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RESEARCH PAPER

A two-phase hybrid product design algorithm using learning vector quantization, design of experiments, and adaptive neuro-fuzzy interface systems to optimize geometric form in view of customers' opinions

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Abstract

One of the most important characteristics of a modern product is the extent to which it meets the needs of customers to gain market share. The conceptual design methods of products based on customer requirements are often feature-based, in which several features are identified between different types of a product. According to customer demands, these features are tuned and the closest is selected as the optimum. The great variety of features of a present-day product can often make this difficult because finding these common features is very complicated or even impossible. To solve this problem, choosing the optimal design is divided into two phases: In the first phase, the main product is divided into some basic categories and based on the customers' opinion, one is selected as the "winning category". In the second phase, the selection of common geometrical features between the members of the winning category is made. Then, the optimization process is done based on customer rating and the closest design to the mentioned rating is selected. The house light switch is used as a case study and the proposed algorithm is implemented on it. High customer satisfaction with the optimized final design, high response rate to survey forms, and the low number of incompatible data, all, indicate the suitability of the proposed algorithm with human interface characteristics, simplicity and efficiency in adapting the product to the customers' view. This method can be used for other industrial products and even for non-industrial products or services.

Keywords: Product Design, Geometric Form, Design of Experiments (DOE), Learning Vector Quantization (LVQ), Adaptive Neuro-Fuzzy Interface System (ANFIS)

1. Introduction

The design of a product consists of various "non-engineering" and intricate aspects which need to be profoundly inspected in order for the product to express a competent presence in the market. As far as the design process of a product is concerned, customer considerations have been of crucial significance for most modern designers and engineers. Manufacturers have traditionally focused on consumers' preferences as a strategic guiding light for designing successful products [1]. The evaluation of each individual design candidate in terms of its ability to meet the demands of the market is a crucial step within the conceptual design stage. In recent years, there is a growing interest in shape design due to the effectiveness of the shape optimization for improving the quality

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characteristics of the products [2]. Hence, optimizing the geometric characteristics of a product, especially from aesthetic perspectives, makes a great deal of contribution to the quality of the product and customer satisfaction.

In the process, modern mathematical patterns and algorithms have shown to be of great reliability and robustness, especially when experimental data and product feature categorizations are involved [2, 3]. DOE-based methods have significantly reduced the number of experiments required to evaluate the effectiveness of any design parameter on the final result or output [4]. In addition, evolutionary-based optimization methods are generally known to be of better robustness compared to other conventional random search methods in terms of a more probable global optimization. Data clustering methods are also becoming a trend in many Engineering problems; Agard, Kusiak [5]—as well as Moon, Kumara, Simpson [6]—suggested that K-means method can be effectively conducted in order to classify product design families; Wu [7] conducted LVQ to classify mechanism types in the course of conceptual design; and finally, Yang [8] applied a type of SVM along with Kansei Engineering principles to the classification of product form features. Furthermore, a design process which consists of successive interactions with the customers—be it in the form of surveys, interviews, rating polls, and so on—and a thorough analysis of the results of those interactions would inevitably lead to a watertight design in terms of customer psychological satisfaction and product credibility. Many similar design approaches have previously shown to be rather effective in conducting a powerful mutual relationship between the design experts and the customers [3, 9-11].

Feature-based algorithms have proved to be abundant in research carried out up to present. These design systems are powerful tools that incorporate the use of features in the process of modeling. They allow product geometry to be represented by higher-level entities which relate directly to certain design functionalities or manufacturing characteristics [12]. These systems have been predominantly adopted for product development in industries [13], and have shown to forge a strong interconnection between product design (CAD), manufacturing (CAM), and process planning (CAPP) [12, 14-16]. Such systems benefit design approaches in both facilitating design manipulations for the user and allowing a geometric reasoning system to perform tasks such as manufacturability analysis, design verification, and heuristic design optimization [12].

In feature-based algorithms, some common features among different groups of a product are identified and, based on these features, rating surveys are conducted among customers. Considering the variety of new products, it is difficult or sometimes impossible to implement such methods because there are times when some of the features in one specific category of a product are completely absent in the other. One primary solution is to consider common features among all the groups of the product. This approach, however, risks limiting the number of features, so much so that studying those features would practically suffer from sufficient precision.

Considering the mentioned difficulties, we seek to propose a method which eliminates such drawbacks, and then we would implement the very method on a case study to assess its practicality. In addition to solving the problems mentioned, our method should possess sufficient flexibility in order to provide grounds for its implementation on various products. Also, since the ratings are done by actual people, this method should be consistent with the aspects of human reasoning – i.e. incorporate some type of fuzziness. Other advantages include being computationally cost-effective and easily applicable. Moreover, a method for validating the results should be proposed.

Accordingly, a two-phase method is suggested. In the first phase, the product is categorized into a number of main groups. For instance, a home light switch can be categorized into main groups such as “antique”, “modern”, “smart”, and so on. The groups would most desirably be not too many. At this stage, appropriate classification methods are implemented to determine the winning group or category using customers’ ratings. Classification methods based on neural networks seem to be rather practical in this regard. The most important aspect of the members of the winning category is that they possess several noticeable common features. If it had been otherwise, product categorization might have to be reconsidered or corrected.

In the second stage, common features among the members of the winning category are identified, and with a focus on their geometric features, ranges are assigned to their values. After tuning those geometric features on specific levels inside their specified ranges—using DOE—and creating 3-D CAD models, these experimental design candidates are rated by the customers. DOE-based methods are extremely helpful in the process in terms of reducing the number of experiments needed to assess the design candidates. Using the level of the features as input and the score as output, a fitness function is developed to be optimized for an optimal design solution. Such a function could be acquired using an artificial neural network. To find the global optimal design solution, the optimization process should be capable of finding all the optima while still remaining cost-effective, and meta-heuristic methods such as Genetic Algorithm, create such conditions. Consequently, the optimal values for each of the features, which represent a condition most consistent with customers’ ratings, are determined. To validate the results, a 3-D model is created with the parameters now set on their optimal values. Customers are once more asked to rate this design, and if the results were higher than a specific threshold, the validation would be satisfactory.

In the present study, first, in section 2, the research methodology, including phases one and two of the proposed algorithm, is described in terms of theory and implementation in a step by step manner. In section 3, the algorithm is implemented in a case study, house lighting switch, and the final design is presented. Section 4 includes a discussion of the results and the degree of appropriateness and efficiency of the proposed algorithm, which states whether the existing method answers the basic research questions or not. In section 5, the research conclusion is presented and references are listed at the end.

2. Methodology

As noted in the introduction, in feature-based methods, some common features among all the different categories of a product are identified and then rated by the experts. On the other hand, the variety of new products would make it almost impossible to do so because there are some features in one specific category of the product which are completely absent in another. Furthermore, if we consider only the common features, our study would end up with a lack of satisfactory precision.

To solve this issue, a two-phase algorithm is introduced as follows; in the first phase, we divide the product into main categories consisting of more common types of features amongst them; in the second phase, optimization shall be carried out on the features of the winning (chosen) category—decided in the first phase.

2.1. *Phase-1: Categorization and Deciding the Winning Category*

2.1.1. *Choosing the Main Categories of the Product and Deciding the Features of each Category*

One of the most proper ways to select the various categories of a product is to use the tags and labels provided by online shopping sites, relevant product catalogues and websites, and design encyclopedia provided online by experts. Assume we have some m images and we could divide them into p main groups. Now, we must identify the characteristics – and not necessarily the features – common amongst the members of each group. For instance, luxury could be a common characteristic among the products with an ornamental perspective. We assume that the number of these common characteristics is n. To evaluate each member in terms of having a particular characteristic, design experts are provided with the images along with a list of possible characteristics. Considering properties of human inference and the approximate aspect of the opinions of the experts, a fuzzy method as of Table 1 was proposed.

Table 1. Linguistic Variables and their equivalent fuzzy triangular numbers [17].

