Linking quality function deployment with conjoint study for new product development process

Conference Paper · September 2005

DOI: 10.1109/INDIN.2005.1560409 · Source: IEEE Xplore

2 authors:

Atanu Chaudhuri
Durham University Business School

Malay Bhattacharyya
Indian Institute of Management Bangalore

International Journal of Production Research
Publication details, including instructions for authors and subscription information:
http://www.informaworld.com/smpp/title~content=t713696255

A combined QFD and integer programming framework to determine attribute levels for conjoint study

Atanu Chaudhuri; Malay Bhattacharyya [a]
[a] Indian Institute of Management, Bangalore 560 076, India

First Published:August2009

International Journal of Production Research
Vol. 47, No. 23, 1 December 2009, 6633–6649

A combined QFD and integer programming framework to determine attribute levels for conjoint study†

Atanu Chaudhuri[a]** and Malay Bhattacharyya[b]*

[a]*Deloitte Support Services India Pvt. Ltd, 4th Floor Block C, Deloitte Drive, Road No. 2, Hitec City Layout, Madhapur, Hyderabad-500081, India;* [b]*Indian Institute of Management, Bangalore 560 076, India*

(*Received 6 August 2007; final version received 14 July 2008*)

Conjoint Analysis (CA) and Quality Function Deployment (QFD) are two popular tools for new product design; marketers frequently use the former and engineers the latter. Typically, in a conjoint study, the attributes and their levels are determined through focus group discussions or market surveys. Sometimes, the market researchers exclude some critical features or include unrealistic attribute levels resulting in infeasible product profiles. Inappropriate selection of attribute levels may render the conjoint study less useful. In QFD, the New Product Development team attempts to identify the technical characteristics (TCs) to be improved (included) to meet the customer requirements (CRs) through a subjective relationship matrix between CRs and TCs. At present there is no methodology that uses the output of QFD to generate feasible product profiles to be used in CA and therefore improve its usefulness. In this paper, QFD is used along with an integer programming (IP) model to determine the appropriate TCs and consequently the right attribute levels. These attribute levels are then used in a conjoint study. It is also proposed to measure the elements of the so-called relationship matrix in QFD in a way so that the right levels of the attributes can be generated from the IP solution. The proposed method is illustrated through a commercial vehicle design problem with hypothetical data.

Keywords: new product design; conjoint analysis; QFD; *Integer Programming*

1. Introduction

In a fiercely competitive business world, organisations must endeavour to design products and services to satisfy customer expectations. Nevertheless, it is not always possible to offer all the features desired by customers. The production team, the marketing team, the product designers and the financial experts are required to work together to decide on the bundle of features that would maximise customer satisfaction and simultaneously meet some of the financial goals of the organisation, including profit maximisation.

Quality Function Deployment (QFD) is a tool, which is widely used across industries to translate the 'Voice-of-Customer' through necessary Technical Characteristics (TCs)

*Corresponding author. Email: malayb@iimb.ernet.in

†An earlier version of the paper was presented at the 3rd International IEEE Conference on Industrial Informatics, INDIN 2005, Perth, Western Australia, 10–12 August 2005.

**Atanu Chaudhuri was a doctoral student at Indian Institute of Management, Lucknow, India when this work was carried out.

ISSN 0020–7543 print/ISSN 1366–588X online

DOI: 10.1080/00207540802350757
http://www.informaworld.com

and to identify the means to deploy the available resources in the different stages of planning, designing and manufacturing of new products (Akao 1990).

Another tool in this area is Conjoint Analysis (CA), which is used to derive the customer 'preference structure'. It is used to calculate the utilities that the customers derive from the products. CA also called 'trade-off analysis', helps to fathom how people make complex decisions. The basic assumption underlying the technique is that complex decisions such as purchase decisions are based not on a single factor or criterion, but on several factors 'considered jointly'. Usually, in a conjoint study, the consumer is presented with a series of choice decisions about products or services. The CA uncovers the consumer's 'preference structure' from his/her overall ratings or rankings of the products/services/ideas in a realistic manner. A labelled rating scale is used with labels such as 'Most Preferred', 'Moderately Preferred', 'Preferred', 'Not Very Much Preferred', and 'Least Preferred'. Similarly, for rank ordering, the respondent is asked to give the highest rank to the 'Most Preferred' stimulus, and lowest rank to the 'Least Preferred' stimulus. CA allows the inclusion of attributes whose utilities do not necessarily increase (decrease) monotonically with increasing levels of the attributes. CA also enables segmentation of respondents based on the importance ratings for each attribute. The segmentation helps in aggregation of customer demands from individual preferences.

Both QFD and CA play important roles in designing products and selecting the right product to be launched. While QFD is used to determine the TCs to ensure maximum customer satisfaction, CA is used to identify products that generate maximum utility to the customers. Many organisations use only one of the two approaches but those that use both, use them independently.

In this paper, we develop a methodology to demonstrate how QFD and CA can be used in conjunction, and point out the benefits of such an approach. We present an approach to show how QFD and Integer Programming (IP) can be used to generate inputs for CA, and illustrate the approach using hypothetical data of commercial vehicles.

1.1 *Literature review*

The literature is analysed covering three aspects of QFD: (1) use of QFD with other approaches viz., CA and Analytical Hierarchical Process (AHP), (2) methodological shortcomings of QFD, and (3) augmentation of QFD using optimisation models.

