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Case Study

# Grey-based Taguchi Method to Optimize the Multi-response Design of Product Form Design

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A B S T R A C T

This paper presents a multi-response optimization method that uses the grey-based Taguchi method as the integrative product form design optimization method, and it serves as a tool for product form design to determine the optimal combination of design parameters in Kansei engineering (KE). This method is unique in that it combines the Taguchi method (TM) and grey relational analysis (GRA), allowing it to take advantage of the benefits of both methods. The TM is used to design experiments and generate combinative product form design samples which can be used to improve product quality. The GRA is applied to multi-response optimization problems. Factor effect analysis and analysis of variance (ANOVA) are used to determine which combinations of design parameters will result in the optimal product design. To demonstrate the applicability of the grey-based TM, a case study of a car form design is presented, and a confirmation test is performed to verify the performance of the optimal product design. The results show that the grey-based TM can deal with optimization problems with multiple Kansei responses and determine an optimal car form design that is representative of the consumers' perception in a systematic manner. The confirmation test results also show that the optimal product design generated by the grey-based TM can be used to improve the overall quality of a product form.

## INTRODUCTION

It is common knowledge that products are designed to meet the needs of consumers. Nonetheless, product designs that are primarily based on the product's functionality are insufficient to attract customers to purchase the product. Consumers make purchasing decisions based on their personal feelings, emotions, impressions, and perceptions. Consumers seek something more than what product designers think. Hence, the appearance and aesthetics of a product are important factors that influence a consumer's purchasing decision. A number of systematic product design studies have been conducted over the years to gain a better understanding of consumer subjective perception. Kansei engineering (KE) has been a prominent study in product design [1], [2] and is considered as one of the most reliable and useful methodologies for dealing with consumers' aesthetic and emotional needs. In recent years, KE has been successfully adopted in various fields of design, such as mobile phone [3], [4], home appliances [5], machine tools [6], digital camera [7], interface design [8], [9], social robot design [10], housing design [11], [12] and urban planning [13], clothes design [15], [16], service design [16], [17], traditional crafts [18], and baby carrier [19].

One of the challenging issues is dealing with the problem of optimization in KE. The perceptions of customers concerning KE, as is known, constitute the multi-response problem. Hence, this should be treated as a problem relating to the optimization of multi-response or multi-criteria. Meanwhile, to obtain the optimal design of product form in KE is a complex process that is time consuming and utilizes other resources, and involves high cost. Therefore, developing a time and cost-effective approach to determine the optimal combination of the product design parameters in KE is an important task. Several attempts have been made to develop a robust design approach for systematic optimization [20]–[22]. These robust design methods propose a simple experimental design to reduce the cost of and time for evaluating the experiment for the optimal design of a product. The Taguchi method (TM), which is a concept of a robust design approach, is widely applied in optimal engineering design. Several studies have been conducted that propose the robust design approach to optimize the product form design using the TM. Lai et al. [20] and Sutono et al. [22] used the TM and analysis of variance techniques to investigate the effect of design parameters in establishing the optimal setting of product design parameters in KE. More recently, Oztekin et al. [21] suggested the Taguchi-based method as a simple, feasible, and versatile

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way for determining the combination of product design parameters at the product design stage by taking into account customers' impressions and feelings. However, these researches are limited to using the Taguchi-based method as a product form design approach to optimize a single response optimization problem involving a combination of product design parameters. Each Kansei response is given the best combination of each design parameter in these investigations. This is understandable, given that the original TM was developed to solve a problem involving the optimization of a single performance criterion [23], [24]. Hence, optimizing the multi-response optimization problem with the TM would be much more challenging. In a multi-response problem, separate optimization for each response may result in serious parameter's setting conflict [25]. Therefore, this work will combine the TM with a multi-response optimization method as a product form design method to solve the multi-response optimization problem based on customer perception of KE. Grey relational analysis is one of the multi-response optimization methods (GRA). GRA is considered in this study due to its simplicity and straightforwardness in mathematical calculation and prioritization [26], [27], as well as its stability [28] in solving the problem of multi-response optimization.

A number of studies have successfully used the TM and GRA in different applications. These methods have been applied in determining the optimal selection of the process parameters on various machining processes, such as for the macro-[29], micro-EDM [30] and wire-EDM [31], turning [32], [33], milling [34], [35], welding [36], and drilling [37], [38]. Kuo et al. [39] also presented the use of a grey-based TM for optimizing multi-response simulation problems, using the integrated circuit packaging problem as a practical case study. Recently, grey-based TM has been used to solve some optimization problems, such as the thin-film process with multiple quality characteristics in color filter manufacturing [40], the flat-plate collector process in solar energy collector manufacturing [41], and green machining of aerospace grade titanium alloy [42]. However, no literature on the use of the TM and GRA to determine the optimal combination of product design parameters (product form design) in KE was found in these studies.

Based on the aforementioned, this paper intends to use the integrative product form design optimization method, which combines the TM and GRA, to solve the problem of multi-response or -criteria optimization in KE. This method is proposed to find the optimal combination of design parameters for product form design that meets consumers' responses/needs to KE. The TM and GRA will be referred to as grey-based TM throughout the rest of this paper.

This paper is divided into the sections listed below. The first section begins with a brief introduction, followed by the study's motivation and objective. The second section provides a brief theoretical overview of the KE, the TM, and the GRA. The proposed integrative design optimization method is discussed in the third section. The following section includes an experimental case study to demonstrate the applicability and confirmation test of the grey-based TM. The following section includes an experimental case study to demonstrate the applicability and confirmation test of the grey-based TM. The following one goes over the findings. Finally, the final section contains the study's concluding remarks.

## METHOD

### *Taguchi Method*

Genichi Taguchi was the first to develop the Taguchi method (TM). This has been accepted as one of the simplest and most effective solutions for parameter design and experimental planning in product design and improvement [43]. The orthogonal array from experimental design theory is used in this method to investigate a large number of variables with a small number of experiments. The TM is fundamentally based on orthogonal arrays (OA), loss functions, and signal-to-noise (S/N) ratios [44]. An OA is first defined using a set of design parameters and levels. The deviation between the experimental and desired values is then calculated using a loss function. The S/N ratio is then calculated by transforming the loss function value. Finally, the S/N ratio is used to calculate the performance characteristic.

The S/N ratio analysis considers three types of performance characteristics: nominal-the-best, smaller-the-better, and larger-the-better. Taguchi et al. [44] go into detail about the TM's concepts and methods. The S/N ratio is calculated as follows.