Linguistic Variables	Triangular Fuzzy Numbers (TFN)
Very Low (VL)	(0,0,0.1)
Low (L)	(0,0.1,0.3)
Medium Low (ML)	(0.1,0.3,0.5)
Medium (M)	(0.3,0.5,0.7)
Medium High (MH)	(0.5,0.7,0.9)
High (H)	(0.7,0.9,1)
Very High (VH)	(0.9,1,1)

The scores given by the experts were fuzzy, and to transform them, the crisp form of the number was used. Assuming the fuzzy triangular number for a fuzzy linguistic variable is in the form of (l,m,n), in which l is the lower boundary, m is the middle point, and u is the upper boundary of the fuzzy number, its equivalent crisp number could be evaluated as below [18]:

$$crisp(l,m,u) = \frac{l + 2m + u}{4} \tag{1}$$

The scores given by expert q are then represented as a matrix A^q in the following form:

$$A^q = \begin{bmatrix} a_{11}^q & \cdots & a_{1n}^q \\ \vdots & \ddots & \vdots \\ a_{m1}^q & \cdots & a_{mn}^q \end{bmatrix} = \left[a_{ij}^q\right]_{m\times n} \tag{2}$$

where a_{ij}^q is the qth expert's score of the ith image in terms of possessing the jth characteristic.

After completing the matrix A^q, $q = 1, \dots, t$, (meaning that all the experts are done with the scoring of the images with respect to the characteristics), matrix X can be defined as the mean score matrix of all the experts, as follows:

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} = \left[x_{ij}\right]_{m\times n} \tag{3}$$

where:

$$x_{ij} = \frac{\sum_{q=1}^{t} a_{ij}^{q}}{t} \tag{4}$$

To form the characteristic vector for each category, assuming an equal number of images for each group, a total of m images, a total of p groups, and equal number of images represented to each expert ($\frac{m}{p}$ images in each group), we have:

$$M = \left[M_{kj}\right]_{p\times n} \tag{5}$$

where

$$M_{kj} = \frac{\sum_{i=1+\frac{m}{p}(k-1)}^{\frac{m}{p}k} x_{ij}}{m/p} \qquad \begin{matrix} k = 1.\dots.p \\ j = 1.\dots.n \end{matrix} \tag{6}$$

And therefore, M_{kj} is the mean score of possessing the jth characteristic for the ith group.

2.1.2. *Rating images, by the customers and calculating their Cumulative Scores*

To collect customer ratings, some of the images were randomly shown to each customer via a rating poll—as such that there was equal number of images selected from each group. Defining the score the uth customer gives to the ith image by $\tilde{Z}_i^u$ and the number of scores recorded for the ith image by L_i—note that since the images are randomly chosen, some images might have more scores recorded than others—and assuming that $\tilde{Z}_i^u$ have a fuzzy characteristic, their crisp equivalent would then be calculated using Eq. (1) and represented as $Z_i^u = crisp\left(\tilde{Z}_i^u\right)$. Now the mean of the scores for the ith image can be represented as:

$$Z_i = \frac{\sum_{u=1}^{L_i} Z_i^u}{L_i} \tag{7}$$

And finally, the customers' score vector would be defined as follows:

$$Z = \begin{bmatrix} Z_1 \\ \vdots \\ Z_m \end{bmatrix} = [Z_i] \tag{8}$$

To calculate the customers' cumulative scores with respect to the characteristics, Eq. (9) below is used, in which C_j is the final customers' score regarding the jth characteristic:

$$C_j = \frac{\sum_{i=1}^{m} Z_i \, x_{ij}}{m \sum_{i=1}^{m} Z_i} \tag{9}$$

where $j = 1.\dots.n$, and the final customers' scores vector would be $C = \left[C_j\right]$.

2.1.3. *Deciding the Winning Category with respect to Customers' Point of View*

To determine the winning category, LVQ (Learning Vector Quantization) has been implemented as a neural network-based classification method which benefits from competitive learning [19-21]. An LVQ network would consist of three layers, each described as follows:

- *Input Layer*: in which a node is provided for each component of the input vector
- *Kohonen Layer*: which learns and acts as the classifier
- *Output Layer*: in which a node is provided for each category or group

Figure 1 indicates the structure of an LVQ network.

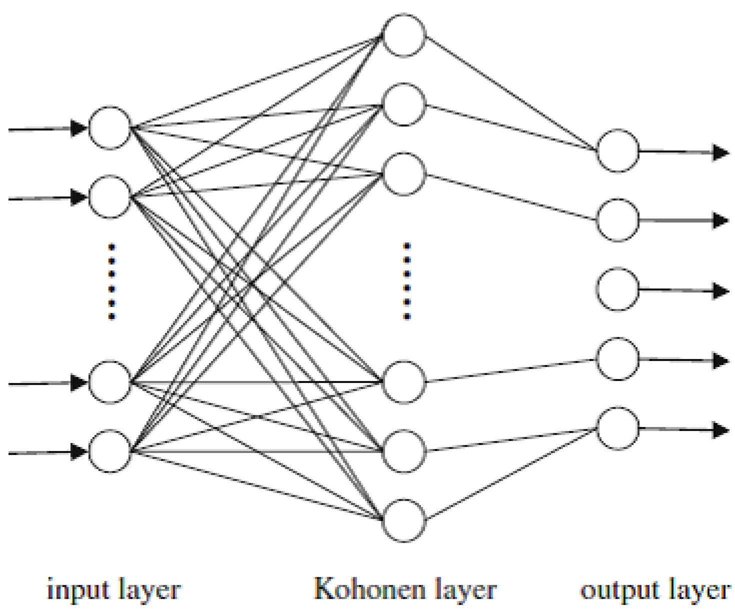

Figure 1. LVQ Structure [20].

During the learning process, the Euclidean distance of the learning vector, x, with the weighted vector for each node in the Kohonen layer, w_i, is calculated using Eq. (10) as below:

$$d_i = ||w_i - x|| = \left\{ \sum_{j=1}^{N} (w_{ij} - x_j)^2 \right\}^{\frac{1}{2}} \tag{10}$$

The nearest node would decide the winner so that its weighted vector would be adjusted depending on the class in which the winning node falls. Then, the two following conditions will be examined:

1) If the winner is the correct class, then:

$$w_{i+1} = w_i + \alpha(x - w_i) \tag{11}$$

2) If the winner is not the correct class, then:

$$w_{i+1} = w_i - \gamma(x - w_i) \tag{12}$$

in which w_{i+1} is the weighted vector after adjustment, w_i is the weighted vector before adjustment, and α and γ are learning parameters. The stopping criterion in which the program terminates is the maximum iteration, defined by the user.

After the program terminates and the training process concludes, the weights are adjusted so that the network could imitate the behavior of the data and decide the category or class into which unknown input data would fall. It goes without saying that the relations above are rather nonlinear and complex.

2.2. *Phase-2: Determining Optimal Design using Customers' Scores*

In this phase, a number of common geometric features among the members of the winning category are investigated, and their values are tuned in a specific range. Then their optimal values – those most corresponding to the customers' scores – are found using an evolutionary optimization method (GA). To do so, the following steps are taken.

2.2.1. *DOE-based Process on the Winning Category*

The design of Experiment processes such as Simple Factorial Design and Central Composite Design are usually complicated and their implementations are generally problematic. As the number of factors increases, the number of experiments to be carried out increases too. To solve this problem, Taguchi proposed specific standard orthogonal arrays by which simultaneous and independent evaluation of two or more factors were made possible [22]. These orthogonal arrays have been defined so that, compared to classic approaches, fewer experiments are required. Here, a loss function is defined as the difference between the results of the experiments and the desired values. Depending on the nature of the problem at hand, this loss function can be defined as SB (smaller is better), LB (larger is better), or NB (nominal is better). In our case, since we aim to maximize the scores obtained from the customers, the nature of the problem is LB. The loss function mentioned is then defined as a Signal to Noise ratio (S/N ratio), represented by η, where:

$$S/N = \eta = -10 \log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right) \tag{13}$$

when n is the number of experiments—defined by the orthogonal arrays—and y_i is the result of each experiment. Followed by the formulation above, ANOVA is also usually implemented to determine which factor is more effective and weighs a heavier impact on the results. Using both S/N and ANOVA, the optimal combination of the design factors (a combination of factors at different levels) is determined.