1.1.1 *Use of QFD with other approaches*

Pullman *et al.* (2002) make a comparison between CA and QFD. They observe that CA is more suited to predict the impact of design changes or alternate product profiles on sales, profitability and cannibalisation. On the other hand, QFD, working at a greater level of detail than CA, can help in developing unique solutions to customer needs. They remark that these methods are complementary and need to be used simultaneously. In reply to the paper by Pullman *et al.*, Katz (2004) observes that QFD is an early stage technique, which promotes creative thinking in designing product features to satisfy customer needs. Since QFD involves capturing customer voice and translating customer needs to product design specifications, it should ideally be placed in the 'early product definition' stage. Katz (2004) also highlights the importance of selecting appropriate features with suitable levels and emphasises that QFD should precede CA. Bhattacharya *et al.* (2005) demonstrate a combined application of AHP and QFD for an industrial robot selection problem. AHP is used to determine the relative importance weights of CRs and pair wise comparison of the different robots on different TCs. They use a standard QFD matrix to determine the relationships between CRs and TCs. Later, they combine cost factors with the subjective measures to rank the robots. While AHP can be used to determine the weights of CRs and for the final ranking of products, it does not capture any information related to customer utility. Also, it does not alleviate some of the fundamental problems of QFD, which we discuss later.

QFD alone cannot be used to decide what products should be launched and what their attributes should be. Similarly, CA alone cannot be used to determine the TCs required for improving the products. Thus both need to be used in conjunction. To the best of our knowledge, there is no study that shows how CA and QFD can be used in conjunction and how this strengthens the overall product development process.

Let us analyse what happens if QFD and CA continue to be used independently. CA generates some product profiles that will maximise customer utility. QFD can be used to decide which TCs to be improved (included). But products using those improved (or new) TCs may generate lower utilities for customers, as QFD does not consider a product in its entirety. Thus, there is a need to link QFD and CA. But how can such a linkage be established? The output of a QFD cannot be used directly to generate product profiles. We outline a methodology that uses IP as a bridge between QFD and CA. We also propose a method for capturing data in QFD in a way (see Section 2) that allows it to be fed as input to IP. The IP output of appropriate TCs along with the corresponding changes in product attributes are used to generate product profiles for CA.

There are also other benefits of linking QFD and CA. For instance, to perform a CA, one must decide the features and their levels beforehand. Since CA is expensive, its ability to handle a limited number of features should not be wasted on unimportant features or unrealistic sets of levels. Before using CA, the attributes and their levels are usually determined by focus group discussions or market surveys. The choice of attribute levels is critical as they are used to generate product profiles. The final choice of the product depends, to a large extent, on the product profiles used in CA. As mentioned above in many cases, a number of product profiles turn out to be infeasible. Our approach of using QFD and IP to generate attribute levels will reduce the chances of generating infeasible product profiles. It also has the potential of reducing the overall time in finalising the set of products to be launched, because best possible product profiles generated from CA need not be evaluated again for technical and cost feasibility.

1.1.2 *Methodological shortcomings of QFD*

Our proposed method of collecting data in QFD (see Section 2), and the methodology of combining QFD and CA address the shortcomings that exist in each of the methods. In QFD, the New Product Development (NPD) team, based on its experience, generates a relationship matrix between CRs and TCs. In a conventional House of Quality (HoQ), the relationships between CRs and TCs are captured as *weak*, *medium* and *strong* and are quantified using a 1–3–9 or 1–5–9 scale (Fung *et al.* 2002). But no explicit justification for the choice of such a rating scale has been provided. Moreover, the relationships between TCs and CRs are traditionally measured by ordinal ranks instead of continuous rating values.

Pullman *et al.* (2002) remark that a judgmental determination of relationships between CRs and TCs does not help in estimating the amount of change in CR brought about by one unit change in TC. So they use an *ad hoc* method to set target values of TCs that have the largest impact on the overall performance of the product. However, as Park and Kim observe, it is more useful to measure the differences between TCs in meeting customer expectations in their magnitude rather than through ordinal importance ranks (Park and Kim 1998). Iranmanesh and Salimi (2003) find that there is a possibility of rank reversals in the selection of TCs (to be improved) if different scales (1–3–9 or 1–5–9) are used. Vanegas and Labib (2001) point out that a TC can have a very high impact on all CRs but because of both positive and negative relationships, customer satisfaction may not be affected at all by modifying the TC. Van de Poel (2007) also acknowledges that the correlation between CRs and TCs need not always be non-negative and constant as assumed in QFD, which results in a methodological shortcoming of the approach. This may happen as increase in satisfaction of some CRs may be accompanied by a reduction in satisfaction of some other CRs.

As pointed out by van de Poel (2007), another shortcoming of QFD is that it assumes that correlations between TCs and CRs are constant. The approach followed in this paper allows for different correlations between different levels of TCs and the corresponding CRs. The relationship between TCs and CRs can vary with percentage changes in TCs.

Other methodological problems in QFD arise because customer demands are product dependent, and therefore cannot always be represented by a linearly additive function and the individual customers cannot be aggregated into a collective customer preference ordering without violating reasonable conditions (van de Poel 2007). These are precisely some of the problems that can be addressed by combining QFD and CA. CA allows the inclusion of attributes whose utilities do not necessarily increase (decrease) monotonically with increasing levels of the attributes. For each respondent, the importance that s/he attaches to each attribute is determined. Then the respondents are clustered based on their derived importance ratings for each attribute and the utilities are recalculated for the different levels of each attribute for the particular segments. The segmentation helps in aggregation of customer demands from individual preferences. We are able to utilise the strengths of both QFD and CA as we de-link the decision of selecting TCs from the product choice decision. QFD is used for selecting the TCs and CA is used to pick the final set of products with IP acting as a bridge between the two. In the proposed approach, the IP output of percentage changes in TCs gives the corresponding changes in CRs and hence the attribute levels (see Sections 2 and 3 for details). CA uses these different attribute levels, obtained from QFD-IP to generate product profiles. By imposing constraints on the minimum requirements of CRs in the IP model we are also able to generate different product profiles, suited for different customer segments.

