CONCURRENT ENGINEERING: Research and Applications

A Grey Relation Approach to the Integrated Process of QFD and QE

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Abstract: During the process of concurrent design, a designer must focus on meeting the changing requirements of customers and reacting to the rapid decrease of the life-cycle of the product in a dynamic market. However, the cost induced by the quality delinquent and aftermarket service is a critical factor in the enterprise profit. This research proposes a product design methodology that integrates the grey relation approach to quality function deployment (QFD) and quality engineering (QE) to solve the problem. It is noted that the process increases customer satisfaction and enhances product quality in response to global competition. Based on the results of systematic market research performed on customer requirements (*CRs*), the hierarchical clustering technique and grey theory have been applied to identify, categorize, and evaluate *CRs* to rank their grey relational importance. The critical design characteristics (*DCs*) have been identified using QFD, which applies the semantic differential method on the relationship matrix cell to evaluate their relationship with *CRs*. The selected *DCs* are then evaluated to determine noise and possible loss of quality using the orthogonal experiment of the Taguchi method. The objective of the optimization process is to integrate QFD and QE into the development process and to optimize the quality of product development. With support from a timer manufacturer, six existing products have been selected to demonstrate the applicability of the approach described above. This robust product design process provides encouraging evidence for a new approach that can improve quality, reduce variation, and increase customer satisfaction and enterprise profit.

Key Words: product development, QFD, grey theory, Taguchi method, quality engineering.

1. Introduction

In current global competitive markets, the progress of computer technology and networks has shortened product life-cycles significantly. No single product can constantly dominate the market without continuous improvement or modification in accordance with customer requirements (*CRs*). Biren [1] suggested that the integration of manufacturing technology and product design into a concurrent engineering process system could be an important factor in quality improvement and in the enhancement of product sustainability in a competitive market. Consequently, several enterprises have tried to implement new concepts in product development to follow the market trend, improve the manufacturing process and enforce better project management to increase overall customer satisfaction and earned profits. Customer satisfaction refers to the voice of the customer (VOC), which is a reflection of customer requirement*s* [2]. There are several techniques that can be applied to translate the VOC into criteria for design evaluation and product specification such as creating interaction matrices, design principles, and quality function deployment (QFD) [2–4]. In general, QFD is currently considered an efficient approach for dealing with the VOC. The QFD technique involves a continuous sequence of design and production processes that help designers to deploy sequential relationships from customer's requirements, engineering characteristics, and manufacturing process to the generation of final product. All phases of QFD use the so-called house of quality (HOQ) parameter to manipulate specific vectors and matrices that can benefit product development in the following four ways: (1) reduce product development time, (2) reduce problem spoilage during production start-up, (3) improve product quality, and (4) increase customer satisfaction [2,5,6]. In traditional QFD processes, designers tend to use a 9-level weighting technique from an analytic hierarchy process (AHP) or a more recent fuzzy analytic hierarchy process (FAHP) to determine the relative importance levels among the identified customer requirements [2]. It is noted that the development of FAHP is based on a fuzzy measure in which a graded value between 0 and 1 is assigned to each identified individual to indicate the degree of evidence or subjective certainty [7]. Note also that the concept of an analytic network process (ANP) was introduced by Saaty [8] to employ a super-matrix to record relative measurements within and between clusters of elements. Saaty considered the AHP as a special case of the ANP. Geng et al. [9] further proposed a fuzzy analytic network process (FANP) in QFD to evaluate the importance weights of design characteristics (*DCs*) based on the consideration of the vagueness and inner-dependence of *CRs* and *DCs*. In a similar way of Geng et al., Lee et al. [10] even used the calculated priorities of *DCs* in a multi-choice goal programming model to find the most suitable *DCs* for product design. Liu [11] even integrated a fuzzy QFD approach and a fuzzy multi-criteria decision making approach into a product design and selection approach. However, Suh [12] developed an independence axiom for product design that suggested the relationship among customer requirements should be independent each other, otherwise the design will be coupled. Therefore, the design of a product can neglect the effect of inner-dependence on *CRs*. Due to the inability of the 9-level weighting or fuzzy technique in precisely evaluating the relative importance level of each individual *customer requirement* in either AHP, FAHP, or FANP, a grey theory [13], which is based on the grey relation distance between parameters, may be more suitable. The difference between the FAHP or FANP theory and grey theory is that the FAHP or FANP theory develops membership functions for the interval of fuzzy real numbers ranging from 0 to 1 and subjectively measures degrees of closeness for the specific attributes or alternatives, while the grey theory collects or specifies the range of values for the specific attributes or alternatives based on the incomplete information and then initializes the values into grey real numbers with the base value of 1 [7,13]. Besides, the measurement of fuzzy numbers requires sufficient expert knowledge, because the measurement of grey numbers is based on the collection of existing data that makes the grey relation approach effective for this study and it will be applied to evaluate and prioritize the customer requirements of QFD.

Ulrich and Eppinger [14] suggested that the development of a new product requires large amounts of feedback from market research to identify critical customer requirements and design characteristics. The effectiveness of the grey theory has been demonstrated in various applications such as grey control, system prediction, process improvement, requirement forecasting, performance assessment, and quality improvement [13,15–19]. Wu [20] used the technique of forecasting in grey theory to compare the importance and prioritize the respective impact of each *customer requirement* identified in a system. Chen [21] further proposed a methodology that integrates grey theory and the clustering technique to cluster and predict the future trend of customer requirements. Considering product adaptability, Li [22] employed the grey relational analysis method to integrate measures for prioritizing different design candidates and customer requirements to meet product design adaptability, manufacturing and assembly costs, and operationability. Although the use of grey theory in QFD may appear to assist designers in developing more effective relationships between customer requirements, it is unable to provide optimum or suitable specifications for product design. Therefore, the Taguchi method in quality engineering (QE) has been proposed as a feasible alternative approach to overcome this limitation.

The Taguchi method has been developed as a foundation for robust design to tackle quality control problems during the design stages and to reduce the variance between each developed product [23]. It has the ability to maximize the information that comes from a small database and consists of a plan of experiments with the objective of acquiring data in a controlled manner. The Taguchi method has been validated as a reliable, quantifiable, and efficient technique to attain maximum quality in optimal machining parameters, control physical properties, and improve production performance [24–27]. In the Taguchi method, a set of repetitive data is transformed into Signal-to-Noise (S/N) ratios, which are defined as the measures of variations in the developed products. In the S/N ratio, the term 'Signal', denoted by 'S', represents the desirable target for products deemed acceptable, and the term 'Noise', denoted by 'N', represents the undesirable value. The ratios of S/N consolidate several repetitions (of two or more data points) into a single value that reflects the amount of variation [28]. During the optimization of the manufacturing parameters, the Taguchi method is implemented through experiments conducted in orthogonal arrays to allow efficient determination of the effects of several parameters [29]. The Taguchi method has also been used in conjunction with artificial neural networks [30,31] to allow the decision-maker to achieve precise forecasts pertaining to optimal design [32]. Therefore, the Taguchi method may be an effective technique to determine the most suitable combination of design specifications for the development of customer-oriented products.

In general, from the marketing strategy standpoint, regardless of the complexity of the technique, customer satisfaction is the most critical factor in designing competitive products. Early involvement of customers, especially at the conceptualization stage of product development, plays an important role in successful product design [33]. During the design and development stage, designers are often faced with multiple disciplines, a variety of *customer requirement* problems and modularity of design. In some cases, the decision variables of one design optimization problem may be the parameters of another, with a compromise required between the two sets. Wang et al. [34] has proposed a proportional integral control policy to tackle the multidisciplinary design optimization problem. Chong and Chen [35] advocate proactive management and forecasting of the dynamic requirements of customers during the development of products for fast shifting markets. A *customer requirement* analysis and forecasting system has been defined to support product development functions with quantitative and qualitative customer requirements information. Dong et al. [36] has demonstrated an option-pricing method for module introduction decision-making that can effectively respond to customer demands and increase the net present value for companies.

In summary, even though the QFD can provide designers with an effective way to link *CRs* with *DCs* in product development, there exists opportunities on the improvement of precisely identification of *CRs* and *DCs*. Currently, many related research efforts have been focused on this issue. However, very limited researches considered the use of QE concept in the next stage of QFD activity to obtain critical *DCs* and head toward the design of products. Therefore, the objective of this research is to develop a product design procedure that incorporates grey theory and the Taguchi method in the identification of relationships between customer requirements and specifications of design characteristics to enhance customer satisfaction, reduce aftermarket costs and prevent the increment of product modification and associated cost. Compared to the traditional QFD approach, this research applies grey theory and the Taguchi method to prioritize *CRs* and manage critical *DCs* that help reduce the risk of design changes at an early stage. Therefore, this research is not limited to the identification of VOC, but it also emphasizes the investigation of problems and the improvement of the design process. With the integration of the two methodologies, the customer requirements can be identified more precisely, the manufacturing process can be implemented in a smooth manner and the probability of loss of the enterprise after the product has been sold to the market can be reduced significantly.

2. The Conceptual Framework of the Development Procedure

The design of a product is primarily based on the specific problems that must be solved or on the requirements that must be met by the product. The designer must clearly define these problems and requirements, so that he or she can direct the design effort toward an appropriate design solution. These specific problems and requirements should then be restructured or grouped to explore their relationships and to decide on the most suitable approach for a successful product design. The specific problems and requirements refer to customer requirements, whereas the design solution refers to design characteristics. Systematic approaches to product design use customer requirements to determine a suitable set of design characteristics and to generate feasible design alternatives. In the current design methods, the QFD approach integrates the deployment of the design and production processes into a system that links the voices of the customers or customer requirements with the design characteristics. The grey theory can be incorporated into the QFD process to precisely identify the relationship between various customer requirements. The Taguchi method can then be introduced to determine the most suitable range of design characteristics that can reduce the variation in the designed product and increase the product quality. Based on the concept of incorporating grey theory and the Taguchi method with the QFD process, the general approach for the development of the proposed procedure is briefly discussed in the following section.

