An intelligent hybrid system for customer requirements analysis and product attribute targets determination

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Aligning its quality initiatives in synchronization with the customer's perception of values is one of the key management strategies for improving the competitive edge of an organization. Therefore, it will be a distinct advantage if one can succeed in effectively capturing the genuine and major customer attributes (requirements), systematically analysing and duly transforming them into the appropriate product attributes (features). This paper puts forward a novel approach for analysing customer attributes and projecting them into the relevant design, engineering and product attributes in order to facilitate decision-making and to guide downstream manufacturing planning and control activities. The proposed hybrid system incorporates the principles of quality function deployment, analytic hierarchy process and fuzzy set theory to tackle the complex and often imprecise problem domain encountered in customer requirement management. It offers an analytical and intelligent tool for decoding, prioritizing and inferring the qualitative, sometimes vague and imprecise Voice of Customer. As a result, the appropriate product attributes can be mapped out and their relevant design targets can be determined quantitatively and consistently. The software supporting the hybrid system is constructed within a generic framework which can be easily customized and configured into specific enterprise models capable of offering more timely responses to the dynamic market demand.

1. Introduction

At a time when supply of most consumer goods has far overtaken demand, market competition is becoming increasingly intense. An organization can no longer be guaranteed growth or even survival if it solely relies on high volume production based on a set of self-defined specifications and quality standards. researches suggest that the traditional reactive technology-led or 'economy of scale' approach was only applicable at a time when markets were less discriminating and 'value for money' seemed to be the key deciding factor for choosing a certain product among many others. However, as the markets become more sophisticated, in addition to competitive pricing and outstanding product performance, a more proactive market-driven strategy is equally important. Being able to offer a wider range of customized services (i.e. 'economy of scope') is becoming increasingly important for gaining a competitive edge (Bennett and Forrester 1993). This shift of emphasis marks the transformation from a product focused era to a market oriented one. In order to be more responsive to the market, one has to go out to the customers and understand their actual needs and wants in order to duly

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respond to their requirements. Apart from conforming to its internal standards, a forward looking enterprise must be more alert in keeping customers satisfied by offering the kind of quality and values perceived by the market at a level at least compatible with if not superior to those of their competitors (Suzaki 1993). Hence, aligning the people, processes and products in a company closely with the evolving needs of the market are among the first steps towards gaining customer satisfaction.

The journey of gaining satisfied customers begins with effective capturing, analysing and understanding their genuine requirements. Customer attributes, sometimes called the Voice of Customer (VoC), tend to be linguistic and usually nontechnical in nature. It can be difficult at times for engineers to translate the VoC into definitive product and engineering specifications. The concepts of quality function deployment (QFD), which originated in Japan in the 1960s and became increasingly popular in the western world in the 1980s, have been widely adopted for customer attributes analysis in various business sectors (Bossert 1991, Cohen 1995). With the QFD approach, the VoC is analysed, categorized and transformed into technical terms for subsequent follow-up actions by engineers at every stage of design and manufacture including parts planning, process planning and production planning etc. Such a multi-stage exercise can be represented by a number of inter-connected structured matrices, each of which can be graphically described in a House of Quality (HoQ) (Hauser and Clausing 1988). The basic building blocks of a conventional HoQ are outlined in Fig. 1.

However, as a product becomes more complex, the information held in the HoQ can become so congested to the extent that the key issues might be over-shadowed or even overlooked. Hence, the interpretation of market-perceived quality and values into a set of appropriate technical actions can be a rather complex process. Different departments or divisions within an organization may not have identical perceptions and ideas of what product quality and values they are to offer. Similarly, as the number of trading partners increases, suppliers and consumers are even less likely to be in any better agreement (Gilmore 1974, Garvin 1988). In addition to these conceptual variations and the multi-dimensional ramifications of product quality and customer perceived values, the process of interpreting customer attributes is further complicated by the inherent ambiguity, vagueness and imprecision innate in the VoC due to various reasons, such as:

- Inadequate understanding the knowledge of the product design or the technology employed;
- Inexactness in describing the problem;
- Distortions or misinterpretations of messages somewhere along the line;
- Insensitivity and complacency of the service suppliers or vendors in detecting or decoding the VoC etc.