The S/N ratio $\eta_{ij}$ of the smaller-the-better characteristic is expressed as follows:

$$\eta_{ij} = -10 \log \left[ 1/\mathrm{n}\left(\sum_{i=1}^{n} y_{ij}^2\right)\right] \quad (1)$$

The S/N ratio $\eta_{ij}$ of the larger-the-better characteristic is expressed as follows:

$$\eta_{ij} = -10 \log\left[ 1/\mathrm{n}\left(\sum_{i=1}^{n} 1/y_{ij}^2\right)\right] \quad (2)$$

The S/N ratio $\eta_{ij}$ of the nominal-the-best characteristic is expressed as follows:

$$\eta_{ij} = 10 \log\left( \bar{y}_{ij}^2 / s^2\right) \quad (3)$$

### *Grey Relational Analysis*

Grey relational analysis (GRA) is a part of grey system theory developed by Deng as an effective method for studying uncertainties in a system model and assisting in prediction and decision-making. The GRA assesses the degree to which each alternative candidate solution in the multiple attributes problem is similar to the ideal alternative solution. All alternative candidate solutions are evaluated using this method based on the relational grade of discrete data sequences [45]. A higher relational grade for an alternative candidate solution indicates that the candidate solution is more similar to an ideal alternative solution, which is the best performance. As a result, the best candidate solution will be kept. Kuo et al. [26] and Kuo et al. [39] proposed the GRA procedure, which is as follows.

#### *Grey Relational Generation*

The first step in GRA is data processing to avoid incorrect results if the factor goals or attribute data directions differ. Hence, all data related to a group of sequences must be transformed into normalization comparability conditions. This is known as grey relational generation. Normalized data transformations are classified into three types: smaller-the-better, larger-the-better, and nominal-the-best. The following is a linear data normalization method for calculating the signal-to-noise (S/N) ratio.

The normalized data of the smaller-the-better transformation can be expressed as:

$$x_{\mathrm{ij}} = (\max \eta_{ij} - \eta_{ij})/(\max \eta_{ij} - \min \eta_{ij}) \tag{4}$$

The normalized data of the larger-the-better transformation can be expressed as:

$$x_{ij} = (\eta_{ij} - \min \eta_{ij})/(\max \eta_{ij} - \min \eta_{ij}) \tag{5}$$

The normalized data of the nominal-the-best transformation can be expressed as:

$$x_{ij} = \left(\eta_{ij} - \text{target}\right) - \min\left(\left|\eta_{ij} - \text{target}\right|\right) / \max\left(\left|\eta_{ij} - \text{target}\right|\right) - \min\left(\left|\eta_{ij} - \text{target}\right|\right) \tag{6}$$

### *Reference Sequence Definition*

After the grey relational generation, the reference sequence is defined to find the alternative for which the comparability sequence is closest to the reference (ideal) sequence. This means that the best alternative choice will occur if all of its performance values are close or equal to 1. Hence, in this study, the reference sequence $X_0$ is defined as $(x_{01}, x_{02}, \ldots, x_{0j}, \ldots, x_{0n}) = (1, 1,.., 1,.., 1)$.

### *Grey Relational Coefficient Calculation*

In order to determine the degree of closeness between $x_{ij}$ and $x_{0j}$, the grey relational coefficient (GRC) is calculated from the normalized data. A larger GRC indicates that $x_{ij}$ and $x_{0j}$ are closer to one another. The GRC, γ, between $x_{\mathrm{ij}}$ and $x_{0\mathrm{j}}$ is defined by:

$$\gamma(x_{0j}, x_{ij}) = (\Delta_{\min} + \zeta\Delta_{\max})/(\Delta_{ij} + \zeta\Delta_{\max}) \tag{7}$$

The distinguishing coefficient is intended to compress or expand the range of GRCs.

### *Grey Relational Grade Calculation*

The grey relational grade (GRG) represents the degree of similarity between the comparable and the reference sequences. The GRG, $\Gamma$, is determined after the GRCs are calculated using equation (7). The GRG is defined as the weighted sum of GRCs, which is expressed as:

$$\Gamma(X_0, X_i) = \sum_{j=1}^{n} w_j \gamma(x_{0j}, x_{ij}) \tag{8}$$

$$\sum_{j=1}^{n} w_j = 1 \tag{9}$$

According to the context of applications, the weighting value of the *j*th criterion is usually assigned by users' judgment or depends on the structure of the proposed problem. A higher value of the GRG implies a closer degree of relation to the ideal data sequence and would be chosen as the best solution.

### ***Multi-response optimization***

The goal of this research is to develop a multi-response optimization method that integrates the TM and GRA algorithms to optimize a product form design. This method's main goal is to determine the optimal combination of design parameters for multi-response optimization problems in KE.

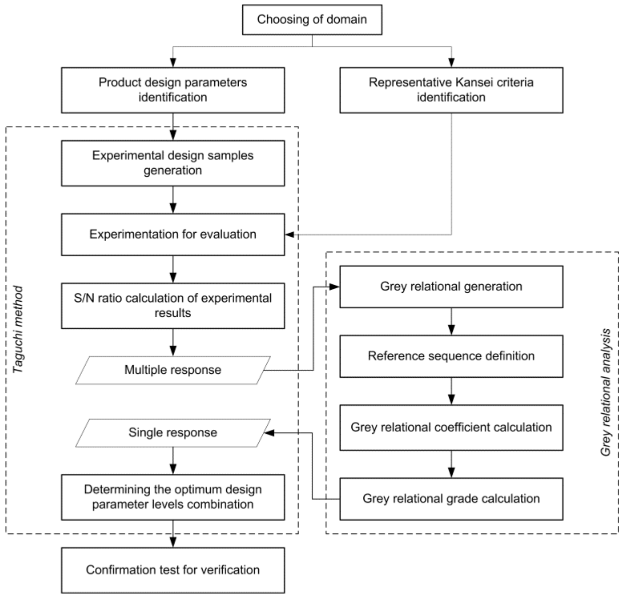


Figure 1. Procedure of the Multi-response Optimization Method using Grey-based TM.

Figure 1 depicts the procedure. This method consists of nine steps, which are as follows:

1. Identify and choose the representative Kansei words as the product design response.
2. Identify the product design parameters and design parameter levels for Taguchi's OA experiment.
3. Choose an appropriate Taguchi's OA and assign design parameters to it. Generate experimental form samples based on the chosen OA.
4. Conduct a questionnaire survey to evaluate each form sample in relation to the representative Kansei response.
5. Using the experimental data, compute the S/N ratios to determine the performance of each representative Kansei response.
6. Perform GRA on the S/N ratios.
7. Analyze the experimental results using GRG and statistical methods.
8. Select the optimal level of design parameters to achieve an optimal design and identify significant design parameters.
9. Conduct confirmation test to verify the optimal combination of design parameters.

