \left[\frac{w_j (f_j^* - f_{ij})}{(f_j^* - f_j^-)} \right], \quad (16)$$

where S_i and R_i represent the utility measure and the regret measure, respectively, and w_j is the preference weight of the j th affective response performance characteristic.

Step 4. Calculate the MPCl value.

The VIKOR index is taken as the MPCl value, which is expressed as follows:

$$Q_i = v \left[\frac{S_i - S^*}{S^- - S^*} \right] + (1 - v) \left[\frac{R_i - R^*}{R^- - R^*} \right], \quad (17)$$

where Q_i represents the MPCl value of the i th alternative and $i = 1, 2, \dots, m$; $S^* = \min_i S_i$, $S^- = \max_i S_i$, $R^* = \min_i R_i$, and $R^- = \max_i R_i$; and v is the weight of the maximum group utility, which is usually set to 0.5.

Step 5. Rank the experimental sample.

The experimental sample with the smallest MPCl value is determined to be the best solution, and it is assigned an order of 1.

3.4. Optimization Design. This stage involves identifying the significant design variables and deriving the optimal design. In the Taguchi method, the objective is to maximize the S/N ratio to minimize variability in the quality characteristics and to maximize the mean quality characteristics. When multiple S/N ratios are transformed into a single MPCl value by using the VIKOR method, it is desirable to minimize the MPCl. On the basis of the MPCl, ANOVA can be applied to identify the significant design variables.

The response table and the response graph, which can be determined from the response values, are used to derive the

optimal design. The response value for each type of design variable can be calculated as follows:

$$R_i = \frac{\sum_{i=1}^m \eta_i}{m}, \quad (18)$$

where R_i is the response value, η_i is the MPCCI value of a design variable with the same level, and m is the number of experimental samples with the same level of the design variable. The smaller the MPCCI, the better the multiple performance characteristics are. Therefore, the optimal design can be identified by determining the smallest MPCCI among all possible combinations of the design variables.

The final step is to verify the performance of the optimized product form design. After a confirmation experiment involving the original and the optimal designs is executed, the evaluation values for MARs can be obtained. On the basis of these values, the S/N ratios and the MPCCI can be calculated. Finally, the quality performances are compared to verify the obtained optimal design.

4. Case Study

A car is a typical example of a mature product. As a concentrated expression of car form design, car profile has been receiving increasing attention in car selection by consumers, and much research has been devoted to it [1, 9, 10, 40]. Therefore, in this study, a car profile was adopted as a case study to demonstrate the proposed approach.

4.1. Design Analysis for Car Profile. A total of 120 profile images of cars currently available in the market were collected. These images were reviewed by a focus group comprising seven car design experts, and morphological analysis was used to construct the design variables that influenced affective responses. These design variables were classified into two categories: one related to the form of different profile parts, as listed in Table 1 and the other related to the ratios of different profile parts that also contributed significantly to the affective responses, as listed in Table 2. The design variables F (ratio of car height to car length), H (ratio of wheel height to car height), and L (ratio of front overhang length to car length) and their corresponding levels were adopted from Chang and Chen [9].

In total, 258 affective adjectives were collected from the academic literature, car magazines, and car company websites. Among them, 20 words were selected as the most relevant to car design. Factor analysis was employed to investigate the factor structure of these words. The 20 affective words were then grouped into four main factors, which accounted for 92.752% of the cumulative variance. The four factors were “Modern,” “Comfortable,” “Rounded,” and “Simple.” These factors were used as the basis for determining the quality characteristics of affective responses.

4.2. Taguchi Experiment for Car Profile Design

4.2.1. Taguchi Experiment Design. In this study, 13 design variables with three levels were investigated; therefore, the number of possible design combinations was 1,594,323 (3^{13}),

which was too large to prepare experimental samples for the affective response experiment. To reduce the number of experimental samples, OA was adopted. Only the main effects were of interest, and interactions between design variables were not studied. The number of DOFs of each design variable was 2 (number of levels minus 1); thus, the total number of DOFs was 26 (13×2). The experimental design followed an L_{27} OA, and the design layout is presented in Table 3. Overall, 27 combinative designs were employed as the experimental samples, as shown in Figure 3.