Owing to a combination of these factors, the interpretation of the linguistic VoC into some definitive engineering characteristics and product attributes will probably involve certain transformations which might well be non-linear in nature. This research puts forward a hybrid approach for processing the VoC and offers an intelligent system for responding to various market demands with the appropriate design targets.



Figure 1. The basic functional building blocks of a HoQ.

2. The acquisition of customer attributes

Customer attributes have been recognized as a major driving force for a company's continuous strife for improved product functionality, consistent quality performance, and a timely and uninterrupted supply, all available at a competitive price. In order to offer a remarkable standard of service, this entire chain of activities must be effectively managed from initial product conception through design, engineering, customization, production, distribution as well as after-sales services.

Customer requirements are becoming increasingly rigorous and dynamic these days to the extent that they behave like moving targets at times. However, it is equally valid that being able to effectively capture and understand the needs and wants of the customer and to respond to them promptly in one's product offerings is a prerequisite for gaining market acceptance and customer satisfaction.

As has been vividly demonstrated in successful enterprises world-wide, a thorough understanding of these customer and market related messages has helped them formulate those product attributes which are considered charming, attractive and distinctive by the customers (Kuehn and Day 1962, Dale 1994).

2.1. Capturing, categorizing and prioritizing customer attributes

The process of satisfying customers or outperforming their expectations begins with effectively soliciting their differing needs and wants which may be non-technical and imprecise in nature. Customer attributes might come from different customer groups in various market sectors through different channels, such as interviews, questionnaires, feedback from sales agents and retailers, customer comments and complaints as well as field maintenance reports. Based on their impacts on the target customer groups, there are essentially four types of customer attributes/requirements (Kano et al. 1984), i.e. expected requirements, high-impact requirements, low-impact requirements and hidden requirements. They have different marketing impacts and consequences as they are fulfilled. Further studies show that the importance of customer attributes can be explicitly stated or implicitly revealed (Edwards 1968). In the former case, the importance is usually stated by the customers in the form of product functions and features, whereas the effectiveness of the implicit attributes can only be reflected through their contributions towards the overall performance of the products. The VoC usually comes in qualitative forms, however, their performance measures and other associated data should as far as possible be expressed quantitatively so as to facilitate other downstream analyses and planning.

Owing to their diverse and linguistic nature, customer attributes usually need to be categorized prior to further analyses. The concept of the 'affinity diagram' (Bossert 1991) was adopted in this research to take advantage of its creative properties instead of solely relying on logical or intellectual reasoning as with other statistical methods. With this approach, team work and the active participation from all related departments are required to interpret the captured customer attributes into simple and representative expressions or phrases. These statements can then be bundled into a number of affinity groups, and the phrase that manages to capture the primary theme and key points of the group is selected as the header while its group members can be stratified in a tree structure. Affinity diagrams are applicable to 'map the geography' of the key areas under circumstances where the problems tend to be complex and the facts and thoughts are in chaos. Through team efforts, the scope of thinking can be substantially expanded, and the creation of new ideas becomes more possible.

The resulting categories obtained from the affinity diagram are then prioritized to assist more effective resource deployment. In order to encourage objectivity and consistency in attributes prioritization, a well proven decision-making methodology, the 'analytic hierarchy process' (AHP) (Saaty 1990, 1994) was adopted in the proposed hybrid model. This technique decomposes a problem into levels of prioritized subordinates and alternatives with known reliability and consistency according to their inter-relationships. The prioritization process begins with comparisons on the customer attributes pairwisely through intuitive reasoning against an identified design goal or a specific market focus. In this work, the mechanics of AHP is supported by a proprietary software package, Expert Choice (1986). As a result, the relative weights of importance among categories as well as among the individual attributes in each category and sub-category can be established through combining the distinct features of the affinity diagram and AHP.

2.2. Mapping the customer attributes onto the relevant product attributes

To duly address each customer attribute, its technical as well as financial implications have to be considered in order to arrive at certain feasible solutions, and some of the ideas might be initially generated by the customers themselves. These solutions can be collectively called the Voice of Designer (VoD) taking the form of product attributes or design features. With these details, a knowledge-base interlinking the customer demands and the enterprise responses can be established to facilitate the formulation of marketing and corporate strategies.