2.2.2. *Modeling Customers' Scores using ANFIS*

Adaptive Neuro-Fuzzy Interface Systems are artificial neural networks consisting of five layers: layer one, input layer; layer two, fuzzy operation; layer three, normalization; layer four, normalization of each rule firing strength, and layer five, output layer. Figure 2 shows the general structure of an ANFIS in its simplest form for a system with inputs of g and h [23-25].

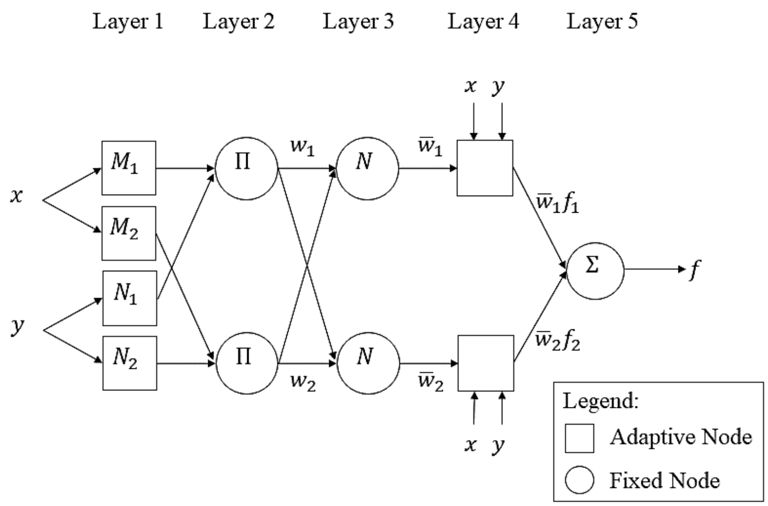

Figure 2. General Structure of ANFIS for a system with inputs of **g** and **h.**

The output of ANFIS is a combination of its inputs and does not signify a fuzzy nature. Hence, it is regarded as a Sugeno type of network. Two rules applying to the system in Figure 2 can be represented as follows:

1) If g is A_1 AND h is B_1, then $f_1 = p_1 g + q_1 h + r_1$ (14)

2) If g is A_2 AND h is B_2, then $f_2 = p_2 g + q_2 h + r_2$ (15)

To train this network, first, the input vector moves through the network in a Forward Pass. Then the error between the actual output and the desired output would propagate backward through the network in a Backward Pass, a process similar to error backpropagation in artificial neural networks. In the first layer, the output of each node would be calculated using Eq. (16) and Eq. (17):

$$O_{1i} = \mu_{A_i}(g) \qquad for\ i = 1.2 \tag{16}$$

$$O_{1i} = \mu_{B_{i-2}}(h) \qquad for\ i = 3.4 \tag{17}$$

Therefore, O_{1i} demonstrates the degree of membership for every member of the inputs group. The Membership Function μ could be any function such as sigmoid, bell-shaped, and so on.

In the second layer, each fixed node has an output calculated as below:

$$O_{2i} = w_i = \mu_{A_i}(g)\mu_{B_i}(h) \qquad for\ i = 1,2 \tag{18}$$

In the third layer, the firing strength of each rule would be calculated from Eq. (19):

$$O_{3i} = \overline{w}_i = \frac{w_i}{\sum w_i} \tag{19}$$

In the fourth layer, the nodes have an adaptive manner and their outputs are determined using Eq. (20):

$$O_{4i} = \bar{w}_i f_i = \bar{w}_i (p_i g + q_i h + r_i) \quad (20)$$

Evidently, the network parameters p_i, q_i, and r_i have to be determined through the course of training in order to emulate the behavior of our data. In the fifth layer, there exists a single node which is a linear combination of the outputs derived from the fourth layer. The final output would then be obtained according to Eq. (21):

$$O_{5i} = \sum \bar{w}_i f_i = \frac{\sum w_i f_i}{\sum w_i} \quad (21)$$

At this stage, considering the number of common geometric features amongst the members of the winning category, their respective orthogonal array is used to determine the values of the features in order to approach DOE. Using a CAD modeling software, these features are assigned their respective DOE values and then the created models are rendered (photographically visualized) in order to be rated by the customers in a fuzzy manner through rating polls—Google Forms with the images of the experimental models in random scrambled order. The results of this fuzzy rating survey would be transformed in the form of crisp using Eq. (1), and then normalized to the range of $[0,1]$. S/N ratio charts would then be applied to the resultant data as described in section 2.2.1, as well as an initial optimal value evaluation for the features – their optimal levels as design factors corresponding to the best score among the customers – using the very charts. Meanwhile, ANOVA would demonstrate the effectiveness of each design feature (factor). These data, meaning the scores by the customers, would now contribute to the training of ANFIS, a system working as the objective function for later optimization of the design features.

2.2.3. *Optimization of the Winning Geometry using GA*

The genetic Algorithm is one of the general-purpose stochastic search methods, especially suitable for complex optimization problems [26]. The main concept of GA is to emulate Natural Selection and Survival of the Fittest. This algorithm starts with creating an initial population of answers, followed by successive implementations of the GA Operators—i.e. Selection, Crossover, and Mutation—which is capable of reserving the parts of the solution necessary for creating a global optimal solution. GA-based methods have shown to be much more robust compared to conventional gradient-based methods [23]. One of the fundamental flaws of gradient-based methods is the computational cost concerning its development [23, 25]. Other major problems with such methods include running into noisy objective function spaces, imprecise gradients, and conflict with design variables with categorical natures and topology optimization [25]. On the other hand, GA has no problem dealing with any of the situations above. In fact, GA simultaneously expands the span of the answers in various directions, which would eventually raise the chances of finding the optimum solution [27].

In the current research, the cost function consists of the model created in section 2.2.2 using ANFIS and is normalized in the range of zero to one. In keeping with the purpose of the study, the most desirable condition is to maximize the value given by this function. To adopt this approach for the usual approach to GA—i.e. minimizing the cost function—the normalized output would be multiplied by -1, and so we have:

$$\textit{Fitness Function} \qquad f(x_1.\dots.x_n) = -f_{ANFIS}(x_1.\dots.x_n) \tag{22}$$

The resulting model with the geometric features at optimal values is compared with that obtained from Taguchi's analysis and is then once more evaluated by the customers to assure the reliability of this approach.

3. Implementation of the Proposed Method in a Case Study

3.1. *Implementation of the First Phase*

The product chosen for this purpose is the house light switch. With a search through online shopping sites, relevant product catalogues and websites, and design encyclopedia provided online by experts, it could be understood that there exist various types of this product. Using the tags and labels available at the sources mentioned, six categories of the light switches were discovered, including analog, mechanical touch, normal, push-button, smart touch, and vintage. Now if ten images were to be selected for each group, there would be 60 images of the product in total. In other words, here, $m = 60$ and $p = 6$. A few examples of these images are shown in Figure 3.

Figure 3. Examples of house light switches found on the internet (images courtesy of 'credentials').

A group of five Industrial Design experts were provided with all the images to each propose common characteristics among the categories. The opinions of the experts conclude a stamp of approval used to the proposition that five characteristics, namely "modernity", "loudness", "unity", "smartness", and "luxury", could be proposed as common characteristics among all the types of house light switches. In the next step, the experts were asked to rate each of the 60 images in terms of having the characteristics above using linguistic variables mentioned in Table 1. An example of such a rating table is shown in Table 2.

Table 2. An example of the table used for rating the images by the experts.

Experts	Category	Modernity	Loudness	Unity	Mechanical (0) or Smart (5)	Luxury
Expert 1	Analog	2	2	2	1	3
	Mechanical Touch	4	1	4	4	4
	Normal	2	4	3	0	2
	Push Button	4	3	3	1	3
	Smart Touch	5	0	4	5	4
	Vintage	1	4	2	0	4

The order of the images in the table is according to their category; for instance, images 1 to 10 fall into the “analog” category, while images 11 to 20 fall into the “mechanical touch” category. Also, the key letters used here refer to the linguistic variables of Table 1.

As for the next step, the scores resulting from the ratings by the experts were transformed into their crisp form using Eq. (1), and using each of the experts’ ratings, $q = 1 \; to \; 5$, the matrices A^q were constructed. Here, using Eq. (3) and Eq. (4), the mean score matrix of all the experts, X, was created as in Table 3.