## RESULT AND DISCUSSION

This study uses the grey-based TM to present a multi-response optimization method as an integrative design optimization method for product form design to determine the optimal combination of design parameters based on customers' perceptions of multi-Kansei response. To demonstrate the experiment study using the grey-based TM, the form design silhouette of a car was chosen as an illustrative case. Consumers in Malaysia were the target of the experiments. It has been recognized that the automotive industry is becoming one of the most important industries in Malaysia. The Malaysian Automotive Association [46] forecasted that there will be an increasing trend in market share for automobiles between 2016 and 2020 with a growth of 10.76%. This will be a very


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Table 1. Initial Kansei Word Pairs Used in This Study

| No. | Kansei word pairs | No. | Kansei word pairs |
|---|---|---|---|
| 1 | Elegant – inelegant | 9 | Cute – not cute |
| 2 | Stylish – unstylish | 10 | Sporty – not sporty |
| 3 | Youthful – oldish | 11 | Formal – casual |
| 4 | Sleek – lusterless | 12 | Grand – not grand |
| 5 | Modern – ordinary | 13 | Streamlined – not streamlined |
| 6 | Powerful – powerless | 14 | Classic – poor |
| 7 | Rugged – fragile | 15 | Bold – plain |
| 8 | Spacious – confined | 16 | Masculine – feminine |

Table 2. Final Representative Kansei Word Pairs

| Cluster | Kansei word-pairs | Kansei response |
|---|---|---|
| 1 | Modern – ordinary | Modern |
| 2 | Elegant – inelegant | Elegant |
| 3 | Sporty – not sporty | Sporty |
| 4 | Youthful – oldish | Youthful |

challenging period for the automotive industry, in which passenger cars have the largest market share. Although national cars dominate the current Malaysian automotive market, eventually, the steady increase of imported European and Japanese cars will result in a decline in the sales of national cars. This scenario reflects that the automotive industry is a highly competitive market, and, therefore, only automobiles with high appeal to consumers will thrive in such a market. A number of manufacturers are moving towards a consumer-oriented approach in automobile design due to increased competition. The current car form design evaluation experiments were carried out using only the silhouette of the side and front view as the basic characteristics of the car's form, which will be the key to designing and developing a three-dimensional form for designers.

### *Determination of the Kansei Response*

A total of 16 initial Kansei word-pairs were collected to describe the aesthetics and emotional perception of consumers towards a car form design, as shown in Table 1. These word-pairs are selected by eliminating adjectives gathered from relevant KE literature, car magazines and the Internet based on the relationship and similarities in the definitions (i.e. synonyms). The selected Kansei adjectives are expected to represent as much as possible the complete semantic description.

Table 3. Design Parameters and Corresponding Levels

| Factor | Design parameter | Parameter Level 1 | 2 | 3 |
|---|---|---|---|---|
| A | Ratio of car height to car length [H/L] | 0.326 | 0.273 | 0.220 |
| B | Ratio of fore region length to overall length [$L_F$/L] | 0.360 | 0.425 | 0.490 |
| C | Ratio of front height to overall height [$H_F$/H] | 0.600 | 0.540 | 0.480 |
| D | Gradient of front bumper [$\theta_1$] | 0.000 | 15 | 30 |
| E | Gradient of hood [$\theta_2$] | 0.000 | 3.000 | 6.000 |
| F | Gradient of A-pillar [$\theta_3$] | 20 | 25 | 30 |
| G | Ratio of rear region length to overall length [$L_R$/L] | 0.140 | 0.235 | 0.330 |
| H | Ratio of rear region height to overall height [$H_R$/H] | 0.710 | 0.680 | 0.650 |
| I | Gradient of C-pillar [$\theta_4$] | 20 | 30 | 40 |
| J | Gradient of rear bumper [$\theta_5$] | -1600 | 0 | 16 |
| K | Gradient of trunk [$\theta_6$] | 2 | 4.000 | 6.000 |
| L | Gradient of rear fender bottom [$\theta_7$] | 00 | 60 | 12 |
| M | Gradient from side top [$\theta_8$] | 14 | 22 | 30 |

Prior to commencing the study, the initial Kansei word-pairs were analyzed further to determine the representative Kansei response of product design. To keep things as simple as possible and to ensure reasonable consistency, the number of representative Kansei responses used in the experiment should be less than or equal to seven [47], [48]. To this end, 112 participants (56 males and 56 females) were asked to rate the collected initial Kansei word-pairs using the semantic differential method via a questionnaire. Following the acquisition of the semantic differential data, factor and cluster analysis were used to extract the initial Kansei word-pairs and select the most representative Kansei word-pairs [49]. The Kansei wor- pairs with the shortest distance to the centroid of each cluster were chosen as the cluster's representative word-pairs. Table 2 shows the final representative of Kansei word-pairs used as the Kansei response that were adapted from the work of Sutono [50] and Sutono et al. [51] which include Modern, Elegant, Sporty, and Youthful.

### *Determination of the Product Design Parameters*

Instead of using the full factorial approach used in standard KE, the Taguchi experimental design method was adopted as it is

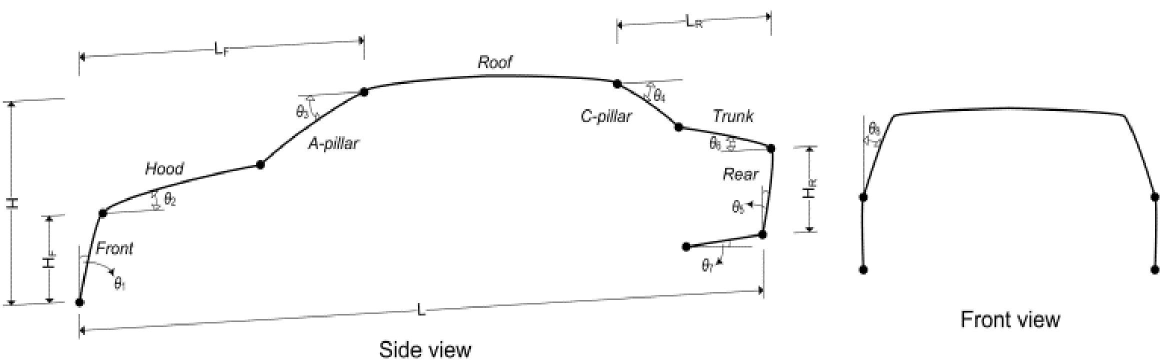


Figure 2. Design Parameters for Car Form Design

efficiently reduced the number of experiments required. In the Taguchi experiments, the control factors are the product design parameters that elicit customers' Kansei perception. The related KE study [20], [52] of car design was initially reviewed to identify the appropriate design parameters of a car design. The design parameters that most likely influenced Kansei perception were then identified. Table 3 shows the thirteen identified design parameters, which were modified and adapted from Lai et al. [20] and Nordgren [52], as well as their corresponding level settings. Figure 2 depicts the position of the identified design parameters in relation to the overall car design. The insignificant design parameters for the impression effect evaluation are kept fixed and excluded from the design parameter settings.