The concept of QFD (Bossert 1991, Cohen 1995) has been widely used in manufacturing industry for analysing customer attributes and subsequently projecting them on to the relevant product and engineering attributes. As illustrated in Fig. 2, an HoQ is primarily a graphical tool for describing the relationship and correlation between the attributes, and quite often showing the relative performance of the competitors in the same information architecture (Hauser and Clausing 1988). In this conventional HoQ, the relationships between the attributes are usually described by symbols, such as space, Δ , O..., etc. each of which is assigned a numerical value on a selected scale. For instance, with the 1–3–9 scale, zero stands for 'not related', 1 for 'possibly related', 3 for 'moderately related' and 9 for 'strongly related'. Alternatively, other scales, such as 1–5–9, can also be applied.

To go beyond the qualitative representation of attributes relationships in a conventional HoQ the authors propose to express the information in numerical terms using the AHP technique. The resulting QFD data can be represented quantitatively in a focused HoQ as shown in Fig. 3. In the process of mapping customer attributes towards the relevant product attributes, it is not unusual to find that while a product/ engineering attribute works very well in fulfilling certain customer attributes, it might adversely affect others. Hence, entries to the matrices in a HoQ can be positive as well as negative.

Although the HoQ is in general a comprehensive tool for showing the relationships between attributes, sometimes it lacks the flexibility to deal with the inexactness, undecideability and vagueness innate in the semantics of the VoC. Moreover, the target values, which represent the design/technical specifications for individual product attributes in fulfilling specific customer attributes, are usually decided according to the experience and subjective judgement of the product designers. Accurate target values are essential for supporting subsequent process planning and production activities, however, no systematic and generic methods are available hitherto for determining these product design targets consistently. It may be due to the fact that tremendous product knowledge and design experience supported by intense engineering efforts will be required to construct such a system. In this paper, an effective and analytical methodology for mapping the customer attributes onto relevant product attributes and subsequently determining their target values using Fuzzy inference is expounded. This approach represents a major breakthrough in QFD research and applications.

3. A Fuzzy approach for customer attributes interpretation

In order to overcome some of the inherent limitations in conventional interpretation and mapping of customer attributes onto the relevant product attributes, the Fuzzy Customer Requirements Inference System (FCRIS) was developed in this work. It amalgamates the characteristics of QFD and Fuzzy Set theory, offering a more dynamic and tolerant algorithm for coping with linguistic attribute statements of varying degrees of exactness and precision in the VoC (Zadeh and Kacprzyk 1992, Cox 1994). The system is capable of performing approximate



Figure 2. A basic HoQ for the design of mid-range hi-fi's.

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	Product	Degree of Importance (%)	No of drive units in a speaker	Diameter of unit	Size of speaker box	Drive units location in speaker box	Material of box / drive unit	Sensitivity	Bass roll off	Output power
C	ustomer 🔪	ative	1	2	з	4	5	6	7	8
A	ttributes	Rel	\uparrow	\times	$ \downarrow$	\times	$ \times$	\uparrow	$ \downarrow$	\uparrow
1	Strong bass	30.2	2.7	10.3	4.4	0.8	1.0	2.1	1.6	7.2
5	Reality, low loss and noise	20.5	4.3	6.7	3.2	0.6	0.9	5.2	1.1	1.6
3	Natural sounds	6.5	0.5	2.3	0.7	0.2	0.3	0.2	1.4	0.9
4	Contain multi-disc / MD / other new features	7.1	2.3	0.4	0.9	0.9	1.3	0.4	0.4	0.5
5	Contain all basic functional features (e.g. tuner, etc.)	10.3	3.5	1.6	1.1	0.3	0.6	0.4	0.5	2.3
6	More surround feature selection	2.2	0.6	0.3	0.1	0.1	0.2	0.1	0.2	0.6
7	Large output power	15.7	1.6	3.0	2.3	0.4	0.6	1.2	0.8	5.7
8	Reliable	3.2	0.3	0.3	0.4	0.3	1.4	0.2	0.2	0.3
9	Fashionable appearance & color	4.3	0.6	0.5	0.9	0.2	1.7	c.2	0.2	0.2
Rela	Relative Weight of Importance (%)				14.0	Э.8	8.0	7.0	6.3	19.3

Figure 3. A focused HoQ showing the quantitative relationships between attributes and their relative weight of importance.

reasoning in specific domains based on the knowledge and experience available in the company as well as the requirements of the customer which may not necessarily be sufficient nor explicit. In essence, FCRIS is designed to process the diverse and often imprecise VoC to establish the relevant product design targets using the theory of fuzzy inference.