2.1 Step 1: Identification and Categorization of Customer Requirements

The methods for identifying customer requirements have been discussed in several design textbooks and articles. Historically, relevant customer requirements have been identified through a combination of personal observations, intuitive findings, market surveys, interviews with potential and experienced customers, and systematic approaches to market research. According to the QFD process, customer requirements are categorized using the hierarchical clustering technique (HCT). The categorized customer requirements are then prioritized using grey theory to evaluate their relative importance.

2.2 Step 2: Evaluation of the Degree of Importance for Each Categorized *CR*

In accordance with grey theory, a collection of 5–10 commercially available sample products with similar design characteristics have been identified. Each product in this collection and the categorized *customer requirement* is described in a $n \times m$ matrix. The number of rows in the matrix is equal to the number of identified customer requirements, and the number of columns in the matrix equals the number of identified products. A set of subjects that are experienced in using the products is collected. These subjects are asked to evaluate the satisfaction of using the identified products on a scale of 1–100 for each categorized customer requirement. The typical element in the matrix has a rated value (1–100) that denotes the satisfaction of the identified product 'j'($j = 1, 2, \ldots, m$) for the specific customer requirement category 'i' ($i = 1, 2, \ldots, n$). In this study, a lower value describes a higher degree of satisfaction of using the product. An aggregated matrix array is then formed according to the averaged values collected from the subjects. Note that the product with the highest total value in a specific column of the aggregated matrix is considered the reference product, whereas the remaining samples with lower total values are considered the comparable products. After the generation of the aggregated matrix, grey theory is used to determine the relative weights of the degrees of importance of the identified customer requirements. In this research, the weight of importance for the identified customer requirements uses 100% for ease of calculation.

2.3 Step 3: Employment of the QFD Process to Identify Critical *DCs*

According to the QFD development process, the HOQ presents a concise matrix representation that effectively links customer requirements and design characteristics [2]. In the HOQ matrix, the designer needs to use a planning matrix to determine the relative weight of importance for the each of identified customer requirements. The attributes of columns in the planning matrix that connect with customer requirements of rows include the following five categories: (1) weights of importance of customer requirements, (2) competitive assessment, (3) market niche evaluation, (4) summed weights of customer requirements and (5) normalized weights of importance of customer requirements. Note that the column values of the (1) weights of importance of customer requirements are obtained from Step 2. The column values of (2) competitive assessment and (3) market niche evaluation are based on a determination of the level of customer requirement satisfaction by current competitive products. The column values of (4) summed weights of customer requirements are obtained by the multiplication of (1)–(3). The column values of (5) normalized weights of the importance of customer requirements are determined by dividing each column value of (4) by the total column values of (4). The column values of (5) refer to the relative weights of importance of customer requirements. Having obtained the relative weights of importance for customer requirements, the development process begins to deal with the survey of relationships between customer requirements and design characteristics. A semantic differential method is implemented using a questionnaire based on a five-point scale to assess the relationships between customer requirements and design characteristics. Points 0, 1, 2, 3, 4, and 5 correspond to no relation, very weak, weak, medium, strong, and very strong relation, respectively. The aggregation of the multiplication of the relative weights of importance and the corresponding scale point for each *design characteristic* becomes the weight of importance of the design characteristic. In a similar manner, the normalized weights of importance for column (5) of the planning matrix are obtained as the relative weights of importance of design characteristics. The normalized weights of importance of design characteristics provide valuable information in determining which critical design characteristics are selected for the Taguchi experiment.

2.4 Step 4: Conduction of the Taguchi Experiment for the Identified Critical *DCs*

From Step 3, the design characteristics with highest normalized weights are considered critical design characteristics and are included in the Taguchi experiment to find an optimum combination of critical design characteristic levels for further improvement in product design. During the Taguchi experimental design process, the critical design characteristics are treated as design parameters and appropriate levels for each design parameter are selected so that a suitable orthogonal array can be determined. The experiment of the orthogonal array is based on the quality performance measurement of the S/N ratios. Note that the quality loss function for the general design problems may be a smaller-the-better type.

The procedure described above can be used to reduce design effort, improve competence, and reduce variation in new or redesigned products. Figure 1 shows the development framework of the research. The design of an electronic timer is used as an example to illustrate the steps of the approach.

3. HCT in *CR* Categories

When implementing the HOQ of QFD, the designer must identify a set of customer requirements and the related design characteristics at the initial stage. As mentioned in Step 1, there may be several different ways of identifying customer requirements. However, the information is entangled and must be screened and grouped for further evaluation. In general, a paired comparison method is available to screen the identified customer requirements for independence, consistency, and relevance at the first stage of information collection. After identification of the customer requirements, a semantic differential method is applied to use a questionnaire survey based on a five-point scale to evaluate the significance of the identified customer requirements. The five points 1, 2, 3, 4, and 5 denote the linguistic categories very low, low, medium, high, and very high, respectively. Each tester will judge the identified customer requirements based on the following five attribute indices: cost, assembly operation, performance, accuracy, and part management. These semantic attribute indices are derived using the same identification process used for the customer requirements.

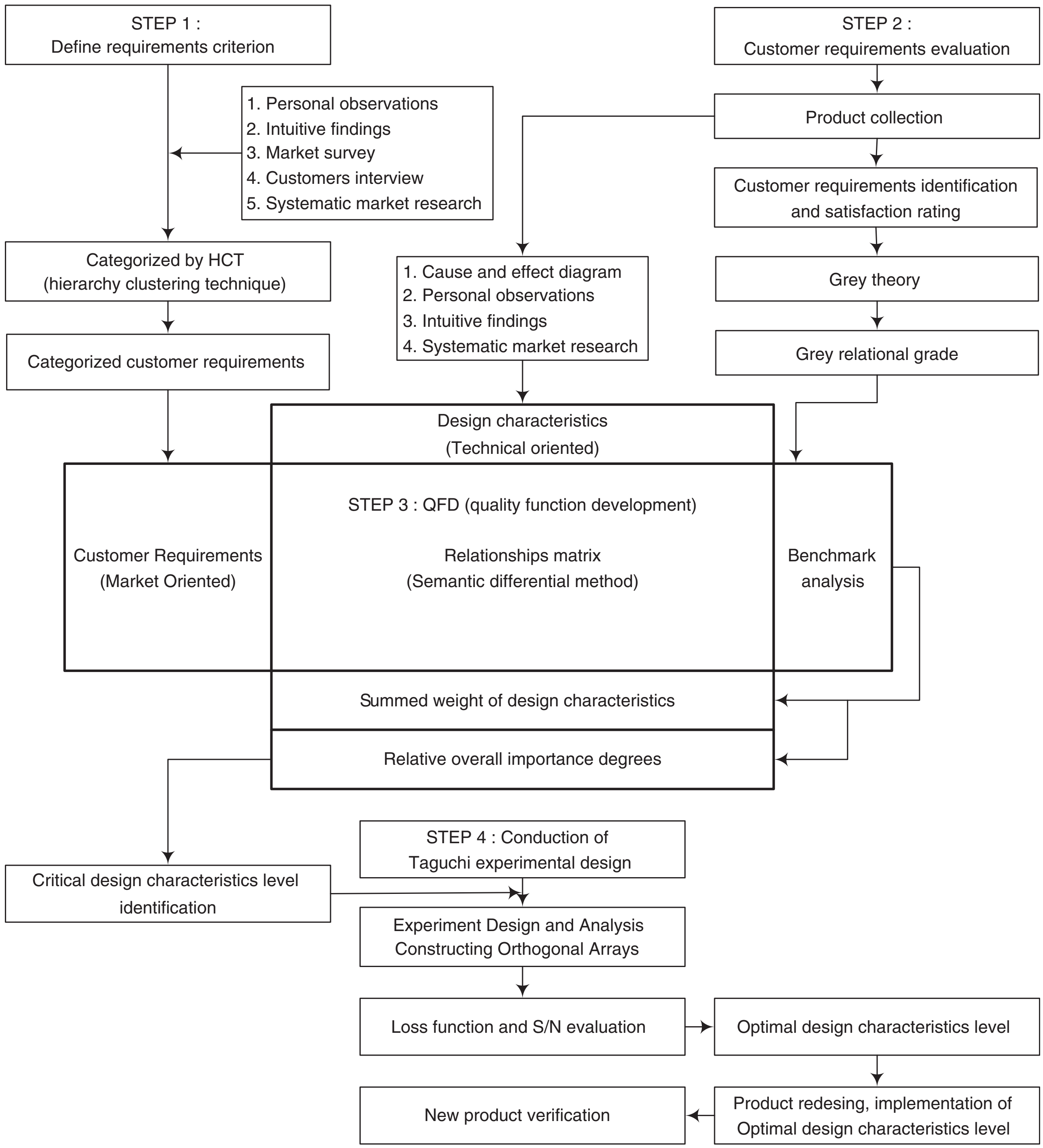

Figure 1. Flow chart of the proposed product design process.

The survey results are then pooled to form a relationship matrix with rows that denote identified customer requirements and columns based upon the five semantic attribute indices. Following the generation of the relationship matrix, an HCT is employed to categorize the customer requirements into a hierarchical tree structure. Note that the Euclidean distance and average linkage are used in this research to compute the distances among the identified customer requirements.

Let CR denote the set of identified customer requirements, where

$$CR = \{CR_i | i = 1, 2, \ldots, n\}.$$

Similarly, let AT denote the set of semantic attribute indices regarding the identified customer requirements, where $AT = \{AT_b | b = 1, 2, \ldots, s\}$.

After the customer requirements and corresponding semantic attribute indices were identified, the selected testers were asked to evaluate the relationships between the customer requirements and semantic attribute indices and then assign a rating scale to indicate their significance. Based on the judgments made by these testers, the HCT was then conducted to categorize the identified customer requirements. The HCT in this research used the furthest neighbor method, incorporating the Euclidean distance method in the Minkowski Metric approach to categorize the identified customer requirements. The furthest neighbor method (*FNM*) is expressed as [37–39]:

$$FNM(CR_c, CR_d) = \max\{De, f\}$$

where $FNM\ (CR_c, CR_d)$ denotes two identified customer requirements, CR_c and CR_d are from the set of customer requirements $CR,\ c,\ d \in n,$ that are categorized for their homogeneity or similarity, $D_{e,\ f}$ denotes the distance between two customer requirements CR_e and CR_f, $e, f \in n$.