### *Design of Taguchi experiments*

As shown in Table 3, the Taguchi experiment design chosen for this case study should accommodate 13 design parameters with three levels. This combination experiment's full factorial would necessitate up to 1,594,323 ($3^{13}$) samples. However, by employing an orthogonal array, the number of experiments required to determine the optimal combination of design parameters in a product design can be effectively reduced. Table 4 depicts the Taguchi experiment design layout using the OA $L_{27}(3^{13})$ used in this study. The orthogonal table's level data for each design parameter are used to generate a basic car form design for Kansei response evaluation. Figure 3 depicts the 27 combinative car form samples generated using Taguchi's OA $L_{27}(3^{13})$.

### *Experimentation*

A total of 219 Malaysian respondents were recruited for the evaluation experiment, with 97 males and 122 females. The participants ranged in age from 18 to 56 years old, with 44.3% being males and 55.7% being females. A questionnaire survey was used to ask participants to rate the 27 combinative car form samples on a 5-point Likert scale in relation to the four-word Kansei response. Following that, a questionnaire survey was conducted to collect subjective perception data from consumers in order to classify the relationship between each design sample and four-word Kansei response. The questionnaire was designed using the semantic differential method [53], which is a measurement tool commonly used in product design, particularly KE, to measure a product's affective and emotional value. To obtain a final utility rating, the data scores in the evaluation experiment for each experimental product form sample and Kansei word response were averaged.

Table 4. Experimental Design using Taguchi's OA $L_{27}(3^{13})$

| **Exp.** | **Level of design parameter** | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **No.** | **A** | **B** | **C** | **D** | **E** | **F** | **G** | **H** | **I** | **J** | **K** | **L** | **M** |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 2 | 1 | 1 | 1 | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| 3 | 1 | 1 | 1 | 1 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
| 4 | 1 | 2 | 2 | 2 | 1 | 1 | 1 | 2 | 2 | 2 | 3 | 3 | 3 |
| 5 | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 3 | 3 | 3 | 1 | 1 | 1 |
| 6 | 1 | 2 | 2 | 2 | 3 | 3 | 3 | 1 | 1 | 1 | 2 | 2 | 2 |
| 7 | 1 | 3 | 3 | 3 | 1 | 1 | 1 | 3 | 3 | 3 | 2 | 2 | 2 |
| 8 | 1 | 3 | 3 | 3 | 2 | 2 | 2 | 1 | 1 | 1 | 3 | 3 | 3 |
| 9 | 1 | 3 | 3 | 3 | 3 | 3 | 3 | 2 | 2 | 2 | 1 | 1 | 1 |
| 10 | 2 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| 11 | 2 | 1 | 2 | 3 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 |
| 12 | 2 | 1 | 2 | 3 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 |
| 13 | 2 | 2 | 3 | 1 | 1 | 2 | 3 | 2 | 3 | 1 | 3 | 1 | 2 |
| 14 | 2 | 2 | 3 | 1 | 2 | 3 | 1 | 3 | 1 | 2 | 1 | 2 | 3 |
| 15 | 2 | 2 | 3 | 1 | 3 | 1 | 2 | 1 | 2 | 3 | 2 | 3 | 1 |
| 16 | 2 | 3 | 1 | 2 | 1 | 2 | 3 | 3 | 1 | 2 | 2 | 3 | 1 |
| 17 | 2 | 3 | 1 | 2 | 2 | 3 | 1 | 1 | 2 | 3 | 3 | 1 | 2 |
| 18 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 2 | 3 | 1 | 1 | 2 | 3 |
| 19 | 3 | 1 | 3 | 2 | 1 | 3 | 2 | 1 | 3 | 2 | 1 | 3 | 2 |
| 20 | 3 | 1 | 3 | 2 | 2 | 1 | 3 | 2 | 1 | 3 | 2 | 1 | 3 |
| 21 | 3 | 1 | 3 | 2 | 3 | 2 | 1 | 3 | 2 | 1 | 3 | 2 | 1 |
| 22 | 3 | 2 | 1 | 3 | 1 | 3 | 2 | 2 | 1 | 3 | 3 | 2 | 1 |
| 23 | 3 | 2 | 1 | 3 | 2 | 1 | 3 | 3 | 2 | 1 | 1 | 3 | 2 |
| 24 | 3 | 2 | 1 | 3 | 3 | 2 | 1 | 1 | 3 | 2 | 2 | 1 | 3 |
| 2 | 3 | 3 | 2 | 1 | 1 | 3 | 2 | 3 | 3 | 1 | 2 | 1 | 3 |
| 26 | 3 | 3 | 2 | 1 | 2 | 1 | 3 | 1 | 1 | 2 | 3 | 2 | 1 |
| 27 | 3 | 3 | 2 | 1 | 3 | 2 | 1 | 2 | 2 | 3 | 1 | 3 | 2 |