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3.1. The basic principles of fuzzy systems

The concept of fuzzy logic or fuzzy sets was initially conceived by Lotfi A. Zadeh (1965). He described the theory of fuzzy sets as a theory in which everything is a matter of degree. A fuzzy set is defined as a class of objects with a continuum of degrees of membership characterized by a membership function which assigns to each object a grade of certainty ranging between zero and one, and thus permitting partial membership. It behaves differently from a conventional Boolean (crisp) set in which only two values, i.e. absolute inclusion (1) or absolute exclusion (0) can exist. Fuzzy systems are applicable to most real life scenarios which tend not to be dichotomous and descriptions of their nature are quite often imprecise. Fuzzy sets offer a strict mathematical framework in which vague conceptual phenomena can be precisely and rigorously dealt with. In other words, there is nothing fuzzy about fuzzy logic. Since its inception, the concept has advanced in various directions and has found applications in many disciplines. Particularly in the last decade or so, fuzzy set theory experienced tremendous growth, showing remarkable results in a wide range of applications. Full discussions of fuzzy set theory can be found in Zadeh (1965, 1975a & b. 1976). Zimmermann (1991) and Cox (1994).

4. General features of the proposed fuzzy customer requirement inference system

The architecture of FCRIS, as described in Fig. 4, comprises the following building blocks:

- (1) A knowledge base, which contains customer and product data, fuzzy rules, or other forms of knowledge required to support design decision-making;
- (2) A user interface, through which the input data and decision support information is communicated between the system and the external environment; and
- (3) An inference engine, which contains an interpreter and an approximate reasoning routine, governing how the data and rules can be applied to infer new knowledge.

4.1. Knowledge acquisition and representation in FCRIS

The knowledge base in FCRIS is divided into the following partitions:

- (1) K-CA, knowledge of the customer attributes, which is captured through various ways and means as described in § 2.1 and expressed in fuzzy sets or fuzzy membership functions.
- (2) K-PA, knowledge of the product attributes, which covers details of product functionality, features and their corresponding engineering characteristics. It is established through group discussions, engineering analyses or by applying self-learning algorithms in specific neural nets. The derived information can be expressed in the form of fuzzy sets or membership functions.
- (3) K-CA-PA, Knowledge of the relationships between the customer attributes and product attributes, which can be established through the interactions and collaborations between the marketing, design, engineering and manufacturing personnel in a company. The data are usually expressed in the form of fuzzy inference rules/propositions.

The interactions of these knowledge-base partitions with other systems components in FCRIS will be discussed in the following sub-sections.



K-CA-PA: Knowledge about the Relationships between CA and PA MBF : Membership Functions

FIR : Fuzzy Inference Rules / Propositions

Figure 4. Architecture of the fuzzy customer requirement inference system (FCRIS).

4.2. The data representation in FCRIS

The problem domain in FCRIS takes care of the interpretation of customer attributes into the relevant product attributes and the determination of their corresponding target values using fuzzy inference. Each attribute is represented by a model variable which is in turn described by the relevant linguistic variables in individual and sometimes overlapping fuzzy sets. The meaning of these fuzzy sets can be enriched by appropriate hedges or qualifiers in order to accommodate the possible ambiguity, vagueness, imprecision and inexactness commonly innate in the semantics of the VoC. The representation of the basic constructs of FCRIS can be described as follows. 4.2.1. The fuzzy space of customer attributes, V

The set of customer requirements (attributes) of a given product can be denoted by an N-dimensional fuzzy vector X, such that

 $X = (X_1, X_2, \dots, X_N)$ in the fuzzy space of V,

where $V = V_1 \times V_2 \times \cdots \times V_N$, and ' \times ' is the Cartesian product operator, i.e. the *i*th input model variable (customer attribute) X_i of a given product, for instance, the 'Top speed' of a motor car, can be defined in the crisp set V_i ($i = 1, 2, \ldots, N$) which represents the corresponding universe of discourse, say from 100 km hr to 250 km/hr.

For each customer attribute X_i , a linguistic variable d_i (i = 1, 2, ..., N) exists in the set of all real numbers, **R**. It represents the relative weight of importance (priority) of X_i in the set of customer attributes X. This priority may be specified directly by the customers themselves or established through analytical means, such as the AHP technique employed in this research. Hence, for the input fuzzy vector X, there exists a real vector d which represents the relative weights of importance for the various customer attributes, such that $d = (d_1, d_2, ..., d_N)$.