To create the characteristic vector of each category, using Eq. (5) and Eq. (6) and by averaging the weighted scores of each category, matrix M was created as shown in Table 4.

In the next stage, the customers had to be asked to rate the images. Since we did not want the customers participating in the rating process to end up with a frustrating experience, some sets of Google Forms were created, each having 18 random images (three images from each category). These Google Forms were randomly created in a way that the categories could not be identified using the order of the images. After the process, the level of their satisfaction with the design—how desirable a design was to the customers—were collected in the form of fuzzy linguistic variables. Again, these fuzzy linguistic variables were transformed into the form of crisp and Z_i^u was determined for each image. Here, considering the number of scores given to each image, L_i, and using Eq. (7), the value of Z_i was calculated for $i = 1 \; to \; 60$, and according to Eq. (8), matrix Z was later created. Table 5 shows the matrix Z derived from the data.

Further, using Eq. (9) vector C, which is the cumulative customers’ ratings, could be calculated.

$$C = [0.533 \quad 0.328 \quad 0.516 \quad 0.455 \quad 0.551]$$

To determine the winning category, an LVQ network with specifications below was used according to section 2.1.3.

- Size of Kohonen layer: 12
- Learning rate: 0.03
- Learning Function: $learnlv1$ (MATLAB)
- No. of training epochs: 250

Table 3.The mean score matrix of all the experts for each of the 60 images.

Category	No. of Pic	Being Modern	Being Noisy	Integrity	Being Smart	Being Luxury
1	1	0.22	0.15	0.21	0.05	0.16
	2	0.09	0.18	0.12	0.15	0.2
	3	0.15	0.22	0.1	0.05	0.18
	4	0.1	0.18	0.09	0.11	0.29
	5	0.21	0.08	0.12	0.05	0.29
	6	0.15	0.16	0.16	0.05	0.17
	7	0.05	0.18	0.08	0.05	0.28
	8	0.08	0.06	0.19	0.1	0.27
	9	0.16	0.18	0.17	0.12	0.27
	10	0.06	0.16	0.07	0.12	0.18
2	11	0.89	0.08	0.8	0.72	0.77
	12	0.79	0.17	0.78	0.79	0.68
	13	0.78	0.13	0.78	0.74	0.66
	14	0.75	0.05	0.8	0.75	0.84
	15	0.71	0.13	0.78	0.67	0.72
	16	0.78	0.12	0.63	0.77	0.78
	17	0.89	0.05	0.71	0.78	0.84
	18	0.86	0.05	0.76	0.68	0.8
	19	0.9	0.05	0.63	0.69	0.68
	20	0.81	0.09	0.68	0.76	0.85
3	21	0.21	0.69	0.2	0.06	0.29
	22	0.15	0.58	0.2	0.17	0.32
	23	0.24	0.51	0.27	0.05	0.28
	24	0.14	0.52	0.19	0.09	0.29
	25	0.29	0.69	0.16	0.05	0.24
	26	0.29	0.58	0.34	0.11	0.19
	27	0.17	0.64	0.3	0.07	0.2
	28	0.26	0.7	0.26	0.14	0.31
	29	0.25	0.66	0.26	0.11	0.24
	30	0.2	0.58	0.17	0.14	0.26
4	31	0.34	0.9	0.35	0.09	0.34
	32	0.24	0.75	0.25	0.17	0.24
	33	0.26	0.78	0.28	0.06	0.32
	34	0.3	0.85	0.41	0.13	0.31
	35	0.41	0.89	0.3	0.15	0.28
	36	0.27	0.86	0.33	0.17	0.26
	37	0.4	0.77	0.25	0.11	0.39
	38	0.26	0.9	0.37	0.05	0.24
	39	0.26	0.89	0.29	0.16	0.38
	40	0.38	0.77	0.42	0.17	0.33
5	41	0.91	0.05	0.95	0.95	0.77
	42	0.95	0.09	0.88	0.82	0.89
	43	0.88	0.11	0.8	0.95	0.87
	44	0.94	0.07	0.9	0.95	0.77
	45	0.95	0.15	0.93	0.94	0.76
	46	0.95	0.13	0.84	0.89	0.89
	47	0.88	0.05	0.92	0.9	0.73
	48	0.87	0.05	0.95	0.95	0.74
	49	0.81	0.05	0.95	0.9	0.83
	50	0.93	0.05	0.8	0.86	0.86
6	51	0.18	0.81	0.3	0.14	0.71
	52	0.26	0.77	0.31	0.13	0.64
	53	0.16	0.72	0.32	0.12	0.66
	54	0.18	0.89	0.37	0.13	0.73
	55	0.2	0.77	0.34	0.05	0.63
	56	0.15	0.83	0.3	0.15	0.72
	57	0.17	0.88	0.26	0.05	0.64
	58	0.11	0.87	0.26	0.16	0.76
	59	0.25	0.9	0.32	0.05	0.61
	60	0.27	0.76	0.21	0.14	0.74

Also, the matrix $X_{60\times5}$ was used as input to the network, and the desired output was defined according to Eq. (23):

$$T = [t_i] = [fix(i/10) + 1] \quad i = 1,...,60 \tag{23}$$

Table 4. Matrix M; characteristic vector of each of the categories

Category No.	Being Modern	Being Noisy	Integrity	Being Smart	Being Luxury
1	0.127	0.155	0.131	0.085	0.229
2	0.816	0.092	0.735	0.735	0.762
3	0.220	0.615	0.235	0.099	0.262
4	0.312	0.836	0.325	0.126	0.309
5	0.907	0.080	0.892	0.911	0.811
6	0.193	0.820	0.299	0.112	0.684

Table 5. Matrix Z derived from the customers' ratings

No. of Pic	Crisp Score	No. of Pic	Crisp Score	No. of Pic	Crisp Score	No. of Pic	Crisp Score	No. of Pic	Crisp Score
1	0.490	**13**	0.904	**25**	0.475	**37**	0.302	**49**	0.596
2	0.248	**14**	0.748	**26**	0.507	**38**	0.439	**50**	0.573
3	0.289	**15**	0.766	**27**	0.574	**39**	0.374	**51**	0.249
4	0.383	**16**	0.955	**28**	0.607	**40**	0.346	**52**	0.052
5	0.487	**17**	0.946	**29**	0.515	**41**	0.659	**53**	0.298
6	0.465	**18**	0.887	**30**	0.511	**42**	0.603	**54**	0.205
7	0.491	**19**	0.963	**31**	0.215	**43**	0.616	**55**	0.194
8	0.378	**20**	0.782	**32**	0.461	**44**	0.701	**56**	0.071
9	0.415	**21**	0.669	**33**	0.414	**45**	0.666	**57**	0.120
10	0.346	**22**	0.639	**34**	0.402	**46**	0.639	**58**	0.311
11	0.930	**23**	0.451	**35**	0.281	**47**	0.470	**59**	0.075
12	0.941	**24**	0.559	**36**	0.243	**48**	0.499	**60**	0.303

in which t_i indicates the code of the ith category. In addition, function fix rounds its argument to zero. Using matrix X as input and vector T as desirable output, the LVQ network was trained. Figure 4 shows the error during the training process wherein the error reaches zero at $epoch = 36$.

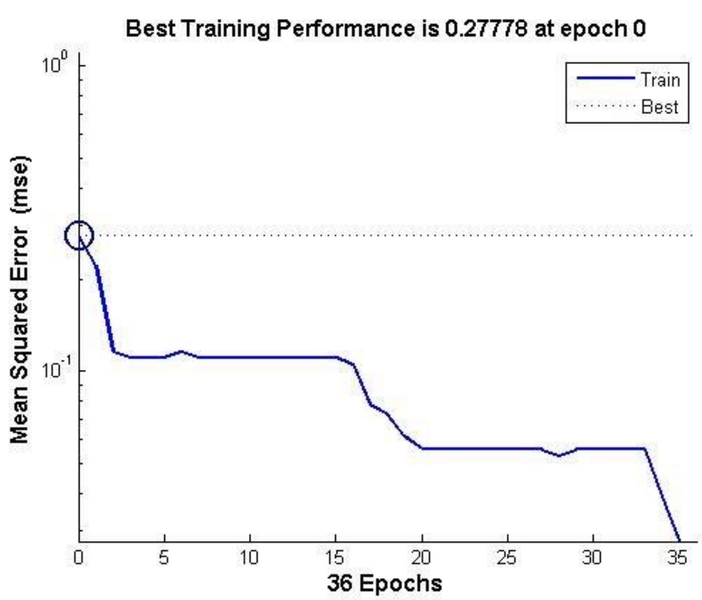

Figure 4. Learning error versus epoch number for the LVQ network

The information gleaned during the model learning phase should be analyzed during the evaluation phase so that its value and, consequently, the efficiency of the model learning algorithm can be determined. To simplify the criteria for evaluating categorization algorithms, we will present them for a problem with two categories (Positive or Negative). Each of the Classification matrix elements is as follows:

TN: the number of actual negative records that the algorithm correctly classified them as negative.