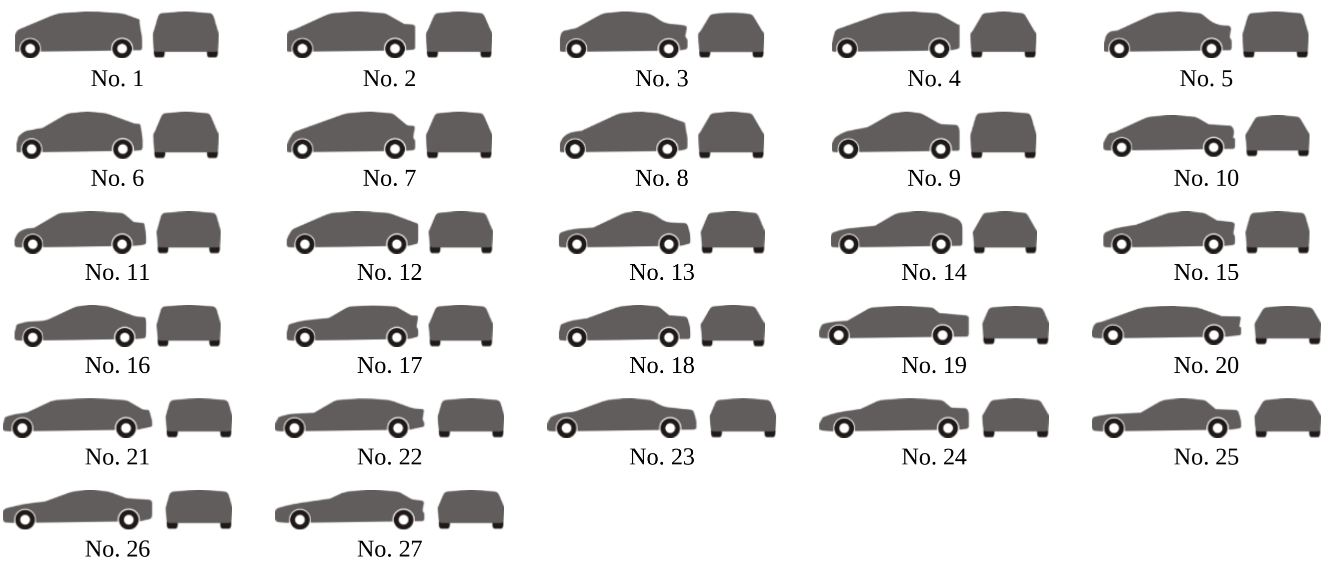


Figure 3. 27 Combinative Product Form Samples Generated for Taguchi's OA $L_{27}(3^{13})$


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### *S/N Ratio Calculation*

For each Kansei word response, the S/N ratio of the larger-the-better performance characteristic was considered in this study. Following that, equation (2) was used to calculate the S/N ratio of each Kansei word response for each experimental product form sample. Table 5 shows the experimental results of the S/N ratio for each of the combinative product form designs in relation to the Kansei words in the Taguchi experiments.

### *Grey Relational Analysis*

After experimentation, GRA was performed to examine the degree of the similarity of each alternative car design to the car design with the best performance based on the experimental results obtained from Table 5. The GRA simplified the optimization process by converting multiple performance response values or coefficients into a single performance response value. According to the GRA procedure, the data on S/N

Table 5. Experimental Results of the S/N Ratio

| No. | Elegant | Youthful | Modern | Sporty | No. | Elegant | Youthful | Modern | Sporty |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 6.113 | 2.158 | 6.772 | 2.032 | 15 | 9.760 | 8.309 | 10.415 | 8.702 |
| 2 | 6.529 | 5.681 | 5.632 | 3.522 | 16 | 9.813 | 5.917 | 9.970 | 7.728 |
| 3 | 5.698 | 6.945 | 7.424 | 5.640 | 17 | 6.559 | 4.979 | 6.550 | 6.459 |
| 4 | 7.867 | 6.489 | 8.086 | 6.492 | 18 | 8.610 | 8.497 | 9.464 | 8.815 |
| 5 | 5.910 | 7.458 | 7.544 | 4.959 | 19 | 6.546 | 1.164 | 4.060 | 1.417 |
| 6 | 8.344 | 8.361 | 7.343 | 6.443 | 20 | 7.727 | 2.241 | 7.413 | 5.279 |
| 7 | 7.127 | 9.538 | 8.837 | 8.937 | 21 | 6.867 | 1.226 | 4.301 | 1.551 |
| 8 | 8.279 | 9.199 | 9.009 | 9.099 | 22 | 6.447 | 3.196 | 5.822 | 5.087 |
| 9 | 7.347 | 8.137 | 6.551 | 6.503 | 23 | 10.282 | 4.244 | 9.406 | 6.235 |
| 10 | 6.988 | 2.224 | 7.092 | 5.558 | 24 | 6.434 | 2.537 | 5.471 | 3.882 |
| 11 | 6.493 | 1.279 | 3.783 | 1.160 | 25 | 6.778 | 3.154 | 3.955 | 5.456 |
| 12 | 7.016 | 3.579 | 7.345 | 4.700 | 26 | 10.664 | 7.314 | 10.019 | 8.743 |
| 13 | 8.590 | 8.550 | 8.838 | 8.374 | 27 | 7.463 | 5.323 | 7.867 | 7.649 |
| 14 | 4.953 | 2.414 | 5.095 | 5.312 | | | | | |