4.2.2. The space of product attributes, P

Similarly, the set of model variables representing the product/engineering attributes can be denoted by an M-dimensional fuzzy vector Y, such that

 $Y = (Y_1, Y_2, \dots, Y_M)$ in the fuzzy space of P,

where $P = P_1 \times P_2 \times \cdots \times P_M$, and '×' is the Cartesian product operator, i.e. the *i*th output model variable (product attributes) Y_i , for instance the 'Engine Power' of a motor car, can be defined in the crisp set P_i (i = 1, 2, ..., M) which covers the corresponding universe of discourse, say from 50 hp to 125 hp. The relative weights of importance of the relevant product attributes can be represented by a real vector w, such that $w = (w_1, w_2, ..., w_M)$.

4.2.3. The rule-base inter-relating the customer and product attributes

For a given product, the relationships between the set of customer attributes, X and the set of product attributes, Y can be described by a number of fuzzy inference rules/propositions in an 'if-then' format. These propositions describe the relationships between the linguistic variables of the customer attributes (input model variables) and those of the product attributes (output model variables).

Example: 'If the Top Speed of a motor car is rather fast and its Seating Capacity is fairly large, then the required Engine Power would be reasonably high'.

The general form of a typical fuzzy inference rule can be expressed as follows:

 R_i : If $(X_{i1} \text{ is } x_{i1}, \text{ and } X_{i2} \text{ is } X_{i2}, \text{ and } \dots, X_{ik} \text{ is } x_{ik})$, then Y_i is y_i ,

where $x_{i1}, x_{i2},...$ and x_{ik} are the linguistic variables corresponding to the input model variables $X_{i1}, X_{i2},...$ and X_{ik} respectively, while y_i is the linguistic variable applicable to the output model variables, Y_i .

For each of the rules R_i (i = 1, 2, ..., k) in the fuzzy rule base, there exists a linguistic variable r_i defined in the interval [0, 1]. It represents the 'certainty factor' which denotes the confidence of the product engineers or designers on the rule, R_i .



Figure 5. The schematic representation of FCRIS.

4.3. The fuzzy inference process in FCRIS

The fuzzy inference process in FCRIS is the mechanism for projecting the output target value for each specific product/engineering attribute by executing the fuzzy rule base against an input set of customer attributes. The schematic representation and the architecture of FCRIS can be shown in Figs. 4 and 5 respectively. The implementation and application of the system take a number of logical stages as explained below.

4.3.1. Fuzzification of the customer attributes

In this stage, the customer attributes and their respective relative weight of importance are fed into the system through a user interface. The data are then transformed into fuzzy numbers or fuzzy sets with the knowledge held in K-CA. During this transformation, specifications against individual customer attributes are converted into the respective grades of certainty (degrees of membership) against the relevant membership function of the corresponding input linguistic variables in the fuzzy sets. These grades of certainty are regarded as the basic 'facts' of the fuzzy inference process.

4.3.2. Evaluation/execution of the fuzzy rule-base

The fuzzy sets or membership functions established during the fuzzification of customer requirements are evaluated against the premise (conditions part) of the fuzzy inference rules held in K-CA-PA. As a result, sub-conclusions are drawn as the grade of certainty (truth) of a predicate in the rule exceeds a pre-set alpha-cut

threshold, and the rule is then fired. The procedures of fuzzy rule evaluation can be explained as follows.

(1) Evaluating the premise of a rule. The grades of certainty of the predicates in the premise of the rule R_i are given by:

The grade of certainty of ' X_{i1} is x_{i1} ' is g_{i1} ;

The grade of certainty of ' X_{i2} is x_{i2} ' is g_{i2} ;

The grade of certainty of ' X_{ik} is x_{ik} ' is g_{ik} respectively; according to fuzzy set theory (Zimmermann 1991), the overall grade of certainty of the premise will take the minimum among the individual grades of certainty of the predicates. Hence, the overall grade of certainty, g_i in the premise of R_i can be denoted as:

 $g_i = \operatorname{Min}\{g_{i1}, g_{i2}, \ldots, g_{ik}\}$

(2) Determining the grade of certainty of the consequent (conclusion part) of the rule. For the rule R_i , the grade of certainty of its consequent will be the same as the overall grade of certainty, g_i of its premise. Hence, the grade of certainty of the consequent ' Y_i is y_i ' is also equal to g_i .