TP: the number of actual positive records that the algorithm correctly classified them as positive.

FP: the number of actual negative records that the algorithm falsely classified them as positive.

FN: the number of actual positive records that the algorithm falsely classified them as negative.

ROC curves are two-dimensional curves in which the True Positive detection Rate (TPR) on the Y-axis and similarly False Positive detection Rate (FPR) are drawn on the X-axis. In other words, a ROC curve shows the relative correlation between profits and costs. The ROC curve allows a visual comparison of classifiers. Also, several points in the ROC space are significant. For example, point (0, 1) shows a complete and flawless classification. In general, one point is better than the other if it is more northwest of the ROC space.

In the case of our trained LVQ network, it is reasonable that as the error reaches zero, the ROC would be as in Figure 5.

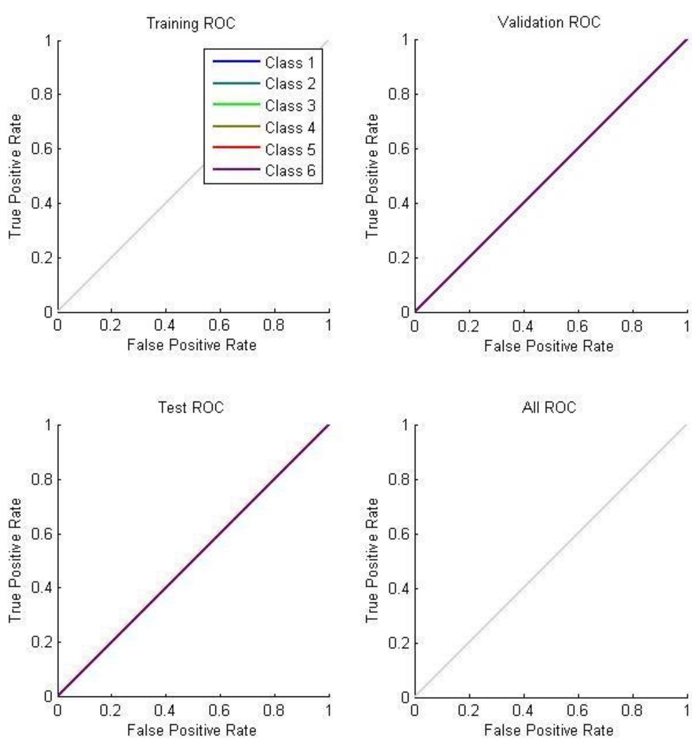

Figure 5. ROC for the trained LVQ network

Finally, the vector C is fed into the network as input to determine the winning category as output. We have:

$$f_{LVQ}(C) = 2$$

Meaning that the winning category would be "Mechanical Touch".

3.2. *Implementation of the Second Phase*

Geometric inspection and visual analysis of "Mechanical Touch" light switch models revealed some common geometric features among them. After analyzing the experts' opinions of the models, five considerably distinct geometric features were detected among the members of the "Mechanical Touch" category (category with code=2). Note that depending on the level of detail desired to be experimented on, these features can add up boundlessly. The levels of each of these geometric features (as our design factors) were as below:

- No. of vertical trims (3 to 9)
- No. of horizontal trims (3 to 9)
- The angle of the trims ($30°$ to $180°$)
- Trim gap width (5 to 15mm)
- Edge fillet radius (5 to 100 mm)

These parameters have been demonstrated in Figure 6.

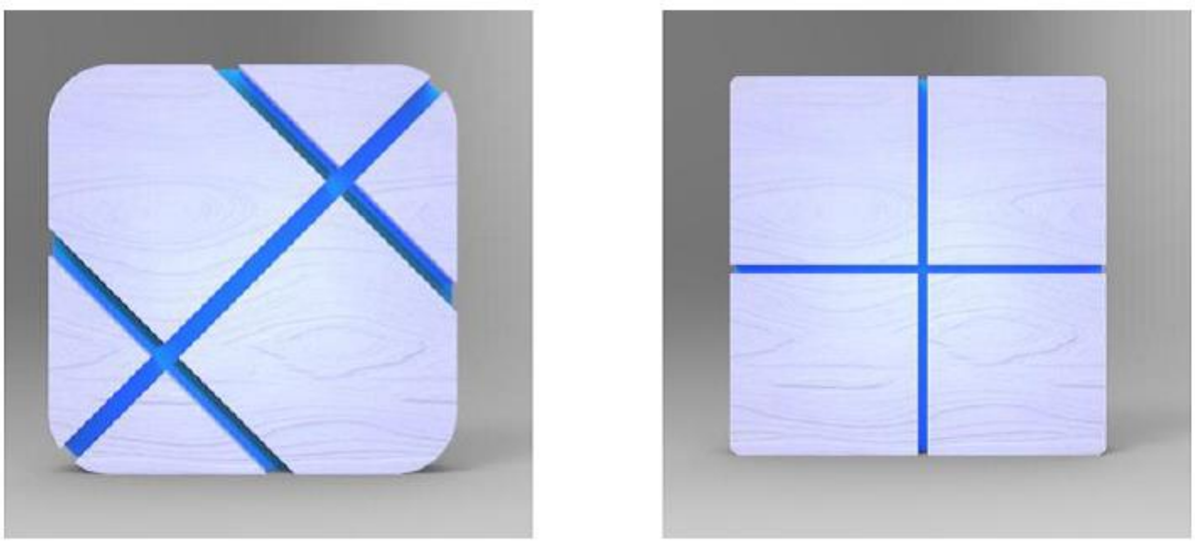

Figure 6. Sample members of the "Mechanical Touch" category in which the geometric features are demonstrated. The geometric differences between these two design candidates indicate the parameters.

As of a DOE method based on Taguchi's orthogonal arrays, five design parameters exist, each with three levels. The parameters and their corresponding levels are shown in Table 6.

The orthogonal array corresponding to five design factors, each with three levels, L_{27}, shown in Table 7 determined the levels of the design parameters for each Taguchi experiment. CAD models with parameters set on the mentioned levels were created and rendered to be rated by the customers.

Table 6. DOE parameters and their corresponding levels

PARAMETERS	LEVELS		
	Level 1	Level 2	Level 3
NO. OF VERTICAL TRIMS	3	6	9
NO. OF HORIZONTAL TRIMS	3	6	9
THE ANGLE OF TRIMS (DEGREE)	30	45	180
TRIM GAP WIDTH	5	10	15
EDGE FILLET RADIUS	5	50	100

Table 7. Taguchi's orthogonal array corresponding to five design parameters, each with three levels with no encoded parameters.

EXPERIMENT	PARAMETER LEVEL				
	No.1	No.2	No.3	No.4	No.5
1	1	1	1	1	1
2	1	1	1	1	2
3	1	1	1	1	3
4	1	2	2	2	1
5	1	2	2	2	2
6	1	2	2	2	3
7	1	3	3	3	1
8	1	3	3	3	2
9	1	3	3	3	3
10	2	1	2	3	1
11	2	1	2	3	2
12	2	1	2	3	3
13	2	2	3	1	1
14	2	2	3	1	2
15	2	2	3	1	3
16	2	3	1	2	1
17	2	3	1	2	2
18	2	3	1	2	3
19	3	1	3	2	1
20	3	1	3	2	2
21	3	1	3	2	3
22	3	2	1	3	1
23	3	2	1	3	2
24	3	2	1	3	3
25	3	3	2	1	1
26	3	3	2	1	2
27	3	3	2	1	3

Figure 7 shows how the design parameters were tuned for each design candidate in CATIA. As can be seen, aiming for a more efficient design approach and reproducibility, the levels of the parameters can be tuned to possess the desired values (desired levels) via the Parameters section in the Design Tree. These parameters could either possess discrete levels of predefined values or continuous editable values. The parameters would then be applied to the design model after receiving user's confirmation.