Tabel 6. Results of the Grey Relational and Reference Sequence

| No. | Sequences after data processing | | | | Deviation sequences ($\Delta_{ij}$) | | | |
|---|---|---|---|---|---|---|---|---|
| | Elegant | Youthful | Modern | Sporty | Elegant | Youthful | Modern | Sporty |
| $X_0$ | 1 | 1 | 1 | 1 | | | | |
| 1 | 0.2030 | 0.1187 | 0.4508 | 0.1099 | 0.7970 | 0.8813 | 0.5492 | 0.8901 |
| 2 | 0.2760 | 0.5394 | 0.2788 | 0.2975 | 0.7240 | 0.4606 | 0.7212 | 0.7025 |
| 3 | 0.1305 | 0.6903 | 0.5491 | 0.5643 | 0.8695 | 0.3097 | 0.4509 | 0.4357 |
| 4 | 0.5102 | 0.6359 | 0.6489 | 0.6716 | 0.4898 | 0.3641 | 0.3511 | 0.3284 |
| 5 | 0.1675 | 0.7516 | 0.5672 | 0.4785 | 0.8325 | 0.2484 | 0.4328 | 0.5215 |
| 6 | 0.5937 | 0.8594 | 0.5367 | 0.6654 | 0.4063 | 0.1406 | 0.4633 | 0.3346 |
| 7 | 0.3806 | 1.0000 | 0.7621 | 0.9796 | 0.6194 | 0.0000 | 0.2379 | 0.0204 |
| 8 | 0.5824 | 0.9595 | 0.7880 | 1.0000 | 0.4176 | 0.0405 | 0.2120 | 0.0000 |
| 9 | 0.4191 | 0.8327 | 0.4173 | 0.6730 | 0.5809 | 0.1673 | 0.5827 | 0.3270 |
| 10 | 0.3562 | 0.1266 | 0.4989 | 0.5539 | 0.6438 | 0.8734 | 0.5011 | 0.4461 |
| 11 | 0.2695 | 0.0137 | 0.0000 | 0.0000 | 0.7305 | 0.9863 | 1.0000 | 1.0000 |
| 12 | 0.3613 | 0.2884 | 0.5371 | 0.4459 | 0.6387 | 0.7116 | 0.4629 | 0.5541 |
| 13 | 0.6368 | 0.8819 | 0.7623 | 0.9087 | 0.3632 | 0.1181 | 0.2377 | 0.0913 |
| 14 | 0.0000 | 0.1493 | 0.1977 | 0.5229 | 1.0000 | 0.8507 | 0.8023 | 0.4771 |
| 15 | 0.8416 | 0.8532 | 1.0000 | 0.9500 | 0.1584 | 0.1468 | 0.0000 | 0.0500 |
| 16 | 0.8509 | 0.5676 | 0.9329 | 0.8273 | 0.1491 | 0.4324 | 0.0671 | 0.1727 |
| 17 | 0.2812 | 0.4556 | 0.4173 | 0.6674 | 0.7188 | 0.5444 | 0.5827 | 0.3326 |
| 18 | 0.6404 | 0.8757 | 0.8566 | 0.9642 | 0.3596 | 0.1243 | 0.1434 | 0.0358 |
| 19 | 0.2788 | 0.0000 | 0.0418 | 0.0324 | 0.7212 | 1.0000 | 0.9582 | 0.9676 |
| 20 | 0.4858 | 0.1287 | 0.5474 | 0.5188 | 0.5142 | 0.8713 | 0.4526 | 0.4812 |
| 21 | 0.3351 | 0.0074 | 0.0781 | 0.0492 | 0.6649 | 0.9926 | 0.9219 | 0.9508 |
| 22 | 0.2616 | 0.2427 | 0.3074 | 0.4946 | 0.7384 | 0.7573 | 0.6926 | 0.5054 |
| 23 | 0.9332 | 0.3678 | 0.8479 | 0.6392 | 0.0668 | 0.6322 | 0.1521 | 0.3608 |
| 24 | 0.2593 | 0.1639 | 0.2545 | 0.3428 | 0.7407 | 0.8361 | 0.7455 | 0.6572 |
| 25 | 0.3196 | 0.2376 | 0.0259 | 0.5411 | 0.6804 | 0.7624 | 0.9741 | 0.4589 |
| 26 | 1.0000 | 0.7344 | 0.9403 | 0.9551 | 0.0000 | 0.2656 | 0.0597 | 0.0449 |
| 27 | 0.4394 | 0.4967 | 0.6158 | 0.8173 | 0.5606 | 0.5033 | 0.3842 | 0.1827 |

Tabel 7. Results of the GRC and GRG

| No. | GRC | | | | GRG |
|---|---|---|---|---|---|
| | **Youthful** | **Modern** | **Sporty** | **Youthful** | |
| $X_0$ | | | | | |
| 1 | 0.3855 | 0.3620 | 0.4765 | 0.3597 | 0.3959 |
| 2 | 0.4085 | 0.5205 | 0.4094 | 0.4158 | 0.4385 |
| 3 | 0.3651 | 0.6175 | 0.5258 | 0.5343 | 0.5107 |
| 4 | 0.5052 | 0.5786 | 0.5875 | 0.6036 | 0.5687 |
| 5 | 0.3752 | 0.6681 | 0.5360 | 0.4895 | 0.5172 |
| 6 | 0.5517 | 0.7806 | 0.5191 | 0.5991 | 0.6126 |
| 7 | 0.4467 | 1.0000 | 0.6776 | 0.9607 | 0.7712 |
| 8 | 0.5449 | 0.9251 | 0.7022 | 1.0000 | 0.7931 |
| 9 | 0.4626 | 0.7493 | 0.4618 | 0.6046 | 0.5696 |
| 10 | 0.4372 | 0.3641 | 0.4995 | 0.5285 | 0.4573 |
| 11 | 0.4064 | 0.3364 | 0.3333 | 0.3333 | 0.3524 |
| 12 | 0.4391 | 0.4127 | 0.5193 | 0.4743 | 0.4613 |
| 13 | 0.5792 | 0.8090 | 0.6778 | 0.8456 | 0.7279 |
| 14 | 0.3333 | 0.3702 | 0.3839 | 0.5117 | 0.3998 |
| 15 | 0.7595 | 0.7730 | 1.0000 | 0.9090 | 0.8604 |
| 16 | 0.7703 | 0.5363 | 0.8817 | 0.7433 | 0.7329 |
| 17 | 0.4102 | 0.4788 | 0.4618 | 0.6005 | 0.4878 |
| 18 | 0.5817 | 0.8009 | 0.7771 | 0.9332 | 0.7732 |
| 19 | 0.4094 | 0.3333 | 0.3429 | 0.3407 | 0.3566 |
| 20 | 0.4930 | 0.3646 | 0.5249 | 0.5096 | 0.4730 |
| 21 | 0.4292 | 0.3350 | 0.3516 | 0.3446 | 0.3651 |
| 22 | 0.4037 | 0.3977 | 0.4192 | 0.4973 | 0.4295 |
| 23 | 0.8822 | 0.4416 | 0.7667 | 0.5809 | 0.6678 |
| 24 | 0.4030 | 0.3742 | 0.4014 | 0.4321 | 0.4027 |
| 25 | 0.4236 | 0.3961 | 0.3392 | 0.5215 | 0.4201 |
| 26 | 1.0000 | 0.6531 | 0.8933 | 0.9176 | 0.8660 |
| 27 | 0.4714 | 0.4984 | 0.5655 | 0.7324 | 0.5669 |

Table 8. Response Table of GRG

| Factor | Design parameter | GRG average | | | Max-Min |
|---|---|---|---|---|---|
| | | **Level 1** | **Level 2** | **Level 3** | |
| A | H/L | 0.5753 | 0.5837[a] | 0.5053 | 0.0784 |
| B | $L_F/L$ | 0.4234 | 0.5763 | 0.6253[a] | 0.2019 |
| C | $H_F/H$ | 0.5377 | 0.5358 | 0.5907[a] | 0.0549 |
| D | $\theta_1$ | 0.5762[a] | 0.5430 | 0.5450 | 0.0332 |
| E | $\theta_2$ | 0.5400 | 0.5551 | 0.5692[a] | 0.0292 |
| F | $\theta_3$ | 0.6486[a] | 0.5557 | 0.4599 | 0.1887 |
| G | $L_R/L$ | 0.4790 | 0.5611 | 0.6242[a] | 0.1452 |
| H | $H_R/H$ | 0.5814[a] | 0.5444 | 0.5385 | 0.0429 |
| I | $\theta_4$ | 0.5738[a] | 0.5536 | 0.5369 | 0.0369 |
| J | $\theta_5$ | 0.5676[a] | 0.5329 | 0.5638 | 0.0347 |
| K | $\theta_6$ | 0.5227 | 0.5626 | 0.5789[a] | 0.0562 |
| L | $\theta_7$ | 0.4951 | 0.5681 | 0.6011[a] | 0.1060 |
| M | $\theta_8$ | 0.5654 | 0.5656[a] | 0.5332 | 0.0325 |
| Total mean value of the GRG = 0.5548 | | | | | |