The calculation formula for $D_{e,f}$ is expressed as follows:

$$D_{e,f} = \left(\sum_{b=1}^{s} \left(CR_{e,b} - CR_{f,b} \right)^2 \right)^{1/2}, \ b = 1, 2, \ldots, s$$

where $CR_{e,\ b}$ and $CR_{f,\ b}$ denote the number of testers who judge the *bth* semantic attribute index, $b = 1, 2, \ldots, s$ for the customer requirements CR_e and CR_f, respectively.

In this research, ***n*** is 10 for the identified customer requirements and ***s*** is 5 for the semantic attribute indices. The HCT then uses a critical distance measure at a combinational level to form a cluster. The choice of the critical distance measure is based on the set of customer requirement members that have the most homogeneous or most similar distinctions. The critical distance measure ultimately determines the number of clusters.

According to the HCT, the identified customer requirements are categorized into specific categories based on five semantic attribute indices. Each category has homogeneous attributes in the categorized customer requirements but has heterogeneous attributes among different categories. Let the set of categories for the customer requirements be denoted as $[CRG_1, CRG_2, \ldots, CRG_g]$ and the set of customer requirements for a specific category CRG_g be denoted as $[CRGM_{h,\ hg}]$, where $h = 1,\ 2, \ldots, g$ corresponds to the categories $CRG_1,\ CRG_2, \ldots, CRG_g$; and $h_g = F_1,\ F_2, \ldots, F_e$, where $F_1,\ F_2, \ldots, F_e$ represent the number of identified customer requirements for the categories CRG_1, $CRG_2, \ldots, CRG_g$, respectively.

4. Grey Theory in Categorized *CRs* Evaluation of QFD

After the identified customer requirements have been categorized, the designer then proceeds to Step 2 to evaluate the categorized customer requirements for the purpose of obtaining the most precise weights of customer requirements. Grey theory is applied in this research to effectively prioritize the importance degree of categories *CRGs* and the corresponding customer requirements $CRGM_{h,\ hg}$. Let P represent the set of m competitive or similar products collected from the market. $P = \{P_j | j = 1,\ 2, \ldots, m\}$. In this research, m is 6 for the collected products. Further, let CRP be an $n \times m$ interaction matrix indicating the customer satisfaction relationships between each identified customer requirement $CRGM_{h,\ hg}$ and collected product P_j, with typical element $CRP_{i,\ j}$, $CRP_{i,\ j} \in (1,\ 100)$, $i = 1,\ 2, \ldots, n,\ (h, hg) = i,\ j = 1,\ 2, \ldots, m$. Note that the weighting value 1–100 is chosen by each subject and the averaged value is assigned to the corresponding matrix cell $CRP_{i,\ j}$. The choice of the higher averaged value for each element of $CRP_{i,\ j}$ is based on the judgment that the selection of a customer requirement $CRGM_{h,\ hg}$ has a certain degree of lower satisfaction or significant effect on the collected product. Some of the considerations that are helpful in making this judgment include safety, convenience, comfort, efficiency, accuracy, economy, and compatibility.

Once the interaction matrix CRP is formed, the grey relation analysis proceeds with the choice of a reference value from each row of CRP to form an m dimensional row vector $CRPRV$, with typical element $CRPRV_j = \max\{CRP_{i,\ j},\ i = 1,\ 2, \ldots, n\}$. The vector $CRPRV$ is called a reference vector. Note that the comparison of values between the reference vector $CRPRV$ and rows of interaction matrix CRP is based on the evaluation criterion that the lowest customer satisfaction category corresponds to the most critical requirement for design consideration. In brief, the largest value in each row of interaction matrix CRP is selected to form the reference vector $CRPRV$.

In performing the grey relation analysis, the values in $CRPRV$ and CRP are initialized first [13]. Let $ICRPRV$ denote an m dimensional row vector describing the status of value initialization of reference vector $CRPRV$, where $ICRPRV_j = \dfrac{ICRPRVj}{ICRPRV1}, j = 1,$ $2, \ldots, m$. Similarly, let $ICRP$ denote an $n \times m$ matrix describing the status of value initialization of the interaction matrix CRP, where $ICRP_{i,j} = \dfrac{ICRP_{i,j}}{ICRP_{i,j}}$, $i = 1, 2, \ldots, n,\ j = 1, 2, \ldots, m.$, Then, the column values of the initialized reference vector $ICRPRV$ are used to compare the corresponding row value of the initialized matrix $ICRP$ to make a relational distance assessment. There are three general approach steps to obtain the grey relation for each customer requirement $CRGM_{h,\ hg}$. They are stated as follows [13]:

Step 1: Calculation of column differences between each row element of $ICRP$ and $ICRPRV$. Let $DFCRPR$ denote an $n \times m$ matrix describing the status of column differences between each row element of $ICRP$ and $ICRPRV$, with typical element $DFCRP_{i,\ j}$, such that

$$DFCRP_{i,j} = \left| ICRP_{i,j} - ICRPRV_j \right|, \quad i = 1, 2, \ldots, n, j = 1, 2, \ldots, m. \tag{1}$$

Step 2: Calculation of coefficient of relation for each cell of $DFCRPR$.

Let $CRCRP$ denote an $n \times m$ matrix describing the degree of relation between each row element of $DFCRPR$ and $ICRPRV$, with typical element $CRCRP_{i,\ j}$, such that

$$CRCRP_{i,j} = r\big((ICRPRV_j,\ DFCRP_{i,j})|, j = 1, 2, \ldots, m\big), \quad i = 1, 2, \ldots, n$$
$$= \frac{\min_i \min_j DFCRP_{i,j} + \lambda \max_i \max_j DFCRP_{i,j}}{DFCRP_{i,j} + \lambda \max_i \max_j DFCRP_{i,j}} \tag{2}$$

Note that λ denotes the distinguished coefficient and ranges between [0, 1]. In most cases, the value of λ is set at 0.5 to represent a neutral consideration.

Step 3: Calculation of coefficient of grey relation for each categorized customer requirement $CRGM_{h,\ hg}$.

Let $GRCRGM$ denote an n dimensional column vector describing the degree of grey relation for each categorized customer requirement $CRGM_{h,\ hg}$, with typical element $GRCRGM_i$, such that

$$GRCRGM_i = r((ICRPRV_j,\ CRCRP_{i,j})|, \quad j = 1, 2, \ldots, m), i = 1, 2, \ldots, n = \frac{1}{n} \sum_{j=1}^{m} CRCRP_{i,j} \tag{3}$$

Note that the coefficients of grey relation in column vector $GRCRGM$ ranges between (0, 1). It is also noted that a higher grey relational coefficient represents higher importance of the effect on the corresponding customer requirement. Therefore, the coefficients of grey relation in $GRCRGM$ are considered importance degrees of the corresponding customer requirement $CRGM_{h,\ hg}$ and will be used in the QFD employment procedure to determine the relative overall importance degrees of customer requirements.

5. Grey Relations in the Employment Procedure of QFD

In the employment procedure of QFD, the first stage of HOQ is implemented primarily for the evaluation of relationships between categorized customer requirements and design characteristics. The evaluation of the relationships between the categorized customer requirements and design characteristics in HOQ refers to a relationship matrix. Note that before dealing with the relationship matrix of HOQ, the designer first needs to determine the relative overall importance degrees of categorized customer requirements. According to the concept of building an HOQ in QFD, the following three factors were considered in this research: importance degrees of categorized customer requirements $GRCRGM$, targeted performance satisfaction TPS, and market niche MN.

Let TPS denote an $\boldsymbol{n}$ dimensional column vector describing targeted performance satisfaction for the corresponding categorized customer requirement $CRGM_{h,\ hg}$, with typical element TPS_i, such that $TPS_i = \{p | p \in R \text{ and } p \in (1,\ 5)\},\ i = 1,\ 2, \ldots, n$. Similarly, let MN denote an n dimensional column vector describing the market niche for the corresponding categorized customer requirement $CRGM_{h,\ hg}$, with typical element MN_i, such that $MN_i = \{q | q \in R \textit{ and } q \in (1, 1.2, 1.5)\}$, $i = 1, 2, \ldots, n$. The values in vector TPS express a competitive assessment that the expected performance satisfaction to be targeted for the corresponding $CRGM_{h,\ hg}$ is based on the comparisons of customer perception between the product of the existing company and those of its competitors. Note that the value is assessed on a five-point scale with points 1, 2, 3, 4, and 5 corresponding to very low, low, medium, high, and very high satisfaction. The values in vector MN express the potential increase in market shares, if the corresponding $CRGM_{h,\ hg}$ are considered and improved in the design. In general, values are assessed on the basics of 1, 1.2, and 1.5. The weighting values of 1–5 and 1–1.5 for TPS_i and MN_i, respectively, are chosen by each subject and then averaged. The averaged values are assigned to the corresponding overall HOQ matrix cells TPS_i and MN_i. After the values of $GRCRGM_i$, TPS_i, and MN_i have been determined, the designer can calculate values for the relative overall importance degrees of categorized customer requirements $CRGM_{h,\ hg}$.

Let $ROICRM$ denote an n dimensional column vector describing the relative overall importance degrees of categorized customer requirements $CRGM_{h,\ hg}$, with typical element $ROICRM_i$, such that

$$ROICRM_j = \frac{GRCRGM_i \times TPS_i \times MN_i}{\sum_{i=1}^{n}\left(GRCRGM_i \times TPS_i \times MN_i\right)} \times 100\%,\quad i = 1, 2, \ldots, n \tag{4}$$

The $ROICRM$ will combine with the relationship matrix to determine the relative overall importance of design characteristics, which are identified by deploying and examining the manufacturing processes. Historically, a combination of personal observation, intuitive findings, and systematic approaches has been used to identify design characteristics. Let DC denote the set of identified design characteristic. $DC = \{DC_k | k = 1, 2, \ldots, a\}$. The identified design characteristics are then evaluated with categorized customer requirements *via* a relationship matrix in HOQ to select some critical design characteristics for further experimental design.