1.1.3 *Augmentation of QFD using optimisation models*

The other class of QFD literature that is relevant to our study is the one considering enhancement of QFD by using optimisation models. Wasserman (1993) considers cost of resources that go into QFD planning and proposes a linear decision model for attribute prioritisation. Bode and Fung (1998) incorporate product design budget into QFD planning and put forward an improved prioritisation approach to effectively allocate design resources to the more important TCs. Park and Kim (1998) present a 0–1 integer programnming model for prioritising TCs. They also incorporate a cost constraint and calculate customer satisfaction. But they measure customer satisfaction in terms of TCs that are addressed in the final product. Dawson and Askin (1999) suggest a non-linear programming model to determine optimum TCs considering constraints on costs and development time. They point out that dependence among TCs also needs to be considered. Fung *et al*. (2002) include financial issues in attaining individual targets of TCs. They represent the correlation between TCs as the incremental change in one TC to change in another by one unit. The costs of improving the degree of attainment of a TC are formulated as a non-linear function of its degree. They introduce the concepts of actual and planned attainment, and primary, actual and planned costs for the attainment of TCs. Franceschini and Rossetto (1998) present a method to determine the existence of dependence among TCs and formulate a 'set covering' problem to choose the minimum set of TCs to cover all CRs. They find that the set of TCs obtained by the traditional prioritisation method is not necessarily the same as that obtained by their 'set covering' approach.

Karsak *et al*. (2003), Chen and Weng (2006) use goal programming for product planning using QFD while Raharjo *et al*. (2006) use quality loss function and 0–1 goal programming to prioritise quality characteristics in a dynamic QFD. They also consider budgetary constraints and minimum customer satisfaction level in their model. Lai *et al*. (2007) use Kano's model and goal programming in optimising product design for personal computers.

Khoo and Ho (1996) provide a framework for fuzzy QFD. Kim *et al*. (2000), Vanegas and Labib (2001), Karsak (2004), Chen *et al*. (2005), Chen and Weng (2006), Liu (2005), Fung *et al*. (2002), Kahraman *et al*. (2006) are the others who use different forms of fuzzy modeling to capture the fuzziness of parameters used in QFD.

Baier and Brusch (2005a,b) use CA to obtain the importance weights of attributes and the relationship matrix between CRs and TCs and perform a Monte Carlo comparison between the traditional and the proposed CA based approach. Thus, Baier and Brusch use CA to improve the validity of QFD. In our proposed approach for a product design problem the output of QFD–IP is used as an input to CA to make CA more useful. Using CA in conjunction with QFD also helps us to overcome some of the methodological shortcomings of QFD.

To summarise, we observe that there is very limited research on the benefits of combining QFD and CA in product development. This paper makes a significant contribution by developing a methodology that links QFD and CA using an IP model. This approach alleviates one of the problems of CA, namely that of subjective identification of attribute levels, and some of the methodogical shortcomings of QFD. This paper also proposes a novel method of capturing the relationship matrix data between CR and TC in terms of percentage changes. This method allows correlations between TCs and CRs to vary according to levels of percentage changes and also allows for positive, negative and zero weights for percentages of TCs. By ensuring flexibility of different constraints on the minimum improvements required for CRs, product profiles for different customer segments are generated.

The paper is organised as follows. Section 2 presents the proposed framework for determining the attribute levels. Section 3 presents the application of the framework in a specific problem context with hypothetical data. Section 4 concludes with some proposals for future work.

2. A framework for determination of product attribute levels

Capturing the relationships between CRs and TCs and the correlations between TCs forms an important step in preparing 'House of Quality' (HoQ) (see Figure 1). In a traditional

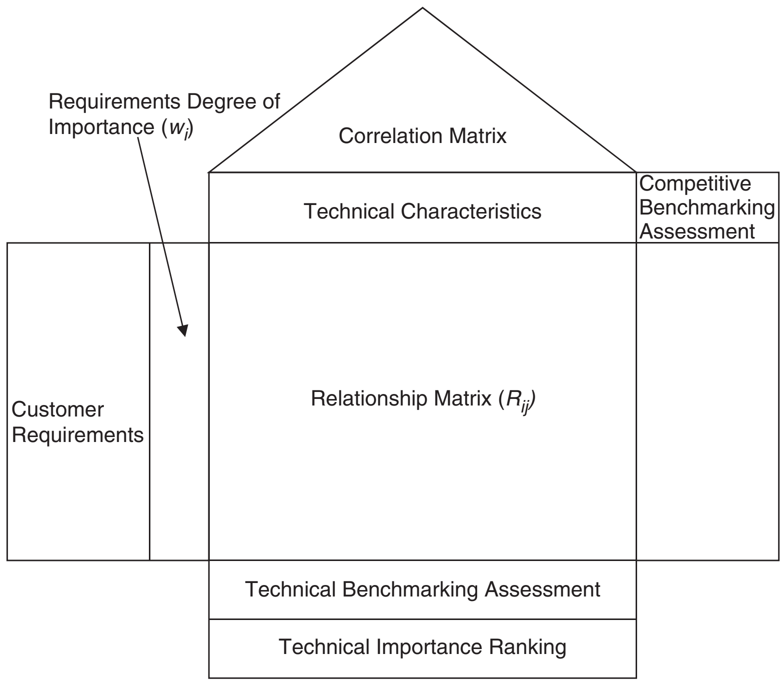

Figure 1. A typical house of quality in a traditional QFD.

HoQ, the relationships $\boldsymbol{R}_{ij}$ are captured as *weak*, *medium* and *strong* and are quantified using a 1–3–9 or 1–5–9 scale (Fung *et al.* 2002). Some authors have also attempted to quantify the relationships using fuzzy numbers. As we have defined the attributes in a manner that there is a one-to-one correspondence between them and the CRs, in the following we shall use the two terms interchangeably.