[a] Maximum design parameter level

ratio were first transferred into comparable sequences for the grey relational generating process via data normalization. For each Kansei word response, the S/N ratio of the larger-the-better performance characteristic was considered in this study. As a result, for the grey relational generating process, the normalized data of the larger-the-better transformation was assumed. Hence, the grey relational generating process was calculated using equation (5), and the result for each combinative product form design based on the respective Kansei criterion are presented in

Table 9. ANOVA Results of GRG

| Factor | Design parameter | DF | SS | MS | F-value | CP (%) |
|---|---|---|---|---|---|---|
| A | H/L | 2 | 0.0333 | 0.0167 | 2.9137 | 4.86 |
| B | $L_F/L$ | 2 | 0.2042 | 0.1021 | 17.8542 | 29.76 |
| C | $H_F/H$ | 2 | 0.0175 | 0.0088 | 1.5302 | 2.55 |
| D | $\theta_1$ | 2 | 0.0063 | 0.0031 | 0.5468 | 0.91 |
| E | $\theta_2$ | 2 | 0.0038 | 0.0019 | 0.3346 | 0.56 |
| F | $\theta_3$ | 2 | 0.1603 | 0.0802 | 14.0174 | 23.36 |
| G | $L_R/L$ | 2 | 0.0955 | 0.0477 | 8.3481 | 13.91 |
| H | $H_R/H$ | 2 | 2 | 0.0097 | 0.0049 | 0.8504 |
| I | $\theta_4$ | 2 | 2 | 0.0061 | 0.0031 | 0.5376 |
| J | $\theta_5$ | 2 | 2 | 0.0065 | 0.0033 | 0.5691 |
| K | $\theta_6$ | 2 | 2 | 0.0151 | 0.0075 | 1.3162 |
| L | $\theta_7$ | 2 | 2 | 0.0530 | 0.0265 | 4.6320 |
| M | $\theta_8$ | 2 | 2 | 0.0063 | 0.0031 | 0.5497 |
| | Error | 12 | 12 | 0.0686 | 0.0057 | 10 |
| | Total | 38 | 38 | 2.1146 | | 100 |
| | $F_{0.05(2,12)}$ = 3.88 | | | | | |

columns 2 to 5 of Table 6. As can be seen in Table 6, $X_0$ is defined as the reference sequence; in addition, $\Delta_{ij}$ was calculated and presented in columns 6 to 9. After calculating $\Delta_{min}$ and $\Delta_{max}$, $\zeta$ is set at 0.5, then all GRCs were enumerated using equation (7). The distinguishing coefficient ($\zeta$) = 0.5 is used, since this value usually provides moderate distinguishing effects and good stability [54]. The results of the GRC for each Kansei response are presented in columns 2 to 5 of Table 7. When calculating the GRG, the relative importance of all the performance characteristics was assumed to be equal. Therefore, based on equation (9) where the overall sum of the weighting values equal to 1, the weighting values of each Kansei responses were set as 0.25. Using equation (8), the GRG was calculated for each Kansei response, and the results are presented in column 6 of Table 7. Table 8 shows the individual GRG response table for each level of each design parameter, as well as the effects of the associated factor. Each parameter's factor effect represents the difference in GRG between the maximum and minimum levels of a single design parameter. A greater effect indicates that the design parameter has a more significant impact on the GRG. Essentially, a higher GRG indicates a greater influence factor effect of the multiple performance characteristics. According to Table 8, the sequence of the individual factor effect is B-level 3 > F-level 1 > G-level 3 > L-level 3 > A-level 2 > K-level 3 > C-level 3 > H-level 1 > I-level 1> J-level 1 > D-level 1 > M-level 2> E-level 3.

According to ANOVA shown in Table 9, the data from this table can be linked to the data in Figure 4, which shows that B, F, G,

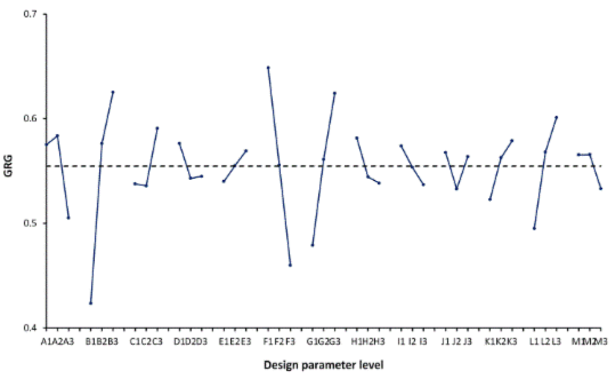


Figure 4. Response Graph of GRG

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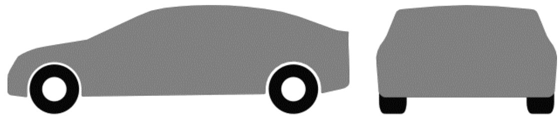
L, and A have the most significant contributions at 29.76%, 23.36%, 13.91%, 7.72%, and 4.86%, respectively. This is due to their corresponding F values being greater than 3.88, which is the critical value of F0.05(2,12) from the Fisher's F-test table. The contributions of the other eight design parameters (C, K, H, J, M, D, I and E) are 2.55%, 2.19%, 1.42%, 0.95%, 0.92%, 0.91%, 0.90%, and 0.56% respectively. As a result, B, F, G, L, and A are the primary design parameters influencing the performance characteristic. Furthermore, Table 9 shows that the percentage of contribution error is 10%, indicating that the experiment has high feasibility and sufficiency. If the percentage of error is less than 15%, the experiment is acceptable without ignoring the major factor; if the percentage of error is greater than 50%, the experiment is unacceptable and some significant factors are lost [55], [56]. Therefore, the multi-response optimization using grey-based TM has been proven to be highly acceptable.

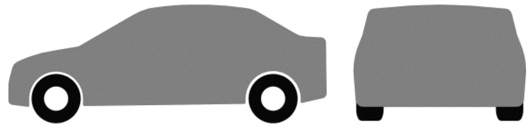
*Confirmation Test*

After the optimal car form design has been determined using the grey-based TM, the final step is confirmation test. A confirmation test was conducted to verify the performance of the optimal product form design generated and the ability of the integrative product form design optimization method using grey-based TM in designing the optimal product form that satisfy the multi-response problem of Kansei needs. Because of KE is based on the consumers' response or consumer-oriented product design, a questionnaire experiment was carried out to verify the performance of the optimal product form design generated with comparing it to the latest cars model which currently available in the market. There are two Malaysian national cars which are chosen to be compared with the optimal designs generated for products competition in experiment. Each of these cars were then converted into a 2D image silhouette in accordance with its specified form parameter level setting and controlled to be the same as the design sample used in our Taguchi experiment. Figure 7 show the compared designs used in this confirmation test.