Let $RCRDC$ denote an $n \times a$ relationship matrix describing the degree of relation between each categorized customer requirement $CRGM_{h,\ hg}$ and design characteristic DC_k, with typical element $RCRDC_{i,\ k}$, such that

$$RCRDC_{i,k} = \{t | t \in R \text{ and } t \in (1, 5)\},\ i = 1, 2, \ldots, n,\quad k = 1, 2, \ldots, a.$$

The value in each element of the relationship matrix $ICRDC$ is assessed by the subject and then averaged to obtain a single value. The assessment criterion is based on a 1–3–5 point scale in which the values 1, 3, and 5 represent weak relation, moderate relation, and strong relation, respectively. With the values of the relative overall importance degrees of categorized customer requirements $ROICRM$ and the relations between categorized customer requirements and design characteristics $RCRDC$, the relative overall importance degrees of design characteristics can be calculated.

Let $ROIDC$ denote an $\boldsymbol{a}$ dimensional column vector describing the relative overall importance degrees of identified design characteristics, with typical element $ROIDC_k$, such that

$$ROIDC_k = \frac{\sum_{i=1}^{n}\left(ROICRM_i \times RCRDC_{i,k}\right)}{\sum_{k=1}^{a}\sum_{i=1}^{n}\left(ROICRM_i \times RCRDC_{i,k}\right)} \times 100\%,\quad k = 1, 2, \ldots, a,\ i = 1, 2, \ldots, n \tag{5}$$

The critical design characteristics of technical benchmarking in QFD can then be determined based on some higher values of the relative overall importance degrees of design characteristics $ROIDC$. The selected design characteristics will be used as control factors for further design of the experiment to find optimum quality of design characteristics that meet the identified customer requirements.

6. Taguchi Method for Design Experiment

According to the result of conducting the QFD process, some critical design characteristics are chosen from the column vector $ROIDC$ These critical design characteristics are considered design parameters and then sent forward to perform a designed experiment. As mentioned earlier, the Taguchi method is used for the simplification of experimental design. While performing the Taguchi method, the designer first needs to identify the levels for each design parameter, which can be represented in a quantitative or qualitative manner. In general, two to three levels are considered for the design parameters to find a suitable form of orthogonal array. The orthogonal array provides information about the combination of levels of design parameters for each run of the experiment. In the Taguchi method, the quadratic quality loss function is developed to provide a better estimation of the loss incurred by manufacturers and consumers as the product performance deviates from its target. Let the quadratic quality loss function $LF(y)$ be the loss due to deviation from the target value (TV). The loss function $LF(y)$ is given by Taylor's series expansion about $y = TV$ and denoted as

$$LF(y) = LF(TV) + [LF'(TV)/1!][y - TV] + [LF''(TV)/2!][y - TV]^2 + \textit{high order terms} \tag{6}$$

It is assumed that the product satisfies the customer when it is performing at the *target value*, i.e., the quality loss should be zero: $L(TV) = 0$. The second term in the Taylor's series is zero because the loss function is minimum at $y = TV$: $L'(TV) = 0$. In practice, the higher-order terms of the expansion are inconsequential due to the loss function being applied close to the target. The high-order terms are relatively small and may be neglected. The loss function is then given as shown in Equation (7), where CLF is a constant called quality loss coefficient.

$$LF(y) \approx [LF''(TV)/2!][y - TV]^2 = CLF[y - TV]^2 \tag{7}$$

Let RPC be the cost to replace or repair the product as a consequence of off-target performance.

The customer tolerance, $CTOL$, corresponds to the off-target performance. The functional limit, $TV \pm CTOL$, is the point at which the product would fail and the total loss at $TV \pm CTOL$ is equal to RPC. Thus, the quality loss coefficient (CLF) can be expressed as $CLF = RPC/(CTOL)^2$.

The S/N ratio is introduced as the most important component of parameter design in the Taguchi method and taken as the critical factor in conjunction with the orthogonal array to evaluate the quality performance. It is used to optimize product design and to reduce the variance in the developed product. For the smaller-the-better quality characteristic, the loss function can be expressed as: $LF(y) = [RPC/(CTOL)^2]y^2 = [RPC/(CTOL)^2]\sigma^2$, where σ^2 is the variance of measurement and expressed as $\sigma^2 = (1/u)\sum y_r^2$, $r = 1, 2, \ldots, u$, where u is the number of experiments in the orthogonal array and y_r is the measured value of test condition with $r = 1\text{–}u$. The S/N ratio is defined as follows [34]:

$$\eta = S/N = -10 \times \log\left(\frac{1}{u}\sum_{r=1}^{u} y_r^2\right) db = -10 \times \log(MSD) \tag{8}$$

where MSD is the mean squared deviation from the *target value* of the quality characteristic and is defined as

$$MSD = (y_1^2 + y_2^2 + y_3^2 + \cdots y_u^2)/u$$

where u is the number of repetitions y_r.

The smaller-the-better quality characteristic is optimized when the S/N response is as large as possible. However, the typical problems in this optimization are the following: (1) response values or quality characteristics are continuous and nonnegative, (2) the desired value of the response is zero, and (3) there is no scaling or adjustment factor. The goal is to minimize the mean and variation.

Conducting Taguchi experiments in terms of orthogonal arrays allows the effects of several parameters to be determined efficiently. The method is an important technique in robust design [40]. The ability to detect the presence of interactions is considered the primary reason for using orthogonal arrays to conduct matrix experiments. Matrix experiments using orthogonal arrays provide a method to evaluate whether the above selections can be successfully achieved based on engineering considerations such as selecting quality characteristics, S/N ratios, control factors and their levels.

7. Implementation of the Integrated Process of QFD and QE

A timer manufacturing company, Nan-Cheng Precision Corp., which is renowned for its strict focus on quality has participated in this study. In line with the spirit of innovation, the manufacturer is constantly improving to make its products more superior. The timers produced by the company are frequently used in daily life or as built-in timers in appliances that are operated in different circumstances. Despite being operated under different conditions such as varying temperatures, humidity and ventilation, it is essential for the devices to work in a proper and precise manner. However, the company has faced repeated customer complaints regarding the accumulated day-by-day deviation of the timer, which requires frequent calibration of the device. The variation in the quality of the timer occurs not only between products but also under different operational environments. The process in this research is proposed and supported by the Nan-Cheng Precision Corp. to increase customer satisfaction. Six timers with different configurations are under evaluation in this research to improve the product quality and consistency of manufacturing.

7.1 Grey Determination of the Relative Importance Degrees for *CRs* and QFD Development

The identification of customer requirements is based on descriptions of customer attributes that can truly respond to customer demands in the market. In the timer design example, the semantic differential method has been applied using a questionnaire survey based on a five-point scale to evaluate the significance of the customer requirements. The interview and market survey has been given to 36 interviewees comprising 23 customers, 5 salesmen, 3 manufacturing engineers, 3 agents, and 2 designers. The selected testers have been asked to evaluate the relationships between the customer requirements CR and semantic attribute indices AT and then assign a rating scale of five points 1, 2, 3, 4, and 5 to indicate their significance. Each semantic attribute index corresponding to customer requirements CR_1, $CR_2, \ldots, CR_{10}$ is calculated by taking the average of semantic attribute indices. As given in Table 1, the values obtained from the survey are 2.16, 1.92, 4.61, 3.58, 3.36, 2.68, 2.59, 3.19, 4.27, and 1.56. Using HCT with a Euclidean distance criterion, the 10 identified customer requirements are evaluated and classified into four meaningful clusters that are defined as follows: (1) usage method, (2) physical property, (3) reliability, and (4) environment.

The new approach using grey theory is introduced to prioritize and evaluate the weights of CRs. The evaluations are conducted by the users and cooperative suppliers based on the six selected products. A weighting value of 1 to 100 is chosen by each subject and the averaged value is assigned to the corresponding matrix cell $CRP_{11,\ 6}$ from the interview based on the

Table 1. The HCT in CR categories.

Panel A: The CR_i and corresponding AT_b

Item	Customer requirement (CR_i)	Average semantic attribute indices (AT_b)
1	Light weight	2.16
2	Rigid body	1.92
3	Humidity resistance	4.61
4	User friendly	3.58
5	Timer accuracy	3.36
6	Heat resistance	2.68
7	Low noise	2.59
8	Plug location	3.19
9	Setting switch reliability	4.27
10	Heavy loading	1.56

Panel B: CRs categorized using the HCT

Category	Category name	CR_i name of each category (corresponding AT_b value)
1	Usage method	(User friendly, timer accuracy, plug location) (3.58, 3.36, 3.19)
2	Physical property	(Light weight, rigid body, heavy loading) (2.16, 1.92, 1.56)
3	Reliability	(Humidity resistance, setting-switch reliability) (4.61, 4.27)
4	Environment	(Heat resistance, low noise) (2.68, 2.59)

assumption that the products have a low degree of satisfaction or the categories have a significant effect on the collected products. After the matrix $CRP_{11,\ 6}$ has been generated, the grey relation analysis is performed with a chosen maximum reference value from each row of cells $CRP_{11,\ 6}$ to form a column vector $CRPRV_{11}$. In this case, each reference column vector $CRPRV_1$, $CRPRV_2, \ldots, CRPRV_{11}$ is calculated as 88.91, 91.48, ..., 86.36, respectively. It should be noted that a higher value of $CRPRV_j$ indicates a lower degree of satisfaction for the selected product.

The initialized reference row vector $ICRPRV_j$ ($j=1, 2, \ldots, 6$) and initialized grey transformed matrix $ICRP_{10,\ 6}$ describe the status of the initialization values of the reference grey transformed vector $CRPRV$ and matrix CRP, respectively. The rated scale $ICRPRV_1$, $ICRPRV_2, \ldots, ICRPRV_6$ are calculated as 1.000, 0.857, 0.829, 0.790, 0.624, and 0.581, and the initialization values of the grey transformed matrix cell $ICRP_{1,\ 1}$, $ICRP_{1,\ 2}, \ldots, ICRP_{10,\ 6}$ are calculated as 1.000, 0.872, ..., 0.851, respectively. Each value of the initialization grey transformed matrix cell is listed in Figure 2.