4.2.2. Evaluating Affective Responses by Using Fuzzy Sets. In this study, 60 graduates (30 women and 30 men, 22–30 years of age) from a university were invited to the industrial design laboratory as experimental participants. Young participants were recruited because young consumers seeking to buy a car usually focus more on car form than those in other age groups do. The experiment was conducted according to the Taguchi experiment design by administering a questionnaire. The questionnaire was composed by combining the 27 experimental samples with the four affective factors, which were rated using five fuzzy linguistic terms, namely, very low (VL), low (L), medium (M), high (H), and very high (VH). Triangular fuzzy numbers were used to represent these five terms, and the corresponding membership functions are shown in Figure 4.

4.2.3. Calculating S/N Ratio of Each Affective Response. Fuzzy sets were used to measure the affective responses. The larger the degree of membership of a characteristic, the higher the UX quality is. Therefore, all quality characteristics fit under the larger-the-better scheme. Thus, the S/N ratios must be computed using (3). Because calculating the S/N ratios involves the arithmetic operations of multiplication and division of triangular fuzzy numbers, alpha cuts were used to compute the S/N ratios. For different alpha levels, the corresponding reciprocals of the squares of the alpha cuts were calculated. The evaluation results of all participants were then integrated according to the reciprocals. On the basis of the integrated values, the S/N ratios were obtained. For example, for the fuzzy linguistics term medium (M), by substituting the alpha levels of 0, 0.100, 0.200, ..., and 1.000 into (7), the alpha cuts were calculated; then, the corresponding reciprocals of the squares of the alpha cuts were determined, as shown in Table 4. By integrating the results of the 60 participants for experimental sample No. 1 concerning affective response of “Modern,” the S/N ratios related to different alpha levels were calculated, as shown in Table 5 and Figure 5. Subsequently, by using (8) for defuzzification, the S/N ratio value of 11.774 was obtained. Thus, the S/N ratios of all the experimental samples related to the affective responses of “Modern,” “Comfortable,” “Rounded,” and “Simple” were derived, and the results are listed in columns 2–5 of Table 6.

4.3. Transformation of S/N Ratios for Car Profile Design

4.3.1. Expressing MARs Preferences. A fuzzy affective response questionnaire with multiple answers was administered to the 60 participants for acquiring their MARs

TABLE 1: Design variables for car form.

Design variables	Level 1	Level 2	Level 3
A (Front bumper)
B (Front part)
C (Top part)
D (Rear part)
E (Rear bumper)

preferences. There were five linguistic labels in this questionnaire, namely, very unimportant (VU), not important (NI), neutral (N), important (I), and very important (VI). By using this questionnaire, the participants could express their MARs preferences accurately, as illustrated in Table 7. After collecting the preferences of all the participants, (9) is used to determine the fuzzy sample mean, and the results are summarized in Table 8. Subsequently, by using (10), the preference weights for “Modern,” “Comfortable,” “Rounded,” and “Simple” were obtained as 0.313, 0.254, 0.156, and 0.277, respectively.

4.3.2. Obtaining MPCl. By using VIKOR, the S/N ratios of the affective response characteristics were transformed into MPCl values based on the preference weights. Initially, the S/N ratios were normalized by substituting them into (11). Next, by combining (12), (13), and (14), the ideal solution and the negative ideal solution were obtained. Subsequently, by substituting these solutions and preference weights into (15) and (16), the utility measure and the regret measure were obtained, respectively, and by incorporating these values into (17), the MPCl value (i.e., VIKOR index) was computed. Finally, by using the MPCl value, the experimental samples were ranked. The MPCl value and the corresponding ranks are listed in columns 6 and 7 of Table 6.

4.4. Optimizing Car Profile Design

4.4.1. Determining Optimal Design through Statistical Analysis. ANOVA was employed to identify the significant design variables and to determine the contribution percentage of each design variable to the MPCl. When pooling the errors, the authors followed the Taguchi recommendation of pooling the design variables until the error DOFs were approximately half the total DOFs of the experiment [41]. Table 9 shows the ANOVA results for the MPCl, and the results clearly indicate that the design variables C (Top part), F, and K (Ratio of rear part length to car length) significantly influence the MPCl. In addition, the design variable F is the most significant because it has the highest contribution percentage among the design variables.