In our proposed approach we define $\boldsymbol{R}_{ij}$, the relationship between CR_i and TC_j, in terms of percentage change in attribute i due to some specified percentage change in TC_j. In other words, we replace $\boldsymbol{R}_{ij}$ by R_{ijk_j}, where R_{ijk_j} represents the *percentage change in* CR_i due to k_j percent change in TC_j. For example, R_{ijk_j} may signify a 6%, 8% or 12% (i.e., $R_{ijk_j} = 6\%$, 8% or 12%) change in attribute i for say, 10%, 15%, and 20% (i.e., $k_j = 10\%$, 15%, and 20%) improvement respectively in the TC_j. The design engineers obtain the subjective ratings between TCs and CRs by thinking in terms of percentage changes in CRs that will be obtained by some specific percentage changes in TCs. Since the traditional QFD only considers 1–3–9 ratings, these important pieces of information regarding percentage changes are lost. There could also be some TCs or features that could be '*present*' or '*absent*' type in the product.

We assume, like in a traditional QFD matrix, that the importance ratings of the CRs are given. The current ratings of the company's own product, competitor's current ratings, and also the target ratings of the company's product are all known or have been estimated. We further assume that all relevant cost data, like cost of improvement of a TC by a certain percentage, and also the cost of introducing a feature are all known. Since we are considering only variants of existing products, we assume that estimates of such costs will be available. Hence we refrain from specifying any cost function for improvement of TCs, which will be more difficult to derive and use in a real life situation. Besides these, the budgetary limit and the minimum improvement thresholds for the attributes are also specified.

The weighted improvement scores of the TCs are obtained, in the conventional way, as the weighted sum of the importance scores of the CRs and the correlation matrix between TCs and customer requirements. We have also considered budgetary constraints, as well as minimum improvement thresholds for the customer requirements. The problem of selecting the appropriate TCs to be improved along with their percentage improvements and the features to introduce with the objective of maximising the weighted sum of improvements in the product, satisfying budgetary and minimum percentage improvement for each or some of the attributes can be formulated as an integer programming (IP) problem. Without the percentage improvement constraints, it becomes a knapsack problem.

2.1 *Model description*

In this subsection we present the mathematical formulation for determining the attribute levels of the selected features using the information in the HoQ of the QFD approach. Since our task is to determine the percentage changes in TCs from a set of finite alternatives and to choose specific features that need to be introduced (or not introduced) given budgetary and performance constraints, integer programming (IP) is used to solve the problem. To explain the model, we introduce some notations below.

Let us define the following:

i: attribute number, where $i = 1, \ldots, p$; j: TC number, where $j = 1, \ldots, q$; k_j: percentage improvement in TC_j, $j = 1, \ldots, q$; m: feature number (*present/absent* type feature), where $m = 1, \ldots, r$

R_{ijk_j}: percentage change in attribute i due to k_j percent improvement in TC_j

$R1_{im}$: percentage change in attribute i due to introduction of feature m in the product

C_{jk_j}: cost of improving TC_j by k_j percent

$C1_m$: cost of providing feature m in the product

w_i: importance score of attribute i

B: the budget

$Y_{jk_j} =$ 1, if TC_j is improved by k_j percent
$= 0$, otherwise

$X_m =$ 1, if feature m is introduced
$= 0$, otherwise

Then the model is

$$\text{Maximise F} = \sum_i \sum_j \sum_{k_j} (w_i R_{ijk_j}) Y_{jk_j} + \sum_i \sum_m (w_i R1_{im}) X_m \tag{1}$$

such that

$$\sum_j \sum_{k_j} Y_{jk_j} C_{jk_j} + \sum_m X_m C1_m \le B \tag{2}$$

$$\sum_{k_j} Y_{jk_j} \leq 1, \quad \text{for each } j, \text{ where } j = 1, \ldots, q \tag{3}$$

$$\sum_j \sum_{k_j} Y_{jk_j} R_{ijk_j} + \sum_m X_m R1_{im} \geq 0, \quad \text{for each } i, \text{ where } i = 1, \ldots, p \tag{4}$$

$$Y_{jk_j} \in \{0, 1\}, X_m \in \{0, 1\} \tag{5}$$

The objective function F in (1) depicts the total weighted change in the overall product for various changes in the TCs. The constraint (2) states that the total cost involved in changing the TCs by certain percentages and providing certain features, if any, should not exceed the budget B. Constraint (3) requires that TC_j can be improved by only one of the possible percentages k_j. Constraint (4) requires that TCs and features should be chosen such that improvement in each attribute i is greater than or equal to zero.

Furthermore, constraints can be added to ensure that minimum improvements are achieved in some or all attributes. The additional constraint will be

$$\sum_j \sum_{k_j} Y_{jk_j} R_{ijk_j} + \sum_m X_m R1_{im} \geq P_i, \quad \text{for each } i \text{ where } i = 1, \ldots, p \tag{6}$$

where P_i denotes the minimum improvement threshold for attribute i.

Given all the required data, the solution of the above IP gives us the set of TCs that should be improved ($Y_{jk_j} = 1$) along with the percentage changes in those TCs and also the features to be introduced ($X_m = 1$). We can then find out from the relationship matrix the corresponding percentage changes in a CR or attribute. By summing these changes across TCs, we can determine the total change in a particular attribute. This step is repeated for all the attributes. As we already know the initial levels of the attributes we can easily determine their changed levels. The solution also tells us which TCs of the other type (absent or present) to be included in the product.

Now by varying the budgetary and other limits and also other constraints we get different solutions and hence different sets of attribute levels.

We can also apply the procedure for different segments to generate more product profiles. For example, one customer segment may have more preference for attributes 1 and 2, while another customer segment may have more preference for attributes 3, 4 and 5. In this way the entire range of attribute levels could be determined for generating product profiles to be used for conjoint analysis.