The three steps described earlier are followed to obtain the grey relation for each customer requirement category and are stated as follows:

Step 1: Calculation of column differences or the distance between each row element of $ICRP_{10,\ 6}$ and $ICRPRV_6$. Let $DFCRP$ be a 10×6 matrix describing the difference between each row element of $ICRPRV_6$ and $ICRP_{10,\ 6}$. Applying Equation (1), the $DFCRP_{1,1}$, $DFCRP_{1,2}, \ldots, DFCRP_{10,6}$ are calculated as 0.000, 0.015, ..., 0.271. Each value of the grey difference matrix $DFCRP_{10,\ 6}$ is listed in Figure 2.

Step 2: Calculation of the coefficient of relation for each cell of $CRCRP_{10,\ 6}$. $CRCRP_{10,\ 6}$ denotes the degree of relation between each row element of $DFCRPR_{10,\ 6}$ and $ICRPRV_6$. Substituting $ICRPRV_6$ and $ICRP_{10,\ 6}$ into Equation (2) gives $CRCRP_{1,\ 1}$, $CRCRP_{1,\ 2}, \ldots, CRCRP_{10,\ 6}$ as 1.000, 0.914, ..., 0.369. Note that the values above are calculated at a λ-value of 0.5 to represent a neutral consideration.

Step 3: Calculation of grey relation coefficient matrix $GRCRGM_{10}$ for each categorized customer requirement by taking the average of row values of $CRCRP_{10,\ 6}$. For example, $GRCRGM_1$ is calculated as 0.783 by averaging 1.000, 0.914, 0.775, 0.726, 0.341, and 0.942. The remaining grey relation coefficients calculated for each customer requirement $GRCRGM_i$, $i=2, 3, \ldots, 10$ are 0.896, 0.747, 0.624, 0.655, 0.789, 0.663, 0.854, 0.645, and 0.642.

It should be noted that a higher $GRCRGM$ value represents higher importance of effect on the corresponding customer requirement. The step-by-step generation of the degree of grey relation for each categorized customer requirement matrix is shown in Figure 2.

The cause and effect diagram is employed to extract the primary design characteristics of a timer. All the design characteristics are generated by two designers and three manufacturing engineers through discussion and brainstorming sessions. Each tester will judge the selected design characteristics based on the following four attributes: process, material, operation, and environment. The objective of the diagram is to achieve high

Customer requirements

Customer requirements	$CRPRV_j$	P_1 $CRP_{i,1}$	P_2 $CRP_{i,2}$	P_3 $CRP_{i,3}$	P_4 $CRP_{i,4}$	P_5 $CRP_{i,5}$	P_6 $CRP_{i,6}$
use friendly	91.48	91.48	79.74	71.65	66.78	84.96	54.00
timer accuracy	74.32	74.32	68.00	60.80	57.28	46.89	45.00
plug location	88.91	83.47	88.91	74.72	65.66	51.33	55.74
light weight	83.17	83.17	45.00	69.41	55.32	67.00	66.43
rigid body	75.50	75.50	75.00	63.90	64.00	66.00	63.52
heavy loading	84.47	84.47	80.47	75.69	72.00	51.54	53.00
humidity resistance	78.73	78.73	60.00	64.41	55.00	67.00	66.28
setting reliability switch	84.92	84.92	77.45	70.46	64.27	51.49	56.32
heat resistance	90.36	88.00	90.36	82.73	63.62	67.40	60.78
low noise	86.36	86.36	80.73	73.91	55.64	71.30	73.50

The grey transformed matrix

$ICRPRV_j$	1.000	0.857	0.829	0.790	0.624	0.581
$ICRP_{1,j}$	1.000	0.872	0.783	0.730	0.929	0.590
$ICRP_{2,j}$	1.000	0.915	0.818	0.771	0.631	0.605
$ICRP_{3,j}$	0.939	1.000	0.840	0.738	0.577	0.627
$ICRP_{4,j}$	1.000	0.541	0.835	0.665	0.806	0.799
$ICRP_{5,j}$	1.000	0.993	0.846	0.848	0.874	0.841
$ICRP_{6,j}$	1.000	0.953	0.896	0.852	0.610	0.627
$ICRP_{7,j}$	1.000	0.762	0.818	0.699	0.851	0.842
$ICRP_{8,j}$	1.000	0.912	0.830	0.757	0.606	0.663
$ICRP_{9,j}$	0.974	1.000	0.916	0.704	0.746	0.673
$ICRP_{10,j}$	1.000	0.935	0.856	0.644	0.826	0.851

The grey differences matrix

$DFCRP_{1,j}$	0.000	0.015	0.046	0.060	0.305	0.010
$DFCRP_{2,j}$	0.000	0.058	0.011	0.019	0.007	0.025
$DFCRP_{3,j}$	0.061	0.143	0.011	0.051	0.046	0.046
$DFCRP_{4,j}$	0.000	0.316	0.005	0.124	0.182	0.218
$DFCRP_{5,j}$	0.000	0.137	0.017	0.058	0.251	0.261
$DFCRP_{6,j}$	0.000	0.096	0.067	0.063	0.014	0.047
$DFCRP_{7,j}$	0.000	0.095	0.011	0.091	0.227	0.261
$DFCRP_{8,j}$	0.000	0.055	0.001	0.033	0.017	0.083
$DFCRP_{9,j}$	0.026	0.143	0.086	0.085	0.122	0.092
$DFCRP_{10,j}$	0.000	0.078	0.027	0.145	0.202	0.271

The coefficient of grey relation

							$GRCRGM_i$ (if λ=0.5)
$CRCRP_{1,j}$	1.000	0.914	0.775	0.726	0.341	0.942	0.783
$CRCRP_{2,j}$	1.000	0.731	0.934	0.893	0.956	0.864	0.896
$CRCRP_{3,j}$	0.721	0.524	0.933	0.756	0.773	0.773	0.747
$CRCRP_{4,j}$	1.000	0.333	0.967	0.559	0.465	0.420	0.624
$CRCRP_{5,j}$	1.000	0.536	0.902	0.731	0.387	0.377	0.655
$CRCRP_{6,j}$	1.000	0.622	0.702	0.715	0.921	0.771	0.789
$CRCRP_{7,j}$	1.000	0.625	0.935	0.634	0.410	0.377	0.663
$CRCRP_{8,j}$	1.000	0.741	0.996	0.828	0.901	0.656	0.854
$CRCRP_{9,j}$	0.858	0.524	0.646	0.649	0.564	0.632	0.645
$CRCRP_{10,j}$	1.000	0.669	0.855	0.521	0.439	0.369	0.642

The grey relational coefficient matrix

Figure 2. The grey relation reasoning of *CRs*.

accuracy for the timer. In other words, the goal is to minimize the difference between the time set in the device and the calibrated standard time. In the timer design example, the set of design characteristics representing the product feature is denoted as $[DC_1, DC_2, \ldots, DC_{18}]$ = [material selection, rotating pin length, surface plating, ..., on/off switch, rigid setting rod]. The individual categories are listed in Table 2.

The targeted performance satisfaction *TPS* denotes a 10-dimensional column vector and the surveyed values from the interviewees are averaged with typical elements TPS_{10} = [3.08, 4.92, 4.01, 2.97, 3.69, 2.82, 3.72, 3.93,

Table 2. The HOQ for product redesign of the electronic timer.

			Material selection	Rotating pin length	Surface plating	Assembly clearance	Manu-facturing time	Edge trimming	Assembly speed	Surface rough-ness	Humidity resistance	Switch contact pressure	Voltage isolation	Isolation seal	Heat generation	Support distance	Switch masking	Ground	On/off switch	Rigid setting rod	Grey relation for *CRs* (GRCRGM)	*TPS*	Market niche (MN)	Competitive assessment	Summed weight of *CR* (ROICRM)	Relative overall importance of *CRs*
1. Usage methods	1.1	Use friendly	2.8	4.7	1.1	2.2	1.5	1.1	1.1	2.1	1.3	3.3	1.8	1.2	1.9	1.8	2.2	1.1	3.1	2.6	0.783	3.08	1.2	6	2.891	7.99
	1.2	Timer accuracy	3.1	3.5	3.1	3.2	2.2	2.7	2.1	4.3	1.7	4.5	2.1	1.9	2.2	4.4	1.1	1.9	1.1	1.2	0.896	4.92	1.5	7	6.620	18.29
	1.3	Plug location	1.5	1.2	1.2	1.6	1.8	1.1	1.1	1.6	1.1	1.1	1.3	1.1	1.1	3.1	1.1	1.1	1.1	1.1	0.747	4.01	1.5	6	4.492	12.41
2. Physical properties	2.1	Light weight	1.3	1.2	1.1	1.1	1.1	1.1	1.5	1.1	1.1	1.2	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	0.624	2.97	1.0	5	1.853	5.12
	2.2	Rigid body	1.3	2.9	1.2	3.7	1.1	1.1	1.5	1.2	1.1	2.8	1.3	1.5	1.1	1.8	1.1	1.1	1.1	1.9	0.655	3.69	1.5	5	3.630	10.03
	2.3	Heavy loading	1.5	1.1	1.6	4.1	1.1	1.1	1.6	1.7	1.2	1.1	1.2	1.1	1.6	3.2	1.1	1.6	1.2	1.1	0.789	2.82	1.0	7	2.224	6.15
3. Reliabilities	3.1	Humidity resistance	3.3	3.5	1.8	3.7	1.1	1.2	2.2	1.8	1.7	1.3	1.6	3.8	1.2	2.5	1.3	2.7	1.1	1.9	0.663	3.72	1.5	6	3.702	10.23
	3.2	Setting switch reliability	1.5	1.2	1.1	1.5	1.2	1.5	1.2	1.2	1.8	1.3	1.1	1.9	1.7	1.1	1.9	1.2	1.1	2.3	0.854	3.93	1.5	3	5.033	13.91
4. Environments	4.1	Working temperature	1.6	1.1	1.4	1.6	1.1	1.3	1.3	1.2	1.2	3.2	2.9	1.1	1.9	1.8	1.1	1.3	1.1	1.2	0.645	4.82	1.2	5	3.736	10.32
	4.2	Low noise	1.5	1.6	1.3	3.2	1.2	1.3	1.1	1.6	1.1	2.3	1.1	1.3	1.1	1.4	1.1	1.1	1.1	1.1	0.642	3.13	1.0	5	2.010	5.55
Summed weight of *DCs*			**74.6**	**83.7**	59.1	**93.0**	47.8	53.9	52.8	**72.3**	50.7	**87.0**	58.9	61.3	56.9	**88.3**	22.2	53.4	45.8	57.1						
Relative overall importance degree (ROIDC %)			**6.67**	**7.48**	5.28	**8.31**	4.27	4.82	4.72	**6.46**	4.53	**7.78**	5.26	5.48	5.09	**7.89**	1.99	4.77	4.10	5.10						

Note: Bold values denote the critical design characteristics.

