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Linking Quality Function Deployment with Conjoint Study for New Product Development Process

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Abstract – **Conjoint Analysis (CA) is a popular marketer's tool for new product design. Quality Function Deployment (QFD) is another approach, frequently used by engineers, for design of new product. Typically, in a conjoint study, the attributes and their levels are determined through Focus Group Discussion or market survey. On many occasions, the researchers leave out some of the more critical features altogether or include attributes with unrealistic sets of levels resulting in infeasible product profiles. In QFD, on the other hand, the New Product Development team attempts to identify the technical characteristics (TCs) that should be improved or included to meet the customer requirements (CRs) by using a subjective relationship matrix between CRs and TCs. QFD is not used to determine the attributes and their levels. As a result, more often than not, QFD captures what product developers "think" would best satisfy customer needs. In this paper, we link QFD with Conjoint and propose a framework for objectively determining the attribute levels using the QFD approach for subsequent use in a conjoint study. For this purpose we obtain the so-called relationship matrix in QFD in a particular way that facilitates achieving our objective. We formulate an integer-programming problem for maximising the weighted sum of improvements in the product, subject to budgetary constraint and minimum percentage improvement for each or some of the attributes. We apply the framework for a commercial vehicle design problem with hypothetical data.**

Index Terms – **New Product Design, Conjoint Analysis, QFD.**

I. INTRODUCTION

In a fiercely competitive business world, organisations around the world must endeavour to design products and services to satisfy or surpass customer expectations. Nevertheless, it is not always viable to offer all the features desired by customers. The production team, the marketing team 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 financial goal of the organisation such as profit maximisation.

Quality Function Deployment (QFD) is widely used across industries to capture Customer Requirements (CRs) and to translate the "Voice-of-Customer" through desired Technical Characteristics (TCs) [15]. These are later used in different stages of planning, design and manufacture of new products. Typically, engineers, technical development personnel and quality experts are involved in these activities.

Similarly, Conjoint Analysis (CA) is a time-tested tool, preferred by the marketing experts, for deciding products to launch, high on customer preferences.

Many organisations use only one of the approaches with a few exceptions that use both but independently. Both approaches have their advantages and disadvantages. Pullman *et al* [4] made a comparison between CA and QFD, and observed that CA is more suited to predict the impact of design changes or alternate product profiles on sales, profitability and cannibalisation, while QFD, working at a greater level of detail than conjoint, can help in developing unique solutions to customer needs. They remarked that these methods are complementary and need to be used simultaneously. In reply to Pullman's paper, Katz [5] expressed concern about the possible misinterpretation of the term 'complementary' with reference to CA and QFD being used simultaneously. He advocated that QFD is an early stage technique, which promotes creative thinking in designing product features to satisfy customer needs. Thus QFD that involves gathering customer voice and translating customer needs to product design specifications should ideally be placed in the 'early product definition' stage. Katz [5] also highlighted the importance of selecting appropriate features with suitable levels and emphasized that QFD should precede CA. A senior level manager in an automobile company in India also sought assistance in setting attribute levels before determining reservation prices, expected market shares and impact of cannibalisation using CA. To our knowledge, QFD has not been used to objectively determine product attribute levels to be used later for CA. Thus firms that are using both QFD and CA are not able to exploit the capabilities of QFD to generate the product profiles. In this paper, we present a framework for new product development process by combining together the QFD and CA approaches. Specifically, we propose a method to use QFD to determine the attribute levels for their subsequent use in CA. Our approach can alleviate this supposedly difficult task of selecting product attribute levels by the NPD team and make them more confident in administering product plans for CA.

To do a CA, one must decide beforehand, the features and also their levels, to be included in the study. Since CA is expensive, its capability to handle only limited number of features should not be wasted on unimportant features or unrealistic sets of levels. Before using CA, the product attributes and their levels are usually determined by focus group discussions or market survey, which may also involve potential customers. The choice of attribute levels is crucial as they are used to generate product profiles using orthogonal arrays. These product profiles are then administered to the respondents for rating or ranking. The final choice of products depends, to a large extent, on the prod-

uct profiles generated. In many cases, a sizable number of the product profiles turn out to be infeasible.

In QFD, on the other hand, the New Product Development (NPD) team based on their experience, which lends some subjectivity to it, generates a relationship matrix between CRs and TCs.

The key requirement of the QFD approach is the construction of the relationship matrix between CRs and TCs. In a conventional House of Quality (HoQ), the relationships are captured as *weak*, *medium* and *strong* and are quantified using a 1-3-9 or 1-5-9 scale [7]. 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* [4] remarked that judgmental determination of relationships between CRs and TCs did not help in estimating the amount of change in CR brought about by one unit change in TC. So they used an *ad hoc* method to set target values of TCs, having largest impact on overall performance of the product.

It will be more useful to measure the differences between TCs in meeting customer expectations in their magnitude rather than ordinal importance ranks [3]. Iranmanesh *et al* [14] found that there is a possibility of rank reversals in selection of TCs (to be improved) if different scales (1-3-9 or 1-5-9) are used. Vanegas and Labib [12] 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. This may happen as increase in satisfaction of some CRs may be accompanied by a reduction in satisfaction of some other CRs.