Examples of rendered images of the models with their geometric parameters tuned according to Table 7 are shown in Figure 8.

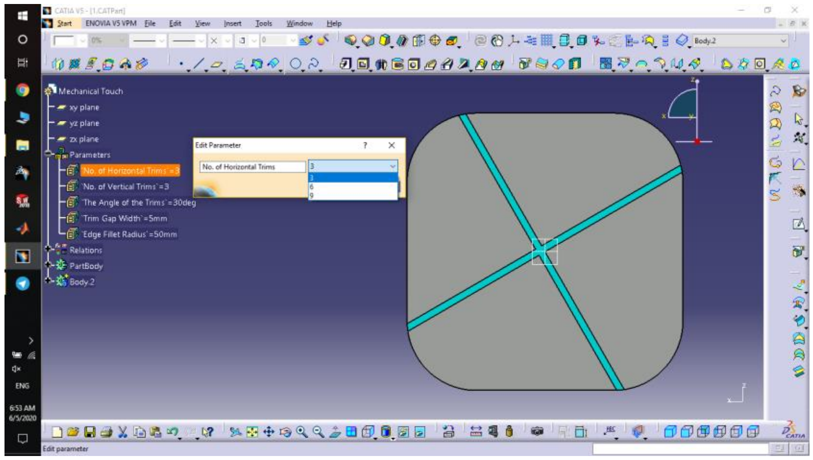

Figure 7- Tuning of the Design Parameters in CATIA. For faster tuning of the design parameters and maximum reproducibility in design, predefined levels of the design features have been used and are accessible via the design tree.

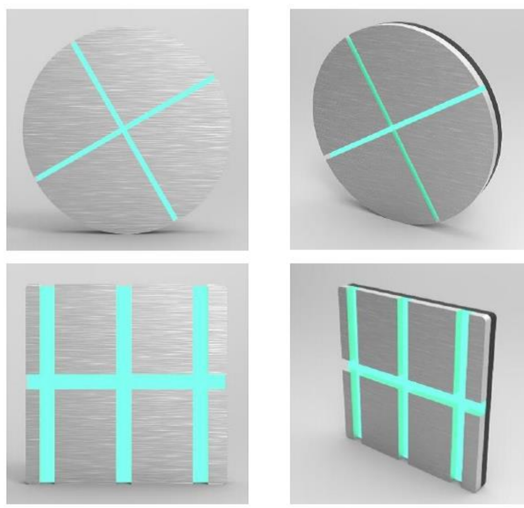

Figure 8. Examples of rendered images of the models with their geometric parameters tuned based on the orthogonal array $\boldsymbol{L_{27}}$

The 27 images created using Table 7 were rated by the customers. They were asked to evaluate these models according to the linguistic variables of Table 1. The results were then transformed into crisp numbers—using Eq. (1) — and the mean of customers' crisp scores was calculated. Customers' average ratings in crisp form for those 27 images have been shown in Table 8.

Table 8. Customers' average ratings for 27 images

NO. OF PIC	SCORE (CRISP)	NO. OF PIC	SCORE (CRISP)	NO. OF PIC	SCORE (CRISP)
1	0.929	**10**	0.401	**19**	0.299
2	0.926	**11**	0.451	**20**	0.298
3	0.924	**12**	0.403	**21**	0.298
4	0.380	**13**	0.487	**22**	0.218
5	0.452	**14**	0.512	**23**	0.252
6	0.373	**15**	0.481	**24**	0.231
7	0.032	**16**	0.553	**25**	0.314
8	0.051	**17**	0.654	**26**	0.351
9	0.022	**18**	0.512	**27**	0.321

After implementing Taguchi's analysis with an LB (Larger is Better) approach and analyzing the S/N ratio, the results would be as of Figure 99.

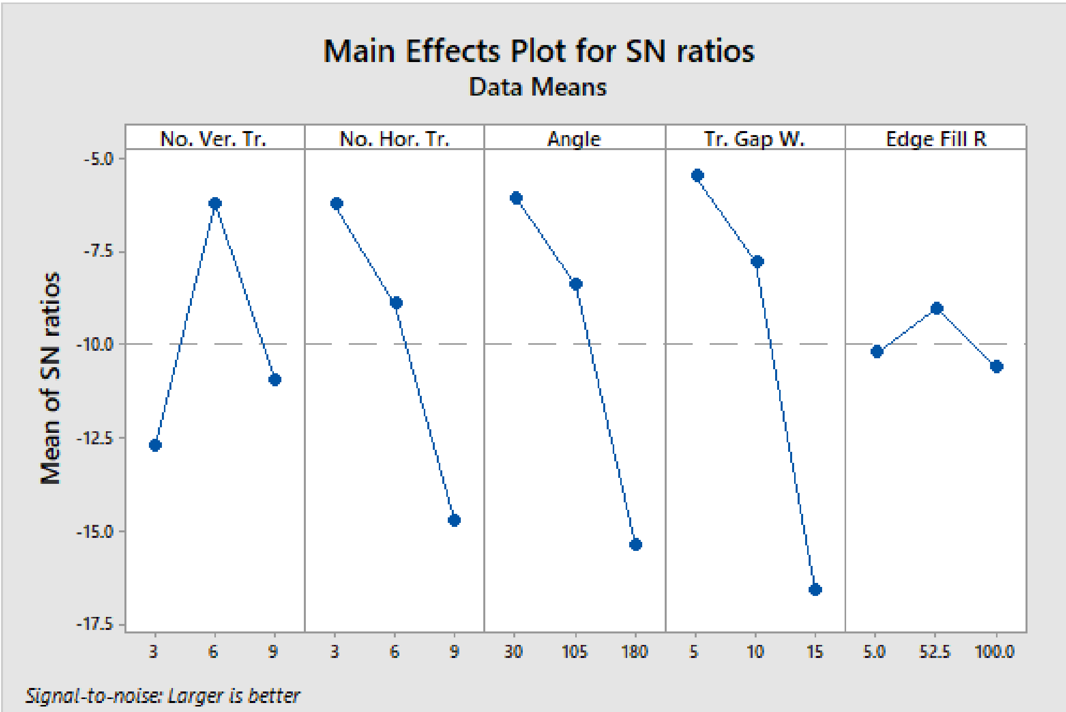

Figure 9. S/N ratio analysis results

As can be seen in Figure 99, each of the five parameters corresponding to the maximum S/N ratio illustrates an initial guess for the optimal design parameter values. Hence, it is safe to say that—since a linear regression model is used in Taguchi analysis—the approximately optimal design vector would be as below:

$$\left(C_{opt}\right)_{S/N} = [6 \quad 3 \quad 30 \quad 5 \quad 52.5]$$

Also, ANOVA was conducted on the data derived from Taguchi's analysis, and the results are depicted in Table 9.

Table 9. ANOVA Response Table for the Signal to Noise Ratio for the Geometric Parameters.

Level	*No. Ver. Tr.*	*No. Hor. Tr.*	*Angle*	*Tr. Gap W.*	*Edge Fill R*
1	**-12.751**	**-6.252**	**-6.064**	**-5.493**	**-10.229**
2	**-6.202**	**-8.913**	**-8.404**	**-7.782**	**-9.045**
3	**-10.942**	**-14.730**	**-15.427**	**-16.619**	**-10.621**
Delta	**6.549**	**8.478**	**9.363**	**11.126**	**1.576**
Rank	**4**	**3**	**2**	**1**	**5**

The results show that "Gap Width" was the most effective and "Edge Fillet Radius" was the least effective design factor.