4.82, 3.13]. The vector expresses a competitive assessment of the product based on comparisons of customer perception between the existing company's product and those of its competitors. The market niche MN is also a 10-dimensional column vector with values assessed as MN_{10} = [1.2, 1.5, 1.5, 1.0, 1.5, 1.0, 1.5, 1.5, 1.2, 1.0]. The summed weight of customer requirements are calculated as a 10-dimensional column vector with elements $ROICRM_{10}$ = [2.892, 6.620, 4.492, 1.853, 3.630, 2.224, 3.702, 5.033, 3.736, 2.010] and the relative overall importance $ROIDC_{10}$ = [7.99, 18.29, 12.41, 5.12, 10.03, 6.15, 10.23, 13.91, 10.32, 5.55]. The evaluated values are illustrated in Table 2.

To create the relationship between the customer requirements and design characteristics $RCRDC_{10,\ 18}$, the rated values of the relationships matrix are generated by giving the weights from the survey at the rating scales of 1, 3, and 5 representing weak relation, moderate relation, and strong relation, respectively. If no relationship exists, then the rated value is left blank or assigned the numerical value '0'. Thus, the relationships between customer requirements and the design characteristics for the timer design example have been evaluated as illustrated in Table 2.

The summed weight of each design characteristic is calculated by the multiplication summation of relative overall importance degrees $ROICRM_{10}$ and the relationship matrix cell $RCRDC_{10,\ 18}$. Considering the example of calculation of material selection, the summed weight of the design characteristics is 74.6 with a relative overall importance degree of 6.67%, which is calculated as shown in the equation below. The results of the summed weight of design characteristics and relative overall importance degrees $ROIDC_{18}$ are calculated as shown in Table 2.

$$\sum ROICRM_1 \times RCRDC_{i,1} = 2.891 \times 2.8 + 6.620 \times 3.1 + 4.492 \times 1.5 + \cdots + 3.736 \times 1.6 + 2.010 \times 1.5 = 74.6$$

$$ROIDC_1\% = 6.67\% = 74.6/[74.6 + 83.7 + 59.1 + 93.0 + 47.8 + 53.9 + \cdots + 45.8 + 57.1]$$

From the relative overall importance of customer requirement, accuracy is found to be the highest customer concern with an importance weight of 18.29%. The second and third concerns are reliability of the setting-switch and the location of the plug with importance weights of 13.91% and 12.41%, respectively. With respect to design characteristics, the highest relative importance weight of $ROIDC$ is 8.31%, given to assembly clearance, and is followed by support distance, which is rated at 7.89%. The third design characteristic concern is switch contact pressure, which is rated at 7.78%. The 4th, 5th, and 6th concerns are rotating-pin length, material selection and surface roughness. The remaining scores are too small to be considered. Thus, in this timer example, the following 6 factors are used as critical design characteristics to guide quality experiment design and product development: assembly clearance, support distance, switch contact pressure, rotating pin length, material selection and surface roughness.

7.2 Experiment Design and Analysis

Due to a full factorial approach being applicable only with limited factors, Taguchi has developed a family of experimental arrays to minimize the number of total experimental runs. At the beginning of the method, the designer uses the six selected critical design characteristics and defines the parameter levels of developing the product based on a combination of past experience, engineering theorems, and functional requirements. In this study, the six selected critical design characteristics are designated A–F, respectively. Material selection is the only characteristic with two levels. The remaining design characteristics all have three levels. The six critical design characteristics listed in Table 3 are stated in the following:

1. Material selection denoted by A – Two-level factor: two selections are available, polytetrafluoroethylene (PTFE) and polyethylene (PE) used on the gears for transmission inside the timer.
2. Surface roughness denoted by B – Three-level factor: the roughness of the pad used on the swing rod affects the sensitivity of the switch. In this timer example, three levels are available at 1.6, 3.2, and 6.3 μ , m.
3. Rotating pin length denoted by C – Three-level factor: excessive length of the rotating pin will reduce the accuracy, whereas an insufficient length will be over-sensitive. In this timer example, three levels are available at 14.0, 15.0, and 16.0 mm.
4. Support distance denoted by D – Three-level factor: the support distance of the main gear ensures that the force is correctly transferred to the followers. Due to the design limitations of the space and rigidness of

Table 3. The six critical DCs of all levels.

Critical *DCs*	Level 1	Level 2	Level 3
A: Material selection (PTFE or PE)	PTFE	PE	
B: Surface roughness (μm)	1.6	**3.2**	6.3
C: Rotating pin length (mm)	14.0	**15.0**	16.0
D: Support distance (mm)	8.0	9.0	**10.0**
E: Assembly clearance (mm)	0.08	**0.10**	0.12
F: Switch contact pressure (g/cm^2)	120	**150**	180

Note: Bold values denote the critical *DCs*.

the gears, the original value of 10 mm is specified as the maximum, and the remaining two levels are set at 8.0 and 9.0 mm.

5. Assembly clearance denoted by E – Three-level factor: although low clearance may increase the accuracy, also it will also increase manufacturing cost and the risk of unqualified. The clearances of the level are set at 0.08, 0.10, and 0.12 mm.
6. Switch contact pressure denoted by F – Three-level factor: the on/off switch is controlled by contact pressure which is affected by the length of the switch arm. Currently, the pressure is set at 150 g/cm^2 and taken as middle value. The lower and upper limits are set at 120 and 180 g/cm^2, respectively.

All the levels available for each design characteristic are summarized below. The values in bold and underlined text represent the critical design characteristic levels that are used currently.

According to these six critical design characteristics and corresponding levels, the timer example in this research uses an L_{18} ($2^1 \times 3^5$) orthogonal array. The chosen array has 18 rows corresponding to the number of tests with one design characteristics at two levels and five design characteristics at three levels.

The timer is tested under the test chamber shown as Figure 3. It is tested in the following three conditions: high temperature, low temperature and high humidity. The high temperature condition (70°C ± 3°C) and low temperature condition (−10°C ± 3°C) are at the humidity level (50% ± 5%). The high humidity condition (90% ± 5%) is at a temperature of 40°C ± 3°C. The standard setting time is 150 min and the deviation is denoted as $\Delta E_{U,V}$, where $U = 1, 2$ and $V = 1, 2,$ and 3. The setting time is defined as the time difference measured between calibrated standard timer and tested timer, where

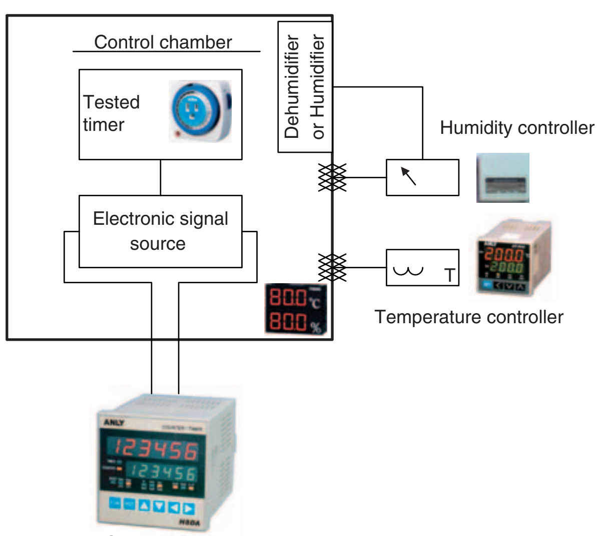

Figure 3. The connections of the QE experiment test chamber.

the suffix U represents the scenario series number and V represents the test chamber condition number. Scenario 1 is measured under a specific set of environmental conditions and scenario 2 is measured under identical conditions but by putting the timer into the chamber 2 h prior to the test. In the timer example, the first run condition of the experiment is measured under the level $A_1B_3C_1D_2E_1F_3$. The measured deviations are denoted as [$\Delta E_{1,1}$, $\Delta E_{1,2}$, $\Delta E_{1,3}$, $\Delta E_{2,1}$, $\Delta E_{2,2}$, $\Delta E_{2,3}$] and equal to [15.2, 17.9, 13.3, 12.7, 14.6, 14.9], respectively. The average setting time is 14.77 s and the standard variation s_d is calculated using Equation (9) below as 1.8151 s. All the deviations and standard variations of the 18 tests are illustrated in Table 4 (Panel A).

$$s_d = \sqrt{\frac{n_t \sum \Delta E_{U,V}^2 - \left(\sum \Delta E_{U,V}\right)^2}{n_t(n_t - 1)}} \tag{9}$$

where s_d is the standard deviation (SD), n_t the number of experiments in each orthogonal array, here $n_t = 6$, $\Delta E_{U,V}$ the measured value of test at chamber condition V.

The parameter $(S/N)_{n_t}$, $n_t = 1, 2, \ldots, 18$ represents the S/N value of each test run. The value can be obtained from Equation (8) and is calculated as listed in Table 4 (Panel A). The parameter $(S/N)_{C_{dc},D_v}$, $C_{dc} = A, B, \ldots, F$ and $D_v = 1, 2, 3$ is the averaged $(S/N)_{n_t}$ ratio that is affected by the value level D_v of critical design characteristics C_{dc}. In this timer example, $(S/N)_{A,1}$ is the average of $(S/N)_{n_t}$ of each test run with critical design characteristics equal to A and under test chamber condition 1. In other words, $(S/N)_{A,1} = -20.1653$ is generated from the average of $(S/N)_{n_t}$, $n_t = 1, 2, \ldots, 9$ and $(S/N)_{A,2} = -18.8247$ is calculated by averaging the $(S/N)_{n_t}$ from $n_t = 10, 11, \ldots, 18$. Considering the smaller-the-better characteristic, Table 4 (Panel B) gives the S/N value, where it can be noted that the S/N is strongly affected by design characteristics E and F, i.e., assembly clearance and switch contact pressure.