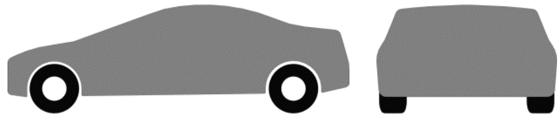
In the comparative evaluation, 80 subjects were taken apart for the confirmation test, 40 males and 40 females ranging in age from 18 to 56 years. The subjects were asked to rank the three design samples on each of four Kansei word responses using the semantic differential method with a 5-point Likert scale. Calculating the data scores for the confirmation test results yielded the S/N ratio of evaluation on each Kansei words response (Tabel 10). It shows that the optimal design concept generated by the grey-based TM (product form design no. 3) outperformed the compared designs in the majority of Kansei responses and overall performance as it obtained the highest Kansei response in terms of elegant, modern, and sporty. Further investigation was conducted using a performance evaluation based on the ranking score to investigate the ability of the integrative product form design optimization method. The S/N ratio magnitude was used to rank the performance of each car form design in each Kansei response (Table 10). The ranks of




a) Design Concept of Competitor 1




b) Design Concept of Competitor 2




b) Design Concept using Grey-based Taguchi Method

Figure 7. Comparison of Design Concept

Table 10. Results of Confirmation Test

| No. | Product Form Design | S/N Ratio | | | | Overall Performance | GRG |
|---|---|---|---|---|---|---|---|
| | | Elegant | Youthful | Modern | Sporty | | |
| 1 | Design concept of Competitor 1 | 8.096 | 6.208 | 9.261 | 8.393 | 7.989 | 0.7145 |
| 2 | Design concept of Competitor 2 | 4.879 | 5.739 | 5.429 | 4.814 | 5.215 | 0.3333 |
| 3 | Optimal design concept generated using Grey-based TM | 11.613 | 5.444 | 11.434 | 8.946 | 9.359 | 0.8779 |
| Best performance in Taguchi's OA experiment | | 10.664 | 7.314 | 10.019 | 8.743 | 9.185 | |
| Improvement in S/N ratio | | 0.949 | (1.870) | 1.415 | 0.203 | 0.174 | |
| Best performance in GRG | | | | | | | 0.8660 |
| Improvement in GRG | | | | | | | 0.0119 |

Table 11. Results of Performance Evaluations by Ranking Score

| No. | Product Form Design (PFD) | Performance Order of Each PFD in Each Response | | | | Total Score |
|---|---|---|---|---|---|---|
| | | Elegant | Youthful | Modern | Sporty | |
| 1 | Design concept of Competitor 1 | 2 | 3 | 2 | 2 | 9 |
| 2 | Design concept of Competitor 2 | 1 | 2 | 1 | 1 | 5 |
| 3 | Optimal design concept generated using Grey-based TM | 3 | 1 | 3 | 3 | 10 |

first, second, and third were then assigned points of 3, 2, and 1, respectively. Table 11 shows the computation results of each car form design's performance evaluation in each Kansei response based on the ranking score. For example, car form design no. 3 was scored with 3 point three times and once with 1 point, and its total score was 10 (3 x 3 + 1 = 10). It also reveals that the optimal design concept generated by the grey-based TM received the highest total score.

Additionaly, the optimized design was compared to the best S/N ratio performance in each Kansei response in the Taguchi's OA experiment, which was used as a reference of comparison. The results confirmed that, in general, the optimal combination of design parameters generated using the grey-based TM is capable of effectively improving the car form design quality with Kansei multi-response characteristics, leading to higher performance, despite the fact that there was no improvement in the Kansei response of the youthful.

## CONCLUSION

A multi-response optimization method using the grey-based TM has been applied for the integrative product form design optimization method. In KE, the grey-based TM was able to effectively determine the optimal design parameters combination of a product design with the multi-response problem. Therefore, the grey-based TM is a useful tool for designers because it combines the advantages of both the TM and the GRA, as well as the following advantages. First, unlike the standard KE methodology, where increasing the number of design parameters results in an increase in the number of experiments required, the grey-based TM is carried out with fewer experiments. This means that the grey-based TM can reduce the complexity of the process to complete the product for design evaluation, which takes time and other resources, and involves high cost. Hence, the grey-based TM is a time- and cost-effective method. Second, in KE, the grey-based TM can handle the multi-response optimization problem for product form design. Furthermore, based on the empirical case study, the results of the analysis of variance clearly show that the consumer Kansei product performance is significantly influenced by the ratio of the fore region's length to the overall length, the gradient of the A-pillar, the ratio of the rear region's length to the overall length, the gradient of the rear fender's bottom, and the ratio of the car's height to the car's length as the major design parameters of the car form design with a total contribution of 79.61%.

In general, unlike the original TM [21], [22], which was only used to determine the optimal combination of each design parameter of a product for each corresponding Kansei response, the grey-based TM was systematically able to determine the optimal combination of a product's design parameter that still represents the customers' multi-Kansei response in a single product design.

In this study, the procedure for calculating the GRG, the corresponding weighting value of the various responses is assigned by the users' subjective judgment or estimation and does not take into account the structure of the problem. Therefore, future studies on the integrative design optimization method would concern the identification of the corresponding weighting value of the various response based on the structure of its response problem. The effectiveness of this approach can also be a useful tool for the designers and decision-makers in other relevant KE applications.

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## NOMENCLATURE

| | | |
|---|---|---|
| DF | : | Degree of freedom |
| SS | : | Sum of square |
| MS | : | Mean square |
| CP | : | Contribution percentage |
| $y_{ij}$ | : | The experimental value |
| $\bar{y}_{ij}$ | : | The mean of the experimental value |
| $n$ | : | The number of the test |
| $s^2$ | : | The variance |
| $x_{ij}$ | : | The sequence obtained after the normalizing the data |
| $\eta_{ij}$ | : | The original sequence of the S/N ratio |
| $\eta_{ij}*$ | : | The desired value of the S/N ratio |
| $X_0$ | : | The reference sequence |
| $\zeta$ | : | The distinguishing coefficient |
| $w_j$ | : | The weighting value of the criterion |

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