2.2 *The case of correlated TCs*

We have mentioned earlier that a TC may have both a positive and negative impact on different attributes. Similarly, a TC may also have a positive or negative impact on other TCs. Though engineers will have an idea as to which TCs might be correlated, specifying the extent of the relationship might be difficult. Also, if two TCs are correlated, they are likely to influence the same attributes, but the converse is not true. Wasserman (1993) uses a normalisation procedure to accommodate correlation between TCs. This procedure is also used by Park and Kim (1998). Engineers are more comfortable with specifying the relationships between TCs and CRs but not the correlation between TCs. So we determine the extent of correlation between TCs using the relationship matrix between CRs and TCs and a threshold level. For this purpose, we use the method outlined by Franceschini and Rossetto (1998). From the relationship matrix between TCs and CRs, we generate a binary matrix, **B**, to indicate the *presence* of relationship between a TC and a CR in the following way.

$$\forall\ i, j, k_j \quad \text{if } R_{ijk_j} \neq 0, \quad \text{then } b_{ij} = 1$$

We then normalise **B** to obtain a matrix **N**. A third matrix **Q** is defined as $\mathbf{Q} = \mathbf{N}^{\mathbf{T}}\mathbf{N}$. Let v_i be the ith column of **B** and q_{ij} be the (i, j)th element of **Q**. The effects of interdependence between the TC_i and TC_j can be represented by the coefficient q_{ij} where $q_{ij} = v_i^T \cdot v_j$. Calculating q_{ij} for all pairs of vectors of **N** will give us the dependence matrix $\mathbf{R_{TC}}$, which shows the extent of correlation between TCs. Below we illustrate the computations of the matrices **B**, **N** and **Q** (see Figure 2).

Once the correlated TCs are identified, the design engineers can specify the additional percentage change in customer attributes due to one TC, affecting another TC. Then the net percentage change in attributes due to percentage changes in TCs can be obtained.

We use the same optimisation model defined by Equations (1)–(6) to select the set of TCs to be improved with the parameter R_{ijk_j} being replaced by

$$RNET_{ijk_j} = R_{ijk_j} + RA_{ijk_j},$$

where $RNET_{ijk_j}$ is the net percentage change in attribute i due to k_j percent change in TC_j and RA_{ijk_j} is the additional percentage change in attribute i due to correlation between TCs. Park and Kim (1998) consider savings from implementing two TCs simultaneously when they use the budgetary constraint. But we are able to specify percentage changes in attributes due to correlated TCs with costs attached to the percentage change in TCs. The costs required to change a TC by a certain percentage will not vary because of being correlated with another TC, so we need not explicitly consider the cost savings.

$$R = \begin{bmatrix} 12 & 3 & 0 \\ 1.5 & 0 & 2.5 \\ 0 & 1.2 & 0 \end{bmatrix}; B = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}; N = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & 0 \\ \frac{1}{\sqrt{2}} & 0 & 1 \\ 0 & \frac{1}{\sqrt{2}} & 0 \end{bmatrix}$$

$$Q = N^T N = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & 0 \\ \frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & 0 \\ \frac{1}{\sqrt{2}} & 0 & 1 \\ 0 & \frac{1}{\sqrt{2}} & 0 \end{bmatrix} = \begin{bmatrix} 1 & \frac{1}{2} & \frac{1}{\sqrt{2}} \\ \frac{1}{2} & 1 & 0 \\ \frac{1}{\sqrt{2}} & 0 & 1 \end{bmatrix}$$

Figure 2. Illustration of building matrix **Q** starting from matrix **R**.

3. Application

For illustrating the proposed methodology, commercial vehicle is considered as an example product. In this problem, a product is already available in the market. The company wants to launch variants of the product, incorporating customer preferences. These products can also cater to different customer segments. The Voice of Customer (VoC) has been obtained to understand the CRs. Some typical CRs and their corresponding product attributes (that capture these customer requirements) are given in Table 1. The TCs that are considered to meet the customer needs are given in Table 2. For this example problem, $p = 6$, $q = 8$, and $r = 2$.

The main components of the QFD matrix for the problem including cost data are contained in Table 3. We explain the data in Table 3.

The data in column 24 show the importance that the customers attach to the attributes on a scale of 1 to 10. Columns 25 and 26 show the average rating of the company's existing product and similar products from competitors, as solicited from customers. Column 27 shows the target rating of the attributes, which are set by the cross-functional product development team consisting of members of research and development, marketing, finance and production teams. Column 28 is the ratio of column 27 and 25. Column 29 is the product of column 24 and column 28. Thus 9 in column 24 multiplied by 1.06 in column 28 gives 9.55. Column 29 is the percentage score of that attribute. Thus $9.55/44.14 \times 100 = 21.62$ where 44.14 is the sum of the attribute scores. Column 3 to column 23 (except the bottom three rows) shows the percentage change in CRs due to the specified percentage change in the TCs. This is how we propose to capture the elements in the

Table 1. Customer requirements and product attributes for commercial vehicles.

Customer requirements (CRs)	Product attributes
Fuel efficiency	1. Fuel economy
Good load carrying capacity	2. Payload
Good pickup	3. Power to weight ratio
Easy drivability on highways	4. Max cruising speed
Easy to climb slopes and navigability in hilly terrain	5. Gradability
Comfortable driver's cabin	6. Driver's cabin

Table 2. Technical characteristics for commercial vehicles.

Technical characteristics (TCs)	
Engine	1. Maximum torque
	2. Compression ratio
	3. Maximum engine RPM
	4. Turbo charger efficiency
	5. Combustion efficiency
Gear box and axle	6. Maximum axle reaction
	7. Overdrive ratio
	8. Variable ratio power steering
Cabin	9. Maximum sleeper berth area
	10. NVH resistant body panel

Table 3. The QFD chart for the commercial vehicle design problem with proposed relationship matrix.