7.3 Validation of Optimal Controlled Critical Design Characteristics Set Points

The optimal set of critical design characteristic combination parameters has been determined by selecting the level with the highest S/N value for each critical design characteristics. This combination should provide the best response that is minimally affected by noise. This optimum result is a superior operating point for this experimental arrangement only. Note that the optimum set points, $A_2B_2C_1D_3E_3F_2$, are not identified in any arrangement in the experiment. The statistical nature of designed experiments warrants that the optimal result is pieced together from the maximum

Table 4. The orthogonal array and corresponding S/N values.

Panel A: The orthogonal array and corresponding S/N values for each experimental run

Run no.	A	B	C	D	E	F	Scenario 1 $\Delta E_{1,1}$	Scenario 1 $\Delta E_{1,2}$	Scenario 1 $\Delta E_{1,3}$	Scenario 2 $\Delta E_{2,1}$	Scenario 2 $\Delta E_{2,2}$	Scenario 2 $\Delta E_{2,3}$	Average	SD	$(S/N)_{n_t}$	Test chamber condition
1	1	1	1	1	1	1	15.2	17.9	13.3	12.7	14.6	14.9	14.77	1.8151	−23.4400	$\Delta E_{U,1}$:70 ± 3°C, humidity 45–55%
2	1	1	2	2	2	2	8.9	9.4	8.6	9.2	8.6	8.6	8.88	0.3488	−18.9771	$\Delta E_{U,2}$:−10 ± 3°C, humidity 45–55%
3	1	1	3	3	3	3	6.3	7.8	7.9	6.3	6.1	7.2	6.93	0.8066	−16.8676	$\Delta E_{U,3}$:40 ± 3°C, humidity 85–95%
4	1	2	1	1	2	2	5.3	8.0	6.8	7.2	6.8	6.8	6.82	0.8773	−16.7310	
5	1	2	2	2	3	3	5.0	7.2	6.3	5.2	4.8	5.6	5.68	0.9131	−15.1845	
6	1	2	3	3	1	1	19.4	16.3	21.3	20.2	19.5	18.1	19.13	1.7397	−25.6656	
7	1	3	1	2	1	3	15.3	14.1	15.0	16.8	15.1	14.3	15.10	0.9571	−23.5941	
8	1	3	2	3	2	1	12.9	15.8	12.1	14.2	14.5	11.6	13.52	1.5943	22.6675	
9	1	3	3	1	3	2	8.3	6.2	8.9	7.4	9.8	8.6	8.20	1.2538	−18.3601	
10	2	1	1	3	3	2	3.2	4.8	5.2	4.6	4.5	5.6	4.65	0.8191	−13.4599	
11	2	1	2	1	1	3	10.3	10.2	12.4	11.4	11.6	12.3	11.37	0.9480	−21.1378	
12	2	1	3	2	2	1	13.3	14.1	13.5	13.0	12.6	12.8	13.22	0.5419	−22.4285	
13	2	2	1	2	3	1	7.0	7.8	6.5	7.4	6.9	7.3	7.15	0.4506	−17.1005	
14	2	2	2	3	1	2	5.4	6.3	5.0	4.7	5.0	5.2	5.27	0.5574	−14.4711	
15	2	2	3	1	2	3	15.6	14.5	17.5	15.4	15.3	16.2	15.75	1.0173	−23.9607	
16	2	3	1	3	2	3	8.2	7.2	8.4	7.3	7.5	7.8	7.73	0.4885	−17.7818	
17	2	3	2	1	3	1	10.3	9.8	10.7	11.3	9.4	10.2	10.28	0.6676	−20.2579	
18	2	3	3	2	1	2	8.4	9.2	9.1	7.9	8.3	9.4	8.72	0.5981	−18.8240	

Panel B: $S/N)_{C_{dc}}, D_v$ at different chamber condition D_v of critical DCs C_{dc}

Level of C_{dc}	Critical DC C_{dc} (where C_{dc} = A, B, C, D, E, F) A	B	C	D	E	F
$D_v = 1$	−20.1653	−19.3851	**−18.6845**	−20.6479	−21.1888	−21.9267
$D_v = 2$	**−18.8247**	**−18.8522**	−18.7826	−19.3514	−20.4244	**−16.8039**
$D_v = 3$		−20.2475	−21.0177	**−18.4856**	**−16.8717**	−19.7544

Note: Bold values denote the optimum level of critical *DCs*.

S/N ratios determined irrespective of the experimental runs from which they originate. To validate the optimum set points, nine tests at the same levels of critical design characteristics have been tested and recorded as given in Table 5 (Panel A). The SD is 0.7013 and optimum S/N level is -11.708. It should be noted that the S/N value is larger than any value in the L_{18} test.

The development of an interval estimate of a population mean for the small sample case requires the sampling distribution of μ, which depends on the distribution of the population. The population has a normal distribution, and the SD σ_d is estimated by sample SD S_v. The interval estimate of a population can be expressed as shown in Equation (10). Due to the small sample size, the population SD is unknown. The sample SD S_v is therefore used to estimate σ_d when sample size $n_t < 30$ and Equation (11) is used to calculate S_v [41] as shown below.

$$\overline{\Delta E} - t_{\frac{\alpha}{2},n_v-1} \times \frac{S_v}{\sqrt{n_v}} \leq \mu \leq \overline{\Delta E} + t_{\frac{\alpha}{2},n_v-1} \times \frac{S_v}{\sqrt{n_v}} \tag{10}$$

$$S_v = \sqrt{\frac{\sum\left(\Delta E - \overline{\Delta E}\right)^2}{n_v - 1}} \tag{11}$$

where $\overline{\Delta E}$ is the average ofS/N, S_v the sample SD of the validation test, n_v the number of the validation test, in this case $n_v = 9$, t the t-value providing an area of $\alpha/2$ in the upper tail of the t-distribution with $n_v - 1$ degrees of freedom.

In this research, estimation of the population mean is under the 95% confidence interval. The t-distribution with $n_v - 1 = 8$ degrees of freedom is the appropriate probability distribution for the interval estimation procedure. The value of t is calculated as follows: $t_{\alpha/2,n_t-1} = t_{0.025,8} = 2.306$. The range of S/N of the validation test within 95% confidence interval is calculated as follows:

$$-11.708 - 2.306 \times \frac{0.7013}{\sqrt{9}} \leq \mu \leq -11.708$$
$$+ 2.306 \times \frac{0.7013}{\sqrt{9}}$$
$$-12.2471 \leq \mu \leq -11.1689$$

Table 5 (Panel B) gives the comparison between the original and the optimal design characteristic levels. The characteristics that remain unchanged are surface roughness, support distance, and switch contact pressure. The changed characteristics are material selection, rotating pin length, and assembly clearance. The material is changed from PTFE to PE. The rotating pin length is adjusted from 15.0 to 14.0 mm to increase the sensitivity. The assembly clearance is enlarged from 0.1 to 0.12 m. The average error of the nine trials with adjusted level is 3.79 s, which is less than the original value of 10.18 s. The improvement in the accuracy is 62.8%. The SD of the error is reduced from 0.9108 to 0.7013, which corresponds to an improvement of 23%. The S/N ratio is also reduced from –19.495 to –11.708, corresponding to an improvement of 39.9%. The redesigned product is shown in Figure 4(b). It should be noted that the number and location of the plug is modified because the plug location is also found to be significant during investigation of *CRs*.

8. Conclusions

Product design is critically important to manufacturing. Even though most manufacturers do not explicitly

Table 5. Comparison of the original and redesigned timers.

Panel A: Deviation between calibrated time and set time of validation tests

Run no.	1	2	3	4	5	6	7	8	9	Average ΔE	SD of ΔE (s)
Validation test ΔE (s)	4.51	3.44	3.63	5.11	2.82	3.20	3.86	3.44	4.12	3.79	0.7013

Panel B: Performance improvement comparisons

	Original level	Optimum level $A_2B_2C_1D_3E_3F_2$	Improvement rate (%)
Critical *DCs*:			
A: Material selection	PTFE	PE	
B: Surface roughness (μm)	3.2	3.2	
C: Rotating pin length (mm)	15.0	14.0	
D: Support distance (mm)	10.0	10.0	
E: Assembly clearance (mm)	0.1	0.12	
F: Switch contact pressure (g/cm^2)	150	150	
Test result:			
Average error ΔE (s)	10.18	3.79	62.8
SD of ΔE	0.9108	0.7013	23.0
S/N ratio	–19.495	–11.708	39.9

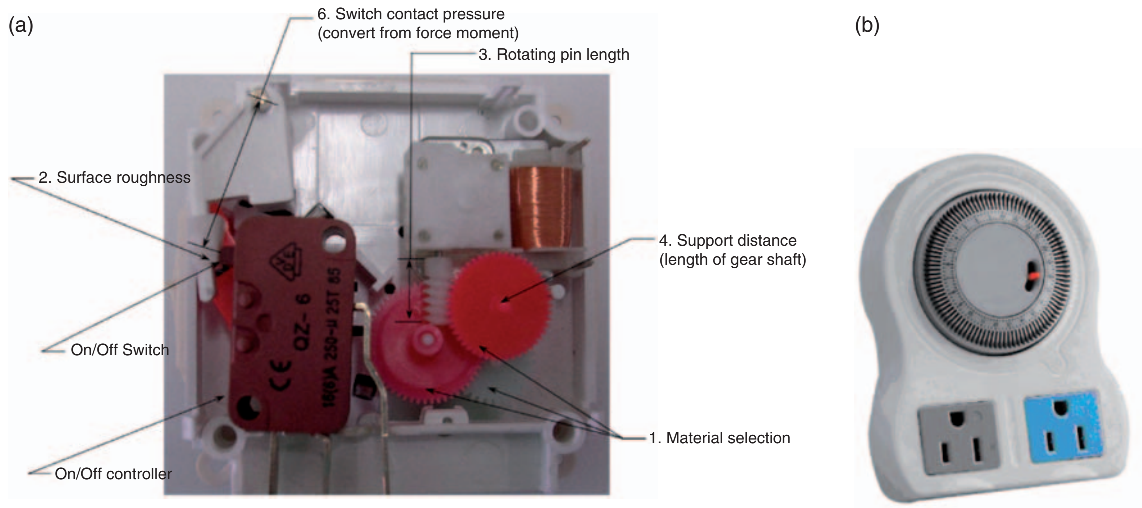

Figure 4. (a) The definition of critical *DCs* and (b) the redesigned timer.

stress enhancing product design, their efforts to improve product quality, increase productivity, and employ computer-aided design/computer-integrated manufacturing systems have integrated some of experience, knowledge, and related technology that might be used to increase the efficiency and effectiveness of product design. If these efforts can be channeled toward the integration of design and manufacturing, it should be possible to make better use of design resources and at the same time produce better products. The research tried to use the concept of grey relation in prioritizing *CRs* of QFD, so that *CRs* and DCs can be more effective linked and then the Taguchi method in determining the optimum combination of DCs.