The relative effects among the design variables determined through ANOVA can be verified by referring to the response table and the response graph. The ANOVA, response table, and response graph provide valuable design insights. The response value for each level of the design variables was computed by using (18), and the results are listed in Table 10. Delta indicates the difference between the maximum and minimum responses. The design variables were ranked according to these delta values, with 1 being the largest value. The total average MPCl of the 27 experimental samples was 0.420. Figure 6 shows the response graph, where

TABLE 2: Design variables for car ratio.

Design variables	Diagrammatic sketch	Level 1	Level 2	Level 3
F (Ratio of car height to car length, $H1/L1$)		0.32	0.37	0.42
G (Ratio of car top part to car height, $H2/H1$)		0.27	0.30	0.33
H (Ratio of wheel height to car height, $H3/H1$)		0.40	0.45	0.50
I (Ratio of chassis height to wheel height, $H4/H3$)		0.20	0.35	0.50
J (Ratio of fore part length to car length, $L2/L1$)		0.18	0.24	0.30
K (Ratio of rear part length to car length, $L3/L1$)		0.09	0.13	0.17
L (Ratio of front overhang length to car length, $L4/L1$)		0.14	0.18	0.22
M (Ratio of rear overhang length to car length, $L5/L1$)		0.17	0.20	0.23

the dashed line indicates the total average MPCI. Clearly, the design variable F has the strongest effect on the MPCI, followed by the design variables C, K, and G (ratio of car top part to car height). Furthermore, the design variable I (Ratio of chassis height to wheel height) has the weakest influence on the MPCI.

The optimal levels of design variables were determined on the basis of a smaller VIKOR value indicating higher quality. Therefore, according to the response table and the response graph, the derived optimal level combination, that is, the optimal design, was $A_3B_3C_3D_3E_1F_1G_2H_2I_3J_2K_1L_1M_3$.

4.4.2. Confirmation Test. The identified optimal design based on MARs was not found in the L_{27} OA. Therefore, a

confirmation test was executed to verify the improvement in performance characteristics. The 60 participants were asked to evaluate the optimal design obtained using the proposed approach, a competitor's design, and the initial design in the OA (Sample No. 1). Table 11 presents a comparison of the three car profile designs. The total S/N ratios of the four MARs increased from 41.051 for the initial design to 62.651 for the optimal design, an improvement of 21.600. The total S/N ratios increased from 59.532 for the competitor's design to 62.651 for the optimal design, an improvement of 3.119; moreover, the S/N ratios of all MARs for the optimal design are greater than those for the competitor design. The obtained optimal product form design is clearly effective; therefore, the proposed approach is valid and feasible.

TABLE 3: Experimental layout determined using L_{27} OA.

Experimental sample No.	Level of design variables										
	A	B	C	D	E	F	G	H	I	J	K
1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2	2	2	2	2
3	1	1	1	1	3	3	3	3	3	3	3
4	1	2	2	2	1	1	1	2	2	2	3
5	1	2	2	2	2	2	2	3	3	3	3
6	1	2	2	2	3	3	3	1	1	1	2
7	1	3	3	3	1	1	1	3	3	3	2
8	1	3	3	3	2	2	2	1	1	1	3
9	1	3	3	3	3	3	3	2	2	2	1
10	2	1	2	3	1	2	3	1	2	3	2
11	2	1	2	3	2	3	1	2	3	1	3
12	2	1	2	3	3	1	2	3	1	2	2
13	2	2	3	1	1	2	3	2	3	1	2
14	2	2	3	1	2	3	1	3	1	2	3
15	2	2	3	1	3	1	2	1	2	3	1
16	2	3	1	2	1	2	3	3	1	2	3
17	2	3	1	2	2	3	1	1	2	3	1
18	2	3	1	2	3	1	2	2	3	1	2
19	3	1	3	2	1	3	2	1	3	2	3
20	3	1	3	2	2	1	3	2	1	3	2
21	3	1	3	2	3	2	1	3	2	1	3
22	3	2	1	3	1	3	2	2	1	3	1
23	3	2	1	3	2	1	3	3	2	1	2
24	3	2	1	3	3	2	1	1	3	2	3
25	3	3	2	1	1	3	2	3	2	1	3
26	3	3	2	1	2	1	3	1	3	2	1
27	3	3	2	1	3	2	1	2	1	3	2

TABLE 4: Calculation of fuzzy number “Medium” for different alpha levels.