Customer Requirements	Attributes	Engine												Gear Box and axle						Cabin			Importance ratings	Current ratings	Current ratings of competitor	Target ratings	Improvement ratio	Scores	Percentage Scores
		1. Maximum torque			2. Compression ratio			3. Max. Engine RPM		4. Turbo charger efficiency		5. Combustion efficiency		6. Maximum Axle reaction			7. Variable ratio PS	8. Overdrive Ratio		9. Maximum sleeper berth		10. NVH resistant body							
		10%	15%	20%	3%	5%	7%	5%	10%	3%	5%	5%	10%	5%	10%	15%		2%	5%	2%	5%								
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
Fuel efficiency	1. Fuel economy									0.8	1.25	3.5	7.5									2	9	8.25	8.5	8.75	1.06	9.55	21.62
Good load carrying capacity	2. Payload													3.5	6	8							9	8	7.5	8.5	1.06	9.56	21.66
Good pickup	3. Power to weight ratio	6	8	12	1.5	2.25	3.5			0.2	0.25	2.5	4.5										7.5	7	7	7	1.00	7.50	16.99
Easy drivability on highways	4. Maximum cruising speed	-4	-6.5	-8				2	3.5									1.5	3.75				7	6.5	6.5	6.75	1.04	7.27	16.47
Easy to climb slopes and navigability in hilly terrain	5. Gradability	3	5		0.5							1	2							-0.5	-1.25	3	6	5	4.5	5	1.00	6.00	13.59
Comfortable driver's cabin	6. Driver's cabin																5			1	3	8	4	3.75	4	4	1.07	4.27	9.67
Weights		76.85	96.84	72.14	32.28	38.23	59.46	32.93	57.63	20.70	31.28	131.75	265.81	75.82	129.97	173.30	48.33	24.70	61.75	2.87	12.01	161.35	1606.00					44.14	100.00
Percentage weights		4.78	6.03	4.49	2.01	2.38	3.70	2.05	3.59	1.29	1.95	8.20	16.55	4.72	8.09	10.79	3.01	1.54	3.85	0.18	0.75	10.05	100.00						
Costs (in thousands of rupees)		30	40	75	45	60	75	20	30	12	20	40	50	30	40	75	15	15	25	15	30	75							

correlation matrix. Now, we show the calculation of weights in the 'Weights' row. Weight of 10% improvement in maximum torque is calculated as $16.99 \times 6 - 4 \times 16.47 + 3 \times 13.59 = 76.85$ and $(76.85/1606) \times 100$ gives 4.78 which is the percentage weight for 10% improvement in maximum torque. Similarly for 3% change in compression ratio, the weight is obtained as $16.99 \times 1.5 + 13.59 \times 0.5 = 32.28$, and $(32.28/1606) \times 100$ gives the percentage weight 2.01. The sum of the weights of all the TCs is $76.85 + 96.84 + \cdots + 161.35 = 1606$.

Table 4 gives the R_{ijk_j} values for the correlated TCs. As described in Section 2.2, we first create a matrix **B** to indicate the correlation among TCs and normalise it to obtain **N** and its transpose $\mathbf{N}^{\mathrm{T}}$. Then we obtain $\mathbf{Q} = \mathbf{N}^{\mathrm{T}}\mathbf{N}$. From the matrix **Q**, we choose a threshold level of 0.8, above which we consider the TCs to be correlated. For our problem, we find two pairs of TCs, namely, (1) maximum torque and compression ratio, and (2) combustion efficiency and turbo charger efficiency to be correlated. Table 4 show the additional percentage impact on the CRs due to correlation among TCs.

We assume $B =$ INR 150,000 (INR – Indian Rupees), where 1 USD is approximately equal to INR 40.

GAMS 21.0 with CPLEX solver is used to solve the IP model given by (1)–(6). The solutions for both uncorrelated TCs and correlated TCs are given in Table 5. Case 1 refers to a problem situation where we have constraints on payload and maximum cruising speed, whereas in case 2, we have constraints on fuel economy and driver's comfort. The percentage improvements in the attributes and the newly generated attribute levels are summarised in Tables 6 and 7, respectively. Note that the improvements required in TCs do not change when correlated TCs are considered – only the weighted sum of improvements in the product (objective function value) changes. This happens as the TCs are positively correlated.

In the case of correlated TCs and Case 1, the optimum IP solution gives an objective function value of 544.16 resulting from 5% improvement in maximum rpm, 10% improvement each in combustion efficiency and maximum axle reaction, 5% improvement in overdrive ratio and the introduction of variable ratio power steering.

The assumed threshold values for the minimum improvement constraints on the attributes are given in the second column of Table 6. Some segments of customers attach more importance to payload and maximum cruising speed and some others to fuel economy and driver's comfort. Minimum thresholds for these attributes are used to ensure that some perceptible differences in these attributes are obtained from the solution. The values of the thresholds are calculated from the detailed Voice of Customer (VoC) data that were collected earlier. As part of VoC, customers were asked about (1) minimum monetary savings they wanted to achieve from improved fuel economy, (2) minimum travel time they wanted to reduce for higher maximum cruising speed, (3) minimum increase in payload, which would help them carry desired load without overloading. These data are then used to arrive at the minimum thresholds.

Table 6 gives the corresponding percentage changes in attributes obtained from the solution in Table 5. Thus solution of Case 1 with correlated TC results in 7.65% improvement in fuel economy, 6% improvement in payload, 4.625% improvement in power to weight ratio, 5.75% improvement in maximum cruising speed, 2% improvement in gradability and 5% improvement in driver's cabin. Table 7 shows the new attribute levels based on the percentage changes given in Table 6.

Table 4. Additional impacts on CRs due to correlations between TCs.

Customer Requirements	Attributes	Engine												Gear Box and axle						Cabin		
		1. Maximum torque			2. Compression ratio			3. Max. Engine RPM		4. Turbo charger efficiency		5. Combustion efficiency		6. Maximum Axle reaction			7. Variable ratio PS	8. Overdrive Ratio		9. Maximum sleeper berth		10. NVH resistant body
		10%	15%	20%	3%	5%	7%	5%	10%	3%	5%	5%	10%	5%	10%	15%		2%	5%	2%	5%	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
Fuel efficiency	1. Fuel economy									0.3	0.5	0.1	0.15									
Good load carrying capacity	2. Payload																					
Good pickup	3. Power to weight ratio	0.5	1.25	2	0.25	0.6	1			0.1	0.15	0.075	0.125									
Easy drivability on highways	4. Maximum cruising speed				-0.25	-0.4	-0.7															
Easy to climb slopes and navigability in hilly terrain	5. Gradability	0.3	0.5		0.1																	
Comfortable driver's cabin	6. Driver's cabin																					

Table 5. Solutions of IP for the illustrative example.