To achieve a more reliable optimum point, GA was then employed. To do so, a fitness function – objective function – needed to be defined. As mentioned in section 2.2.2 the data resulting from

Taguchi's orthogonal array would be used as input and output for an ANFIS. This network was trained using the data and used as a fitness function for optimization by GA. The system defined for our problem had the specifications below:

- Type: Sugeno
- No. of inputs: 5
- No. of outputs: 1
- No. of rules: 32
- No. of Membership Functions for each input: 2
- Type of Membership Function for each input: Triangular
- No. of Membership Functions for output: 32
- Type of Membership Function for Output: Linear

The structure of this ANFIS is shown in Figure 10. The matrices of Table 10 and Table 8 were respectively used as the input and the desired output of the ANFIS, the training error of ANFIS is shown in Figure 11.

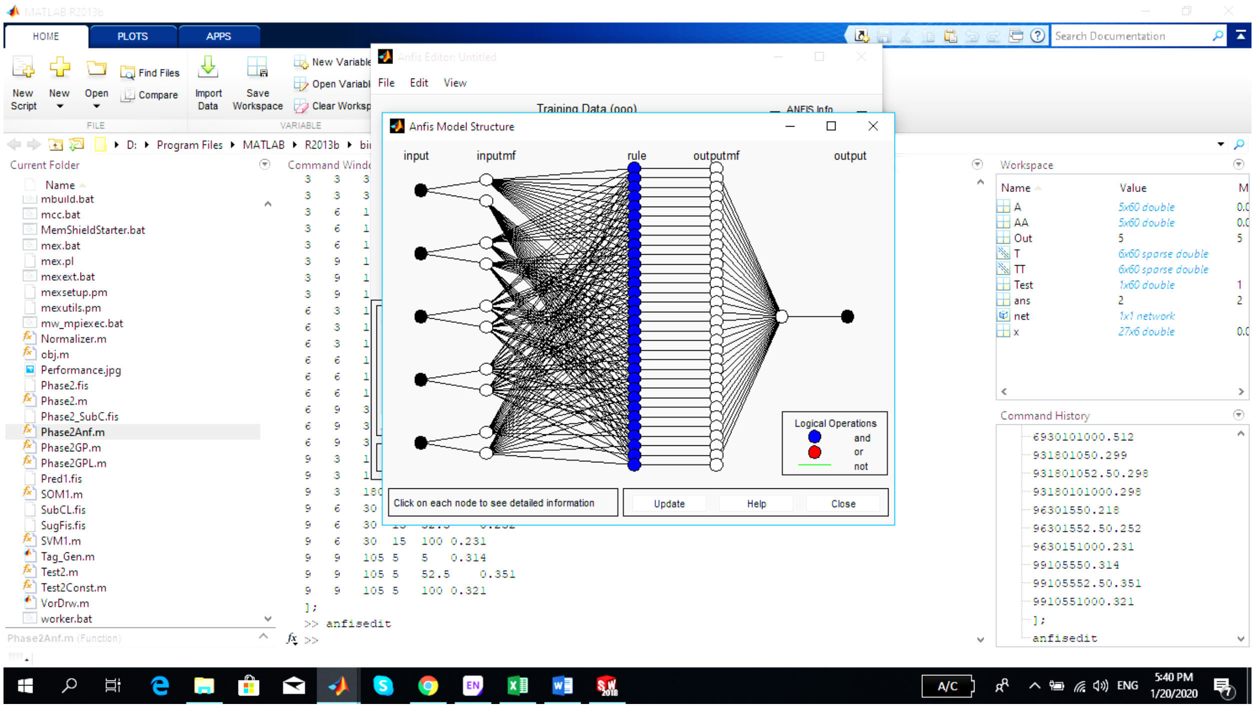

Figure 10. Structure of the ANFIS used for this study

After the training process of ANFIS, our fitness function was ready to be optimized using GA. GA was implemented with the specifications below:

- Lower bound for parameters (LB): [3 3 30 5 5]
- Upper bound for parameters (UB): [9 9 180 15 100]
- Function Tolerance: 1×10^{-8}
- No. of Iterations (Generations): 200
- Discrete Parameters: No.1 & No.2

- Continuous Parameters: No.3, No.4 & No.5
- Population Size: 100
- Selection Function: Stochastic Uniform
- Crossover Ratio: 0.8 (Scattered)

Table 10. Inputs of the ANFIS used for this study.

Experiment No.	**No. Ver. Tr.**	**No. Hor. Tr.**	**Angle**	**Tr. Gap W.**	**Edge Fill R**
1	3	3	30	5	5
2	3	3	30	5	52.5
3	3	3	30	5	100
4	3	6	105	10	5
5	3	6	105	10	52.5
6	3	6	105	10	100
7	3	9	180	15	5
8	3	9	180	15	52.5
9	3	9	180	15	100
10	6	3	105	15	5
11	6	3	105	15	52.5
12	6	3	105	15	100
13	6	6	180	5	5
14	6	6	180	5	52.5
15	6	6	180	5	100
16	6	9	30	10	5
17	6	9	30	10	52.5
18	6	9	30	10	100
19	9	3	180	10	5
20	9	3	180	10	52.5
21	9	3	180	10	100
22	9	6	30	15	5
23	9	6	30	15	52.5
24	9	6	30	15	100
25	9	9	105	5	5
26	9	9	105	5	52.5
27	9	9	105	5	100

After executing the program for three consecutive times, the optimal result vector C was as below:

$$\left(C_{opt}\right)_{GA} = [3 \quad 3 \quad 30 \quad 5 \quad 6]$$

Now we can compare the results for the S/N ratio with results from GA using the fitness function. Indicating the output from ANFIS with f_C, we have:

$$(f_C)_{S/N} = f_C([6 \quad 3 \quad 30 \quad 5 \quad 52.5]) = -0.8944$$

$$(f_C)_{GA} = f_C([3 \quad 3 \quad 30 \quad 5 \quad 6]) = -0.8950$$

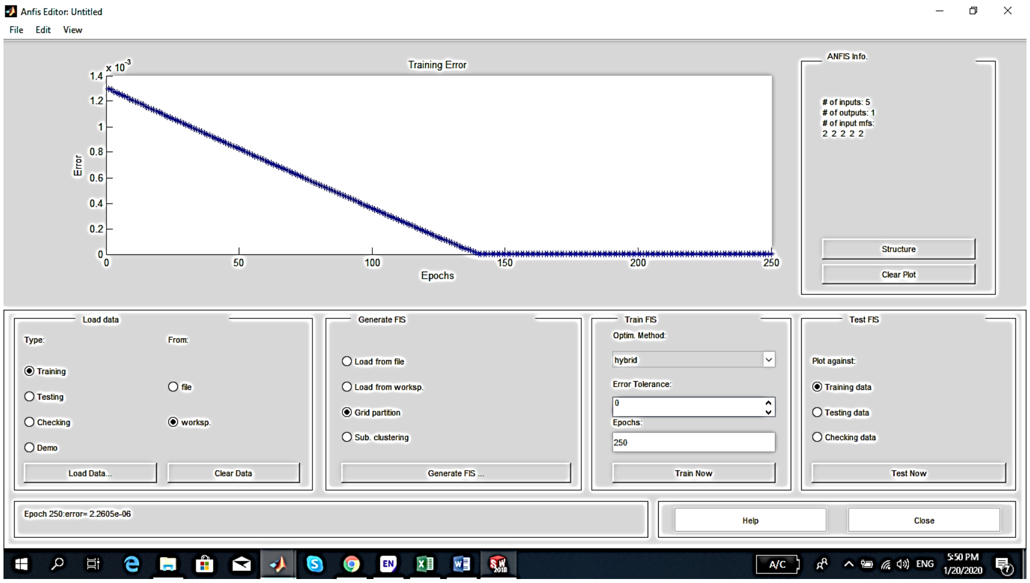

Figure 11. Training error of the ANFIS used for this study

It is evident that the optimal parameter vectors result in approximately identical values for the fitness function. They only differ in the fifth design factor, which was shown to be the least effective factor as ANOVA revealed in Table 9. Therefore, this factor is rendered as the least effective among all the factors, and its variations would have little impact on the results. In the end, the optimal design resulting from customers' ratings can be depicted as in Figure 12.