Alpha level	Alpha cut		Square		Reciprocal	
	Left	Right	Left	Right	Left	Right
0	3.000	7.000	9.000	49.000	0.020	0.111
0.100	3.200	6.800	10.240	46.240	0.022	0.098
0.200	3.400	6.600	11.560	43.560	0.023	0.087
0.300	3.600	6.400	12.960	40.960	0.024	0.077
0.400	3.800	6.200	14.440	38.440	0.026	0.069
0.500	4.000	6.000	16.000	36.000	0.028	0.063
0.600	4.200	5.800	17.640	33.640	0.030	0.057
0.700	4.400	5.600	19.360	31.360	0.032	0.052
0.800	4.600	5.400	21.160	29.160	0.034	0.047
0.900	4.800	5.200	23.040	27.040	0.037	0.043
1.000	5.000	5.000	25.000	25.000	0.040	0.040

TABLE 5: Calculation of S/N ratios for different alpha levels.

Alpha level	Integration of reciprocals		S/N ratio (dB)	
	Left	Right	Left	Right
0	1.306	9.729	15.450	5.116
0.100	1.383	7.968	15.169	6.188
0.200	1.468	6.694	14.878	7.120
0.300	1.562	5.734	14.574	7.945
0.400	1.667	4.986	14.257	8.683
0.500	1.782	4.389	13.926	9.353
0.600	1.912	3.902	13.579	9.965
0.700	2.057	3.499	13.214	10.529
0.800	2.222	3.159	12.830	11.052
0.900	2.409	2.871	12.425	11.539
1.000	2.623	2.623	11.996	11.996

FIGURE 3: Twenty-seven combinative designs used in Taguchi experiment.

5. Discussion

In this study, to obtain the optimal product form design related to MARs, a fuzzy-based hybrid Taguchi method is proposed to derive robust parameter settings. Execution of the proposed method was demonstrated using a case study involving the design of a car profile. Only the main effects of the design variables were considered; no attempt was made to analyze the interactions among the design variables. In

the Taguchi OA, the effects of interactions are mixed with the main effect of a design variable assigned to some other column [32]. Therefore, if the interactions among the design variables is to be included, a suitable OA must be selected according to the specific design problem.

Note that the design variables and their corresponding levels can be changed according to the products available on the market and the research focus. The aim of this study is to present a new approach and, thus, a few aspects of the

TABLE 6: S/N ratios of affective responses and corresponding MPCL.

Experimental sample No.	Modern	S/N ratio (dB)			Simple	MPCI	Rank
		Comfortable	Rounded				
1	0.313	0.254	0.156	0.277	0.592	19	
2	11.774	12.809	6.400	10.068	0.550	18	
3	12.402	12.633	9.447	10.136	0.978	27	
4	6.393	8.662	7.083	10.064	0.307	13	
5	14.076	12.403	11.469	12.131	0.308	14	
6	14.118	12.089	13.723	11.979	0.611	22	
7	9.082	12.402	14.631	10.993	0.186	3	
8	15.079	12.403	12.724	14.085	0.295	12	
9	12.353	11.765	15.734	13.799	0.204	4	
10	13.169	13.450	15.794	13.641	0.226	6	
11	14.415	13.769	13.684	12.415	0.600	20	
12	10.047	10.951	12.518	10.390	0.229	7	
13	13.342	13.186	13.468	13.111	0.284	11	
14	13.263	13.380	13.973	12.113	0.715	24	
15	9.681	11.816	14.942	8.685	0.130	2	
16	15.395	13.196	13.580	13.341	0.607	21	
17	11.500	11.376	5.277	10.352	0.941	26	
18	9.434	7.215	6.837	8.083	0.366	15	
19	13.457	11.093	11.227	12.742	0.251	9	
20	12.247	14.478	14.890	14.025	0.000	1	
21	15.806	14.691	14.547	14.488	0.819	25	
22	11.038	8.256	9.542	8.553	0.654	23	
23	9.462	12.795	7.636	10.244	0.385	16	
24	13.278	12.988	10.468	11.477	0.216	5	
25	13.204	13.416	13.034	14.033	0.385	17	
26	11.418	12.327	13.923	13.238	0.259	10	
27	13.926	12.081	10.633	13.781	0.238	8	
	13.421	13.028	13.238	12.740			

TABLE 7: Multiple answers for fuzzy affective responses.