	% Improvement			
	Case 1[a]		Case 2[b]	
Technical characteristics (TCs)	Uncorr.	Corr.	Uncorr.	Corr.
1. Maximum torque				
2. Compression ratio				
3. Maximum engine RPM	5	5		
4. Turbo charger efficiency				
5. Combustion efficiency	10	10	10	10
6. Maximum axle reaction	10	10		
7. Overdrive ratio	5	5	5	5
8. Variable ratio power steering	y[c]	Y[c]		
9. Maximum sleeper berth area				
10. NVH resistant body panel			y[c]	y[c]
Objective function	538.79	544.16	445.67	451.04

[a]Constraints on payload and maximum cruising speed.
[b]Constraints on fuel economy and driver's comfort.
[c]y denotes the TC is introduced.

Table 6. Constraints on minimum improvement and percentage improvements in attributes.

		% Improvement			
		Case 1[a]		Case 2[b]	
Attributes	Constraints on minimum improvement (P_i)	Uncorr.	Corr.	Uncorr.	Corr.
1. Fuel economy	6	7.5	7.65	9.5	9.65
2. Payload	6	6	6	–	–
3. Power to weight ratio	–	4.5	4.625	4.5	4.625
4. Max cruising speed	4	5.75	5.75	3.75	3.75
5. Gradability	–	2	2	5	5
6. Driver's cabin	7	5	5	8	8

[a]Constraints on payload and maximum cruising speed.
[b]Constraints on fuel economy and driver's comfort.

Table 7. Sample of new attribute levels.

		New attribute levels			
		Case 1[a]		Case 2[b]	
Attributes	Current attribute levels	Uncorr.	Corr.	Uncorr.	Corr.
1. Fuel economy	5	5.375	5.3825	5.475	5.4825
2. Payload	17	18.02	18.02	17.00	17.00
3. Power to weight ratio	18	18.81	18.832	18.81	18.8325
4. Max cruising speed	70	74.025	74.025	72.625	72.625
5. Gradability	14	14.28	14.28	14.70	14.70
6. Driver's cabin	5	5.25	5.25	5.40	5.40

[a]Constraints on payload and maximum cruising speed.
[b]Constraints on fuel economy and driver's comfort.

4. Discussion and conclusion

Conjoint Analysis and Quality Function Deployment are tools for new product development. The marketers prefer the former, while the engineers and technical experts use the latter. Both CA and QFD have the same objective of capturing the customer needs but QFD incorporates those needs in the new product design while CA uses them in choosing the products with the desired attributes. Both tools have their merits and demerits. The success of CA, however, is largely dependent on the identification of the right set of attributes or features of the product and their appropriate levels. For technical as well as practical considerations, it is not feasible to include a large number of features and also a large number of feature levels in a conjoint study (Green and Srinivasan 1990, Green *et al.* 1994). In practice, therefore, the researchers are unable to include all the important attributes and their desired levels. As conjoint study is expensive, it is, therefore, all the more necessary to select the set of attributes and their levels more carefully and objectively so as to avoid infeasible product profiles.

In this paper we have proposed to link QFD with CA through an integer programming based framework to determine the attribute levels. Instead of the conventional way of defining the relationship matrix in QFD, we have proposed to construct the relationship as the percentage change in a CR corresponding to specified percentage change in a TC. We de-link the decision of selecting TCs from the product choice decision by allowing QFD to address the former and CA, the latter, using IP as a bridge between the two. Thus using the strengths of CA, we are able to overcome some of the other methodological problems of QFD that arise as customer demands, being product dependent, cannot always be represented by a linearly additive function and the individual customers cannot be aggregated into a collective customer preference ordering without violating reasonable conditions (van de Poel 2007).

To determine the TCs to be improved along with their percentage improvements subject to budgetary and other constraints an integer-programming problem has been formulated. Using the solution thus obtained the percentage changes in the CRs can easily be computed from the relationship matrix between CRs and TCs. Knowing the initial levels of the attributes, the new levels of the same could then easily be determined. Varying the budgetary and other limits and also considering different market segments one could thus obtain the whole range of attribute levels in a more objective manner. The case of correlated TCs is also considered.

The correlation between CRs and TCs need not always be non-negative and constant as assumed in QFD, which results in a methodological shortcoming of the approach. Such problems can be averted by expressing the relationship measurements in terms of percentage changes in product attributes due to percentage changes in TCs. This also enables the inclusion of negative impacts of improvement in a particular TC on a certain attribute, which might have a positive impact on some other attribute. If the weight of a particular percentage change in TC turns out to be zero, it indicates that on the whole there will be no improvement in the product, considering all CRs due to that percentage change in the TC. In our integer programming formulation, such a percentage change in a TC will obviously not appear as part of the optimal solution. On the other hand, if the weight turns out to be negative, it signifies that negative impact of that percentage change in the TC on one or more CRs is greater than its positive impact. Hence it will also not be selected as part of the optimal solution. This should also alert the engineers that by improving a TC by that particular percentage, they are actually reducing the overall improvement in the product.