4.3.3. Aggregation and defuzzification of the output fuzzy regions

After rule evaluation, all the sub-conclusions relevant to each product attribute are aggregated into a complete conclusion represented by an output fuzzy region.

Example: The k sub-conclusions related to the product attribute, Y_i drawn from the rule evaluation exercise can be expressed together with their respective relative weights of importance in the form of:

$$\begin{array}{l} Y_{j} \text{ is } y_{j1} : g_{j1}, w_{j1}; \\ Y_{j} \text{ is } y_{j2} : g_{j2}, w_{j2}; \\ \dots; \\ Y_{j} \text{ is } y_{j3} : g_{j3}, w_{jk}. \end{array}$$

These sub-conclusions can be amalgamated to give a complete output conclusion ' Y_j is $y_j : w_j$ ' as shown in Fig. 6, where y_j is the aggregated and defuzzified output value of Y_j , and w_j is the relative weight of importance of the product attribute Y_j .

Each output fuzzy region will be defuzzified according to the knowledge held in K-PA to yield an expected output which represents the deterministic crisp target value for the relevant product attribute. The choice of the methods of defuzzification depends on the nature of the analysis as well as the preference and emphasis adopted by the decision makers. For demonstration purpose, the centroid method of defuzzification (i.e. weighted average method of defuzzification) is used here. With the centroid method of defuzzification, the expected output value y_f for the product attribute Y_i can be worked out as follows:

Let $P_j = [a, b]$ be the universe of discourse of the *j*th product attribute



Figure 6. Aggregation of the subconclusions to yield a complete conclusion for a given output model variable.



Target Value for Y

Figure 7. Aggregating and defuzzifying the subconclusions by the centroid method.

represented by the output model variable Y_j , hence *a* and *b* are the lower and upper limits for the domain elements of Y_j respectively. Thus, y'_j (the target value) for the composite conclusion, ' Y_j is $y'_j : w'$ can be given by the centroid of the aggregate output fuzzy region,

i.e.
$$y_f = \int_a^b x\mu(x) dx \int_a^b \mu(x) dx$$

where $\mu_{(x)}$ is the grade of certainty at the given domain point $x \ (x \in [a, b])$



Figure 8. Fuzzy membership functions related to the 'Top Speed'.

in the aggregated output fuzzy region for the model variable Y_j as illustrated in Fig. 7.

5. Case study

To help explain the working principles of FCRIS, the following example demonstrates how a set of incoming customer requirements is fuzzified and analysed using the proposed fuzzy inference process in order to determine the design target value for a given product attribute.

5.1. The scenario

The problem domain in this example is to determine the target value of the product attribute on the 'Engine Power' required to satisfy specified customer attributes on the 'Top Speed' and the 'Seating Capacity' of a given model of motor car. Hence, in this case N = 2 and M = 1.

5.1.1. Fuzzifying the customer and product attributes

The customer attribute 'Top Speed' is denoted by the input model variable X_1 . If the minimum and maximum speed of the model of motor car concerned are 0 and 250 kilometres per hour (km/hr) respectively, the universe of discourse (V_1) for X_1 lies in the real interval [0, 250], i.e. $V_1 = [0, 250]$. For simplicity, the universe of discourse is evenly subdivided into 6 sections (n = 6), therefore V_1 contains 6 discrete elements (real numbers) v_{1l} , such that $v_{1l} = 50 * (l - 1)$ (l = 1, 2, 3, 4, 5, 6), i.e. $V_1 \{0, 50, 100, 150, 200, 250\}$.

If there are four linguistic variables x_{11} 'slow', x_{12} 'moderate', x_{13} 'fast' and x_{14} 'extremely fast' defined in the term set of the input model variable X_1 , the 'Top Speed'. These linguistic variables can be described by the fuzzy sets A_{11} , A_{12} , A_{13} and A_{14} with their corresponding membership functions represented by the following vectors:

$$A_{11} = (1 \cdot 0, 0 \cdot 5, 0 \cdot 0, 0 \cdot 0, 0 \cdot 0, 0 \cdot 0), \quad A_{12} = (0 \cdot 0, 0 \cdot 0, 1 \cdot 0, 0 \cdot 0, 0 \cdot 0, 0 \cdot 0)$$

 $A_{13} = (0.0, 0.0, 0.0, 0.5, 1.0, 1.0), \quad A_{14} = (0.0, 0.0, 0.0, 0.0, 0.5, 1.0)$ respectively,

as illustrated in Fig. 8.