Affective Responses	Very unimportant (VU)	Not important (NI)	Neutral (N)	Important (I)	Very important (VI)
Modern				0.50	0.50
Comfortable			0.40	0.40	0.20
Rounded	0.40	0.50	0.10		
Simple			0.20	0.50	0.30

TABLE 8: Mean of MARs preferences.

Affective Responses	Very unimportant (VU)	Not important (NI)	Neutral (N)	Important (I)	Very important (VI)
Modern	0.000	0.000	0.015	0.287	0.699
Comfortable	0.000	0.000	0.311	0.585	0.104
Rounded	0.069	0.571	0.320	0.040	0.000
Simple	0.000	0.000	0.104	0.640	0.256

FIGURE 4: Membership functions of fuzzy linguistic terms for evaluating affective responses.

case study appear to be incomplete. This may be overcome in future studies. Furthermore, the sample size was 60 in the case study, which supports the use of statistics and interpretation of quantitative data [42]. Therefore, the number of participants was adequate; however, if this approach is applied to product design at companies, the number of participants should be determined by considering the margin of error, confidence level, and total population of the target market [43].

To integrate the multiple performance characteristics pertaining to MARs into a synthetic performance index, it is assumed that the preference weights conform to a linear mode; that is, they satisfy the additive effect and there exists no interactive effect. This approach is simple, easy, and effective for execution. Nevertheless, in practice, the affective responses used as performance characteristics for evaluation are not independent value-wise [31, 44], and the contribution of one performance characteristic of affective responses to product evaluation depends on the condition of the other performance characteristics. For example, in this case study, the MARs for car profile were “Modern,” “Simple,” “Rounded,” and “Comfort.” The contribution of “Modern, Simple, Rounded, and Comfort” may not simply be equal to the sum of the contributions of “Modern,” “Simple,” “Rounded,” and “Comfort,” and there exist interactive effects

FIGURE 5: S/N ratios of fuzzy number “Medium.”

among them. Future research should focus on this topic to improve the precision of MARs integration.

Although car profile design is used as an example, the proposed approach can be applied to other products with various design variables, such as mobile phones [5], digital cameras [4], and running shoes [45]. The proposed method is somewhat complicated and involves many calculation steps. However, it can be properly implemented. More importantly, the method incorporates four simplification stages, namely design analysis, Taguchi experiment, transformation of S/N ratios, and optimization design. These simplification stages compensate for the complexity of the calculation. Therefore, the proposed method can be used as a universal robust design approach to improve product form design quality in terms of MARs.

In brief, the proposed fuzzy-based hybrid Taguchi method is useful for multiobjective optimization of product form design because it has the following advantages:

TABLE 9: ANOVA results for MPCl.

Design variable	DOF	SS	MS	F-value	p-value	Pure SS	Contribution (%)
A*	2	0.055	0.027	-	-	-	-
B*	2	0.037	0.019	-	-	-	-
C	2	0.384	0.192	10.787	0.002	0.348	20.923
D	2	0.103	0.051	2.884	0.095	0.067	4.027
E*	2	0.017	0.009	-	-	-	-
F	2	0.472	0.236	13.273	0.001	0.437	26.237
G	2	0.124	0.062	3.495	0.064	0.089	5.333
H	2	0.121	0.061	3.412	0.067	0.086	5.156
I*	2	0.018	0.009	-	-	-	-
J*	2	0.058	0.029	-	-	-	-
K	2	0.163	0.081	4.570	0.033	0.127	7.632
L	2	0.084	0.042	2.357	0.137	0.048	2.901
M*	2	0.028	0.014	-	-	-	-
Error (pooled)	12	0.213	0.018	-	-	0.462	27.791
Total	26	1.664	-	-	-	1.664	100.000

* pooled design variable, SS=sum of square, MS=mean square.