Such problems can be averted by expressing the relationship measurements in terms of percentage changes in product attributes due to percentage changes in TCs. It also enables us to incorporate negative impacts of improvement in a particular TC on a certain attribute, which might have a positive impact on some other attribute. More importantly, as we can determine which of the TCs to be improved and by what percentage, we can also find out the changed levels of the attributes.

Most QFD studies overlooked the resource constraints, thus giving suboptimal results [7]. Wasserman [13] considered cost of resources into QFD planning and proposed a linear decision model for attribute prioritisation. Bode and Fung [18] incorporated 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 [3] presented a decision model for prioritising TCs. They also incorporated a cost constraint and calculated customer satisfaction by using a Mixed Integer Programming (MIP) model. But they measure customer satisfaction in terms of TCs that are addressed in the final product. Dawson and Askin [1] suggested a non-linear programming model to determine optimum TCs considering costs and development time constraints. They point out that dependence among TCs also needs to be considered. Fung *et al* [7] included financial issues in attaining individual targets of TCs. They represented 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 were formulated as a non-linear function of its degree. The authors introduced the concepts of actual and planned attainment and primary, actual and planned costs for the attainment. Vanegas and Labib [12] incorporated constraints on time, cost and technical difficulty. They define fuzzy membership functions for each constraint and an aggregate type 2 fuzzy set is calculated for each TC. The fuzzy set represents the desirability with respect to meeting customer satisfaction and the optimum value of TC is the one with the maximum degree of membership in the aggregate fuzzy set.

Francheschini *et al* [2] presented 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 found 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 [6] presents a fuzzy multiobjective programming approach to determine the level of fulfilment of design requirements. The author incorporates the relationships between CRs and TCs, importance of customer needs, sales point data and technical difficulty of design requirements in his model by using linguistic variables. Uncertain cost data are represented by triangular fuzzy numbers. By using multiobjective approach, the author is able to incorporate objectives of maximizing the extendibility of design and minimizing the design difficulty apart from the objective of maximizing the fulfilment of design requirements.

The objective of this paper is to use QFD approach to generate feasible levels of product attributes to be used later as inputs for CA. We augment the traditional QFD approach by obtaining the relationships between product attributes and TCs in terms of percentage improvements in product attributes due to percentage changes in TCs. In our problem, customer requirements are converted to product attributes with one-to-one relationship between them. We determine the technical characteristics to be improved and their desired percentage improvements considering budgetary and other constraints.

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

II. A FRAMEWORK FOR DETERMINATION OF PRODUCT ATTRIBUTE LEVELS

Expressing the relationships between CRs and TCs and the correlations between TCs form important steps in preparing "House of Quality" (HoQ). In a traditional HoQ, the relationships R_{ij} are captured as *weak*, *medium* and *strong* and are quantified using a 1-3-9 or 1-5-9 scale [7]. Some authors have also attempted to quantify the relationships using fuzzy numbers. As mentioned earlier, the relationship matrix is one of the most important data requirements for prioritising the TCs in a QFD approach.

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 new proposed approach we define 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 R_{ij} by R_{ijk}, where R_{ijk} represents the *percentage change in* CR i due to k percent change in TC j. For example, R_{ijk} may signify a 6%, 8% or 12% (i.e., R_{ijk} = 6%, 8% or 12%) change in attribute i for say, 10%, 15%, and 20% (i.e., k = 10%, 15%, and 20%) improvement respectively in the technical characteristic j. Our interactions with design engineers indicate that most of them would be comfortable in specifying the relationships between CRs and TCs in terms of ranges of percentage changes.

There could also be some TCs or features like power steering and NVH tested cabins, which could be *present* or *absent* in the product.

We assume, like in a traditional QFD chart, 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. 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. The computation of the attribute importance scores is self-explanatory and is shown in Table 1. 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 maximizing 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.

A. Model description

In the following subsections we present the mathematical formulation for determining the attribute levels of the selected features using the information in the HoQ of the QFD approach. To do this we need to introduce some notations.

B. Indices

i - attribute number, j - TC number, k - percentage improvement in TC, m - feature number (*present/absent* type feature)

C. Parameters

R_{ijk} - percentage change in attribute i due to k percent improvement in TC j

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

C_{jk} - cost of improving TC j by k percent

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

w_i - importance score of attribute i

D. Decision variables

Y_{jk} = 1, if TC j is improved by k percent
= 0, otherwise

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

E. The Model

$$\text{Maximize } \sum_i \sum_j \sum_k (w_i R_{ijk}) Y_{jk} + \sum_i \sum_m (w_i R1_{im}) X_m \qquad \text{(i)}$$

such that

$$\sum_j \sum_k Y_{jk} C_{jk} + \sum_m X_m C1_m \le B \qquad \text{(ii)}$$

$$\sum_k Y_{jk} \le 1, \text{ for each } j \qquad \text{(iii)}$$

$$\sum_j \sum_k Y_{jk} R_{ijk} + \sum_m X_m R1_{im} \ge 0, \text{ for each } i \qquad \text{(iv)}$$

$$Y_{jk} \in \{0,1\},\ X_m \in \{0,1\} \qquad \text{(v)}$$

The objective function depicts the total weighted change in the overall product for various changes in the TCs. The constraint (ii) 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 (iii) requires that a TC j can be improved by only one of the possible percentages k. Constraint (iv) requires that TCs and features should be chosen such that improvement in each attribute i is greater than or equal to zero.