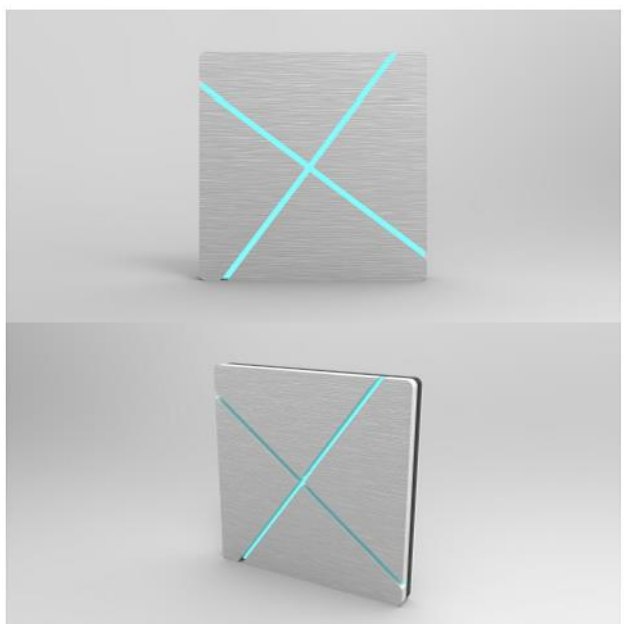
Figure 12. Optimal shape for the design factors

4. Discussion

As mentioned in section 3, the customers or experts' opinion is the input of all phases and procedures in the algorithm. In other words, all opinions are based on human inferences. The use of fuzzy linguistic variables, in this case, rendered the rating very flexible and remains apart from complication and dilemmas in choices. Also, this approach helps to compensate the lack of accuracy in the final results and therefore, there is no need for linear and inaccurate models. To confirm the above assertion, an average of more than 90% of the distributed forms have been answered by the interviewees, which implies the importance and suitability of implementation of the fuzzy system in this case.

To determine the common parameters between the main categories of the product, each of the five experts has been required to propose their desired parameters. Then, their common opinions, which were stated in various words occasionally, were selected and afterward, the selected parameters were sent to each of the five experts for approval. In the end, after the experts' confirmation, all those common confirmed parameters were chosen as the parameters of the groups. The importance of this agreement is that the experts' idea about each of these five parameters is completely justifiable. Absence of inconsistent data in their ideas is proof for the justifiability of the agreement.

After aggregation and averaging of experts' opinions, the characteristic vector of each category was obtained.

Figure 12 represents the comparison of six competing categories in phase 1, which indicates that the categories are in proportion to enough separation and distinction. In the case striking similarities happen in some parameters, a very obvious distinction is recognizable in other parameters. As represented in Figure 12, characteristics number 1, 2 and 5 are in a very close match in categories number 2 and 5. Therefore, the distinction between these two categories will be possible through the differences in characteristics number 3 and 4. Also, between groups 3 and 4, features number 1, 2 and 3 are more distinct, while features number 4 and 5 are close to each other, so a distinction can be made through only 3 properties. If linear methods such as regression or the Euclidean distance, were implemented in these cases, the positive and negative values of distinct parameters could have covered each other thereby hampering the results, which leads to the necessity of the use of a non-linear intelligent classification system such as LVQ.

The error chart as well as ROC (Figure 4 and Figure 5), indicate that after a limited number of iterations (36 iterations), the error has reached zero and the training has been completed. At the same time, the smaller number of neurons in the Kohonen layer relative to the number of categories guarantees that a one-on-one correspondence cannot happen between input and output and that the result of the LVQ is not corrupted. As it is seen in Figure 5, the ROC Chart implies an a-hundred-percent correct detection. Investigating this result from another point of view indicates ample distinction between categories in phase 1. Moreover, the members of any picked categories enjoy enough similarities.

In the second phase, the most prestigious method to rely on is the design of experiments (DOE). This is the case with different methods such as Simple Factorial Design or Central Composite Design. However, since surveys must be taken from people and the number of experiments in the two mentioned methods is huge, using these methods is practically impossible. The reason behind this impracticality is that these surveys may be too long and exhausting for people, which leads to inadequate accuracy in responding or even reluctance to take the survey. Hence, we have to use the orthogonal arrays of Taguchi which are capable of significantly reducing the number of experiments while having desired coverage on data on the valid domain. Evaluation of the final results of this section implies 90% cooperation of people who are asked to take the survey.

In some studies, it was observed that a special software is developed for setting geometric parameters and measuring them so that the user can set the parameters using this software. Although developing such kinds of software is of value, this approach cannot appear effective regarding the time taken and expertise requirement in many industrial design projects. Therefore, it is better to use one of the existing geometric platforms with enough comprehensiveness, which in this case is CATIA.

After this stage, information from the design of experiments and customer reviews should be linked through a function. According to the existence of nonlinear information and complex relationships between them, one of the best methods is artificial neural networks. Also, due to the nature of existing data and the fuzzy basis of some of them, one of the best choices is neuro-fuzzy neural networks. To the error reaching zero in less than 150 iterations indicates the appropriateness of this type of neural network to define the function of the input process optimization.

One of the potential optimization problems, in this case, can be falling into the loop of iterations and obtaining a local minimum instead of a global one. Although there is no optimization method capable of assuring a global minimum in this case, the use of stochastic methods can certainly reduce the risk of this issue. It is also noteworthy that classic methods, in this case, can be very time-consuming and computationally costly. Therefore, a suitable choice can be a metaheuristic method such as Genetic Algorithm. The high customer satisfaction rate (about 92% based on re-polling) of the rendered image based on the parameters with the optimal values (Figure 12) indicates the correctness of the optimization process.

As a final statement, given the simplicity, flexibility, compliance with human characteristics, low computational cost and use of common and accessible software, this approach can be utilized for a wide range of products requiring industrial design based on customer tastes and geometric parameters.

5. Conclusion

For a product to have a successful presence in the market, it is necessary to consider various non-engineering aspects based on the factors providing customer satisfaction. This is done in the conceptual design phase of the product design. In this regard, the geometric and visual characteristics are specifically attentive to industrial designers, and their impact on customers' satisfaction is usually remarkable.

Considering the variety of modern products and the weaknesses of feature-based methods—i.e. the shortage of the number of common features between different categories of a product—there is a demand for design approaches which are flexible, simple, consistent with human comprehension, capable of optimizing based on a limited number of data with low computational cost and high efficiency as well as agility, and able to be implemented on a wide range of products.

The method proposed in this research is a two-phase algorithm in the first phase of which the product is divided into a number of main categories and then using a fuzzy survey taken from experts, a characteristic vector is determined for each main category. In the next step, the average of customer reviews is determined by scoring the selected images of the products and then, using the neural network, the closest characteristic vector from the main categories is selected.

In the second phase, a number of common geometric features are identified inside the selected group using the DOE and based on Taguchi's orthogonal arrays, which have fewer experiments than other methods and lead to an increase in speed and efficiency. Thereafter, using the CATIA platform, a parametric design will be prepared and rendered so that the customers can perform a fuzzy scoring to each rendered picture. In the next stage, utilizing an adaptive fuzzy neural network, a relationship between inputs and outputs is established and the network is used as an optimization fitness function using a genetic metaheuristic algorithm. The result of the optimization is re-tuned in CATIA and rendered in KeyShot, and then it is placed for the customers' votes. The high satisfaction score of this stage is indicative of the effectiveness of this method.

Absence of inconsistent data besides the non-exhausting procedure of this approach implies its compliance with human interface characteristics, flexibility, and simplicity which is a result of the utilization of fuzzy logic. Using the method LVQ, which is a nonlinear and complicated method, not only reduces the error but also increases accuracy. The ROC graph can be proving proof. Also, the genetic algorithm increases speed and results in a relatively accurate solution close to the absolute minimum rather than a local one. Implementing the design of experiments yields superior accuracy and comprehensiveness of the survey besides the simplicity and non-exhausting procedure that comes out of Taguchi’s orthogonal arrays. The use of the CATIA platform helps the method to be both facilitated and hastened. The adaptive neuro-fuzzy system used in the second phase will result in the accuracy and speed of the procedure as well. Thus, we can claim that we have achieved a system which is flexible, simple, compatible with human deduction, capable of optimizing based on a limited number of data with low computational cost and high efficiency, as well as agility and applicable to a vast range of products.

This method, can also be used in cases rather than the conceptual design of industrial products and in the survey-based processes related to humans.

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