TABLE 10: MPCl response table.

Level	A	B	C	D	E	F	G	H	I	J	K	L	M
1	0.448	0.472	0.588	0.459	0.388	0.273	0.513	0.391	0.438	0.482	0.364	0.351	0.464
2	0.455	0.401	0.352	0.468	0.450	0.394	0.352	0.356	0.439	0.371	0.365	0.487	0.408
3	0.356	0.387	0.320	0.333	0.421	0.593	0.395	0.512	0.383	0.407	0.530	0.421	0.388
Delta	0.099	0.085	0.268	0.135	0.062	0.320	0.161	0.156	0.056	0.111	0.166	0.136	0.076
Rank	9	10	2	7	12	1	4	5	13	8	3	6	11

Total average MPCl is 0.420. The bold numbers indicate the optimal levels of design variables.

TABLE 11: Results of confirmation test.

	Initial design combination in OA (Sample No. 1)	Competitor's design combination	Optimal design combination
Level combination	A ₁ B ₁ C ₁ D ₁ E ₁ F ₁ G ₁ H ₁ I ₁ J ₁ K ₁ L ₁ M ₁	A ₃ B ₁ C ₃ D ₂ E ₂ F ₁ G ₃ H ₂ I ₁ J ₃ K ₂ L ₁ M ₃	A ₃ B ₃ C ₃ D ₃ E ₁ F ₁ G ₂ H ₂ I ₃ J ₂ K ₁ L ₁ M ₃
Sketch
Modern	11.774	15.806	16.115
Comfortable	12.809	14.691	15.526
Rounded	6.400	14.547	15.136
Simple	10.068	14.488	15.874
Total	41.051	59.532	62.651
Improvement	21.600	3.119	–

FIGURE 6: Response graph of MPCl.

(1) Compared with the traditional affective engineering method, which uses only the mean of affective response evaluations, the proposed approach uses the S/N ratio, which considers both the mean and variation [32]. As a result, the obtained optimal product form design is more robust.

(2) The proposed approach adopts fuzzy sets to measure affective responses. Compared with the conventional method, which uses a semantic differential scale or a Likert scale, the proposed method can consider the imprecision and vagueness in the process of evaluating affective responses [13].

(3) To express preferences, a fuzzy questionnaire with multiple answers is used. In comparison with the commonly used questionnaire, which allows only a single answer [22], the proposed approach reflects consumers' preferences more accurately.

(4) Because of the use of VIKOR as an MCDM method, the proposed approach can combine all objectives into an MPCl. According to the MPCl, the optimal design can be achieved; in addition, great design insights can be obtained.

It should be mentioned that, to obtain the optimal product form design, Taguchi method can be integrated with other different methods, such as Kano [9, 10], grey relation analysis [9, 10], fuzzy logic [1], TOPSIS [9], and fuzzy integral [31]. The purpose of this paper is to propose a novel approach to optimize product form design, and no effort is made to perform a comparison study of the proposed approach with other approaches. In future studies, the authors will focus on

making comparison studies to derive which approach is more suitable for product form design.

6. Conclusion

In this study, the authors propose a fuzzy-based hybrid Taguchi method to optimize product form design concerning MARs. Design analysis is performed first to determine the design variables and affective responses. A Taguchi experiment is then designed with the design variables as control factors and the affective responses as quality characteristics. Fuzzy sets are used to measure the affective responses, and a fuzzy questionnaire is used to collect consumers' preference weights for MARs. By employing VIKOR, the multiple S/N ratios obtained from the Taguchi experiment are mapped into an MPCl. On the basis of the MPCl, ANOVA is executed, and the response table and the response graph are obtained; thus, the optimized product form design, which can maximize quality and minimize variability, is determined.

The proposed approach is a robust design approach that can transform multiple performance characteristics pertaining to MARs into a single performance characteristic and, consequently, can simplify optimization problems. Moreover, this approach can provide valuable design insights. In this study, the authors have focused only on product form design; further research could integrate product form with color and material.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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