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

$$\sum_j \sum_k Y_{jk} R_{ijk} + \sum_m X_m R1_{im} \ge P_i, \text{ for each } i \qquad \text{(vi)}$$

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} =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 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, some customers may have more preference for fuel economy and driver's comfort while some other customers may have more preference for payload, power to weight ratio and maximum cruising speed. In this way the entire range of attribute levels could be determined for generating product profiles to be used for conjoint analysis.

F. The case of correlated TCs

We have mentioned earlier that a TC may have both positive and negative impact on different attributes. Similarly, a TC may also have positive or negative impact on other TCs. Though engineers will have an idea as to which TCs might be correlated, but specifying the extent of 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 [13] used a normalization procedure to accommodate correlation between TCs, which was also used by Park *et al* [3]. But engineers are more comfortable with specifying the relationships between TCs and CRs but not the correlation between TCs. So we have decided to 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 Francheschini *et al* [2]. 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.

$$\forall\ i, j, k \text{ if } R_{ijk} \neq 0, \text{ then } b_{ij} = 1$$

We then normalize **B** to obtain a matrix **N**. A third matrix **Q** is defined as $\mathbf{Q} = \mathbf{N}^T\mathbf{N}$. 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 ith and jth TC can be represented by the coefficient q_{ij} where $q_{ij} = v_i^{\ T}.v_j$. 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.

Table 3 Solutions of IP for the Illustrative example

Technical characteristics (TCs)	% Improvement			
	Case 1[a]		Case 2[b]	
	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	227.5	229.78	189.5	191.78

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

Once the correlated TCs are identified, the designers 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 to select the set of TCs to be improved with the parameter R_{ijk} being replaced by $RNET_{ijk}$. $RNET_{ijk} = R_{ijk} + RA_{ijk}$, where $RNET_{ijk}$ is the net percentage change in attribute i due to k percent change in TC j and RA_{ijk} is the additional percentage change in attribute i due to correlation between TCs. Park *et al* [3] 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.

III. APPLICATION

The product considered is commercial vehicles. Since the final objective is to generate product profiles using the attribute levels from QFD, it is decided to have products, which can cater to multiple segments even within the same product category (say multi axles). Some typical customer requirements (CRs) and their corresponding product attributes (that capture these customer requirements) are given in first two columns of Table 1. The technical characteristics (TCs) that are considered to meet the customer needs are given in second row of Table 1. The main components of the QFD chart for the problem at hand including cost data are contained in Table 1.

Table 2 gives the RA_{ijk} values for the correlated TCs. 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, maximum torque and compression ratio, and combustion efficiency and turbo charger efficiency to be correlated.

We assume B = Rs. 150000. The assumed threshold values for the minimum improvement constraints on the attributes are given in second column of Table 4.

Table 4 Constraints on Minimum Improvement and Percentage Improvements in Attributes

Attributes	Constraints on Minimum Improvement (P_i)	% Improvement			
		Case 1[a]		Case 2[b]	
		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 5 Sample of new attribute levels

Attributes	Current Attribute levels	New Attribute levels			
		Case 1[a]		Case 2[b]	
		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

GAMS 21.0 with CPLEX solver is used to solve the IP model given by (i) – (vi). The solutions for both uncorrelated TCs and correlated TCs are given in Table 3. 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 Table 4 and Table 5 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.

IV. 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 and incorporating them in the new product design as much as possible. 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 ([16], [17]). 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 conjoint through an integer programming based framework to determine the attribute levels using QFD approach. One of the key components of the QFD chart is the relationship matrix between the customer requirements (CR) and the technical characteristics (TC) of the product. Instead of the conventional way of defining the relationship matrix, we have proposed to construct the relationship as the percentage change in a CR corresponding to specified percentage change in a TC. Then 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 be easily computed from the relationship matrix between CRs and TCs. Knowing the initial levels of the attributes, the new levels of the attributes could then be easily determined. Varying the budgetary and other limits and also considering different market segments one could thus obtain the whole range of attribute levels in an objective manner. The case of correlated TCs is also considered. We have illustrated the framework for design of commercial vehicles with the help of hypothetical data. We believe that this linking of QFD and conjoint will definitely help improve the new product development process if implemented carefully. An interesting extension of this framework could be to model the relationship matrix and other parameters like importance ratings, costs etc. as fuzzy numbers. The authors propose to take this up in a subsequent a paper.

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Table 1 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							

Table 2 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																					