The application of grey theory in QFD and the subsequent integration with QE for the proposed process has led to a distinct improvement in the development of the product. The *CRs* have been acquired and clustered through customer survey and HCT, respectively, and their weights have been obtained by incorporating grey theory into the evaluation process. The critical design characteristics can be identified by adding the multiplication of summed customer requirement weight and the rating in relationships matrix from the QFD process. To reduce the large number of required experiments, this study further employs an optimized experimental design using the Taguchi method for setting up the different combinations of the respective controlled critical design characteristics. The optimal parameter combination is identified from the assessment of loss function.

Applying the proposed process to the actual design work, six design characteristics of a timer are identified as critical characteristics, and three of these are modified from their original setting. The optimal setting scenario determined in this study improves the quality of accuracy by changing material selection, rotating pin length, and assembly clearance. Validation tests have verified that the proposed procedure has yielded encouraging results that have translated into an improvement in customer satisfaction at Nan-Cheng Precision Corp.

The proposed robust design process has been validated with encouraging result with respect to the optimization problem. However, this procedure is not limited to a specific area of manufacturing. The process has been applied successfully to manufacturing of plasma coating used in aero engine components, leading to significant improvements in hardness and bonding force. It is believed that this research effort incorporating QFD and QE into the design work will assist designers in linking customer requirements and manufacturing processes during product development, thereby enhancing customer satisfaction and increase manufacturing efficiency. However, the complexity of customer requirements and products in the current diversified market may require simultaneous consideration of a larger number of responses. Further research is required to refine the proposed process using the Fuzzy-model and multiresponse methodologies to extend these applications.

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References

1. Biren, P. (1996). *Concurrent Engineering Fundamentals: Integrated Product and Process Organization*, Vol. I, New Jersey: Prentice Hall PTR.

2. Cohen, L. (1995). *Quality Function Deployment: How to Make QFD Work for You*, Massachusetts: Addison-Wesley.
3. Cross, N. (2000). *Engineering Design Methods: Strategies for Product Design*, 3rd edn, New Jersey: John Wiley & Sons.
4. Dieter, G.E. (2000). *Engineering Design: A Material and Processing Approach*, New York: McGraw-Hill.
5. Cristiano, J.J., Liker, J.K. and White, C.C. (2000). Customer-driven Product Development Through Quality Function Deployment in the US and Japan, *Product Innovation Management*, **17**(4): 286–308.
6. Zheng, L.Y. and Chin, K.S. (2005). QFD Based Optimal Process Quality Planning. *Advanced Manufacturing Technology*, **26**(7–8): 831–841.
7. Klir, G.J. and Folger, T.A. (1988). *Fuzzy Sets, Uncertainty, and Information*, Englewood Cliffs, New Jersey: Prentice Hall.
8. Saaty, T.L. (1997). *The Analytic Network Process*, Pittsburgh: RWS.
9. Geng, X., Chu, X., Xue, D. and Zhang, Z. (2010). An Integrated Approach for Rating Engineering Characteristics' Final Importance in Product-Service System Development, *Computers and Industrial Engineering*, **59**(4): 585–594.
10. Lee, A.H.I., Kang, H.-Y., Yang, C.-Y. and Lin, C.-Y. (2010). An Evaluation Framework for Product Planning Using FANP, QFD and Multi-choice Goal Programming, *Production Research*, **48**(13): 3977–3997.
11. Liu, H.T. (2011). Product Design and Selection Using Fuzzy QFD and Fuzzy MCDM Approaches, *Applied Mathematical Modeling*, **35**(1): 482–496.
12. Suh, N.P. (1990). *The Principles of Design*, New York: Oxford University Press.
13. Deng, J.L. (1982). *Grey System Fundamental Method*, Wuhan, China: Huazhong University of Science and Technology.
14. Ulrich, K.T. and Eppinger, S.D. (2003). *Product Design and Development*, 3rd edn, New York: McGraw-Hill.
15. Morita, H., Kase, T., Tamura, Y. and Iwamoto, S. (1996). Interval Prediction of Annual Maximum Demand Using Grey Dynamic Model, *Electrical Power and Energy Systems*, **18**(7): 409–413.
16. Liang, R.H. (1999). Application of Grey Relation Analysis to Hydroelectric Generation Scheduling, *Electrical Power and Energy Systems*, **21**(5): 357–364.
17. Mu, H., Kondou, Y., Sato, Y., Zhou, W., Ning, Y. and Sakamoto, K. (2004). Grey Relative Analysis and Future Prediction on Rural Household Biofuels Consumption in China, *Fuel Processing Technology*, **85**(8–10): 1231–1248.
18. Narender, S.P., Raghukandan, K. and Pai, B.C. (2004). Optimization by Grey Relational Analysis of EDM Parameters on Machining Al-10%SiCp composites, *Materials Processing Technology*, **155–156**: 1658–1661.
19. Chang, S.C. (2005). The TFT-LCD Industry in Taiwan: Competitive Advantages and Future Developments, *Technology in Society*, **27**(2): 199–215.
20. Wu, H.H., Liao, A.Y.H. and Wang, P.C. (2005). Using Grey Theory in Quality Function Deployment to Analyses Dynamic Customer Requirements, *Advanced Manufacturing Technology*, **25**(11–12): 1241–1247.
21. Chen, C.H. and Yan, W. (2008). An In-process Customer Utility Prediction System for Product Conceptualization, *Expert Systems with Applications*, **34**(4): 2555–2567.
22. Li, Y., Xue, D. and Gu, P. (2008). Design for Product Adaptability, *Concurrent Engineering: Research and Applications*, **16**(3): 221–232.
23. Fowlkes, W.Y. and Creveling, C.M. (1995). *Engineering Methods for Robust Product Design*, Massachusetts: Addison-Wesley.
24. Kim, J.K., Han, C.H., Choi, S.H. and Kim, S.H. (1998). A Knowledge-based Approach to the Quality Function Deployment, *Computers Industrial Engineering*, **35**(1–2): 233–236.
25. Zhou, J.G., Herscovici, D. and Chen, C.C. (2000). Parametric Process Optimization to Improve the Accuracy of Rapid Prototyped Stereolithography Parts, *Machine Tools and Manufacture*, **40**(3): 363–379.
26. Davim, J.P. (2003). Design of Optimization of Cutting Parameters for Turning Metal Matrix Composites Based in the Orthogonal Arrays, *Materials Processing Technology*, **13**(1–3): 340–344.
27. Ghani, J.A., Choudhury, I.A. and Hassan, H.H. (2004). Application of Taguchi Method in the Optimization of End Milling Parameters, *Materials Processing Technology*, **145**(1): 84–92.
28. Ross, P.J. (1996). *Taguchi Techniques for Quality Engineering*, New York: McGraw-Hill.
29. Yang, W.H. and Tarng, Y.S. (1998). Design Optimization of Cutting Parameters for Turning Operations Based on the Taguchi Method, *Materials Processing Technology*, **84**(1–3): 122–129.
30. Chang, C.S., Liao, R.C., Wen, K.L. and Wang, W.P. (2004). A Grey-based Taguchi Method to Optimize Design of Muzzle Flash Restraint Device, *Advanced Manufacturing Technology*, **24**(11–12): 860–864.
31. Casalino, G., Curcio, F. and Memola, C.M.F. (2005). Investigation on Ti6Al4V Laser Welding Using Statistical and Taguchi Approach, *Material Processing Technology*, **167**(2–3): 422–428.
32. Wang, T.Y. and Huang, C.Y. (2007). Improving Forecasting Performance by Employing the Taguchi Method, *European Journal of Operational Research*, **176**(2): 1052–1065.
33. Chen, C. and Wang, L. (2008). Integrating Rough Set Clustering and Grey Model to Analyses Dynamic Customer Requirements, *Proceedings of the Institution of Mechanical Engineers. Part B, Engineering Manufacture*, **222**(2): 319–332.
34. Wang, Z., Chen, Q., Hu, J. and Huang, H. (2010). A Proportional-Integral Control Policy of Two Coupled Concurrent Design Optimization Processes, *Concurrent Engineering: Research and Applications*, **18**(1): 55–63.
35. Chong, Y.T. and Chen, C.H. (2010). Customer Needs as Moving Targets of Product Development: A Review, *Advanced Manufacturing Technology*, **48**(1–4): 395–406.
36. Dong, M., Yang, D. and Wang, Y. (2010). Optimal Decisions in Product Modularity Design Using Real Option Approach, *Concurrent Engineering: Research and Applications*, **18**(1): 31–39.
37. Lehmann, D.R. (1979). *Market Research and Analysis*, Homewood, Illinois: Richard D. Irwin.
38. Kusiak, A. (2000). *Computational Intelligence in Design and Manufacturing*, New York: John Wiley & Sons.

39. Chen, M.-S., Lin, M.-C., Wang, C.-C. and Chang, C.A. (2009). Using HCA and TOPSIS Approaches in Personal Digital Assistant Menu-Icon Interface Design, *Industrial Ergonomics*, **39**(5): 689–702.
40. Phadke, M.S. (1989). *Quality Engineering Using Robust Design*, Englewood Cliffs, New Jersey: Prentice Hall.
41. Anderson, D.R., Sweeney, D.J. and Williams, T.A. (2007). *Statistics for Business and Economics*, London: Thomson Learning.

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