We have illustrated the framework for design of commercial vehicles with the help of hypothetical data. We believe that this linking of QFD and CA will definitely help improve the new product development process. We also want to bring out some of the caveats while using this approach. Companies need to have a well planned process to capture VoC and translate that information to be used for QFD. Also the design function of the organisation should have the requisite technology and systems to determine the impact of the feasible percentage changes of the TCs on the CRs. The VoC data should also be used to determine the minimum percentage changes of the attributes. Failure to collect and document such information can still result in some product profiles, which will not be accepted by customers. Generating this rich information from VoC and QFD can help in improving the outcomes of the expensive exercise of CA. But collection of VoC and conducting QFD can also be expensive and time consuming and may deter some companies from investing in these exercises. But companies which already conduct VoC, QFD and CA as part of the product development process, can significantly improve the outcomes of these exercises by using our approach. One limitation of our approach is that we have only considered a situation, where variants of existing products are to be launched and thus assumed some basic information regarding costs are available. It will be worthwhile to explore how our approach can be used to launch entirely new products. Another interesting extension of this framework could be to model the relationship matrix and other parameters like importance ratings, costs etc. as fuzzy numbers, which will be particularly useful in a setting where only ranges of percentage improvements, cost data and importance of attributes may be available. The authors propose to take this up in a subsequent paper.

Acknowledgements

The authors wish to thank all three anonymous referees for their constructive comments and suggestions.

References

Akao, Y., 1990. *QFD: Integrating Customer Requirements into Product Design*. Cambridge, MA: Productivity Press.

Baier, D. and Brusch, M., 2005a. Linking conjoint analysis and QFD for optimal product design. *In*: D. Baier, R. Decker and L. Schmidt-Thieme, eds. *Data analysis and decision support*. Berlin: Springer, 189–198.

Baier, D. and Brusch, M., 2005b. Improving the predictive validity of quality function deployment by conjoint analysis: a Monte Carlo comparison. *Operations Research Proceedings 2005*, Selected papers of the Annual International Conference of the German Operations Research Society (GOR), Bremen, 7–9 September 2005, 619–624.

Bhattacharya, A., Sarkar, B., and Mukherjee, S.K., 2005. Integrating AHP with QFD for robot selection under requirement perspective. *International Journal of Production Research*, 43 (17), 3671–3685.

Bode, J. and Fung, R.Y.K., 1998. Cost engineering with quality function deployment. *Computers & Industrial Engineering*, 35 (3–4), 587–590.

Chen, L.H. and Weng, M.C., 2006. An evaluation approach to engineering design in QFD processes using fuzzy goal programming models. *European Journal of Operational Research*, 172 (1), 230–248.

Chen, Y., Fung, R.Y.K., and Yang, J., 2005. Fuzzy expected value modelling approach for determining target values of engineering characteristics in QFD. *International Journal of Production Research*, 43 (17), 3583–3604.

Dawson, D. and Askin, R.G., 1999. Optimal New Product Design using quality function deployment with empirical value functions. *Quality and Reliability Engineering International*, 15 (1), 17–32.

Franceschini, F. and Rossetto, S., 1998. Quality function deployment: How to improve its use. *Total Quality Management*, 9 (6), 491–500.

Fung, R.Y.K., Tang, J., Tu, Y., and Wang, D., 2002. Product design resources optimisation using a non-linear fuzzy quality function deployment model. *International Journal of Production Research*, 40 (3), 585–599.

Green, P.E. and Srinivasan, V., 1990. Conjoint analysis in marketing: new developments with implications for research and practice. *Journal of Marketing*, 54 (4), 3–19.

Green, P.E., Tull, D.S., and Albaum, G., 1994. *Research for marketing decisions*. 5th ed. Delhi: Prentice Hall of India Private Limited.

Iranmanesh, S.H. and Salimi, M.H., 2003. An investigation of rank reversal when using fuzzy importance levels in QFD analysis. *International Journal of Reliability, Quality and Safety Engineering*, 10 (2), 195–203.

Kahraman, C., Ertay, T., and Büyüközkan, G., 2006. A fuzzy optimization model for QFD planning process using analytic network approach. *European Journal of Operational Research*, 171 (2), 390–411.

Karsak, E.E., 2004. Fuzzy multiple objective programming framework to prioritise design requirements in quality function deployment. *Computers & Industrial Engineering*, 47 (2–3), 149–163.

Karsak, E.E., Sozer, S., and Alptekin, S.E., 2003. Product planning in quality function deployment using a combined analytic network process and goal programming approach. *Computers & Industrial Engineering*, 44 (1), 171–190.

Katz, G.M., 2004. Practioner Note: a response to Pullman *et al.*'s (2002) Comparison of quality function deployment versus conjoint analysis. *The Journal of Product Innovation and Management*, 21 (1), 61–63.

Khoo, L.P. and Ho, N.C., 1996. Framework of a fuzzy quality function deployment system. *International Journal of Production Research*, 34 (2), 299–311.

Kim, K., *et al.*, 2000. Fuzzy multicriteria models for quality function deployment. *European Journal of Operational Research*, 121 (3), 504–518.

Lai, X., Tan, K.C., and Xie, M., 2007. Optimizing product design using quantitative quality function deployment: a case study. *Quality and Reliability Engineering International*, 23 (1), 45–57.

Liu, S.T., 2005. Rating design requirements in fuzzy quality function deployment via a mathematical programming approach. *International Journal of Production Research*, 43 (3), 497–513.

Park, T. and Kim, K., 1998. Designing an optimal set of design requirements using house of quality. *Journal of Operations Management*, 16 (5), 569–581.

Pullman, M.E., Moore, W.L., and Wardell, D.G., 2002. A comparison of quality function deployment and conjoint analysis in new product design. *The Journal of Product Innovation and Management*, 19 (5), 354–365.

Raharjo, H., Xie, M., and Brombacher, A.C., 2006. Prioritizing quality characteristics in dynamic Quality Function Deployment. *International Journal of Production Research*, 44 (23), 5005–5018.

Vanegas, L.V. and Labib, A.W., 2001. Fuzzy quality function deployment (FQFD) model for deriving optimum targets. *International Journal of Production Research*, 39 (1), 99–120.

Wasserman, G.S., 1993. On how to prioritise design requirements during the QFD planning process. *IIE Transactions*, 25 (3), 59–65.

van de Poel, I., 2007. Methodological problems in QFD and directions for future development. *Research in Engineering Design*, 18 (1), 21–36.