Figure 9. Fuzzy membership functions related to the 'Seating Capacity'.

Similarly, another customer attribute 'Seating Capacity' can be denoted by the model variable X_2 . If the minimum and maximum seating capacity of a car are two and nine respectively, the universe of discourse (V_2) of the model variable X_2 lies in the real interval [2,9], i.e. $V_2 = [2,9]$. The interval is evenly subdivided into n_2 $(n_2 = 8)$ sections in the universe of discourse of V_2 which contains 8 discrete domain elements, v_{2l} such that $v_{2l} = 1 + l$ (l = 1, 2, 3, 4, 5, 6, 7, 8), i.e. $V_2 = \{2, 3, 4, 5, 6, 7, 8, 9\}$.

If there are four linguistic variables x_{21} 'small', x_{22} 'medium', x_{23} 'large' and x_{24} 'very large' defined in the term set of the input model variable X_2 , the 'Seating Capacity', their corresponding fuzzy sets can be described by the following membership vectors:

$$A_{21} = (1 \cdot 0, 0 \cdot 5, 0 \cdot 0, 0 \cdot 0), \quad A_{22} = (0 \cdot 0, 0 \cdot 5, 1 \cdot 0, 0 \cdot 5, 0 \cdot 0, 0 \cdot 0, 0 \cdot 0, 0 \cdot 0),$$
$$A_{23} = (0 \cdot 0, 0 \cdot 0, 0 \cdot 0, 0 \cdot 5, 1 \cdot 0, 0 \cdot 5, 0 \cdot 0, 0 \cdot 0), \quad A_{24} = (0 \cdot 0, 0 \cdot 5, 1 \cdot 0)$$

respectively as illustrated in Fig. 9.

On the other hand, the product attribute 'Engine Power' is denoted by the output model variable Y_1 with 0 and 125 horsepower (hp) as its minimum and maximum limits respectively. Hence, the universe of discourse of Y_1 lies in a real interval [0, 125], i.e. $P_1 = [0, 125]$.

If this interval is evenly divided into 6 sections (m = 6), thus P_1 contains 6 discrete domain elements p_l , such that $p_l = 25 * (l - 1)$ (l = 1, 2, 3, 4, 5, 6). Therefore, $P_1 = \{0, 25, 50, 75, 100, 125\}$. Assuming there are four linguistic variables y_1 'low', y_2 'medium', y_3 'high' and y_4 'very high' defined in the term set of the output model variable Y_1 , the 'Engine Power', the membership functions of their respective fuzzy sets can be represented by the following vectors:

$$B_1 = (1 \cdot 0, 0 \cdot 5, 0 \cdot 0, 0 \cdot 0, 0 \cdot 0, 0 \cdot 0), B_2 = (0 \cdot 0, 0 \cdot 0, 1 \cdot 0, 0 \cdot 0, 0 \cdot 0, 0 \cdot 0),$$

$$B_3 = (0 \cdot 0, 0 \cdot 0, 0 \cdot 0, 0 \cdot 5, 1 \cdot 0, 1 \cdot 0), B_4 = (0 \cdot 0, 0 \cdot 0, 0 \cdot 0, 0 \cdot 0, 0 \cdot 5, 1 \cdot 0)$$

respectively as illustrated in Fig. 10.



Figure 10. Fuzzy membership functions related to the 'Engine Power'.

5.1.2. Representing the fuzzy rules

The fuzzy rule-base relevant to the problem domain can be evaluated as follows:

For Rule 1: 'If the Top Speed is slow and the Seating Capacity is small, then the Engine Power is low' i.e. 'If $X_1 = x_{11}$ and $X_2 = x_{21}$, then $Y_1 = y_1$ '.

Hence, the predicates of this rule can thus be represented by a conditions matrix C_1 , such that:

$$C_{1} = A_{11} \times A_{21} = (12 \cdot 0, 0 \cdot 5, 0 \cdot 0, 0 \cdot 0, 0 \cdot 0, 0 \cdot 0) \times (1 \cdot 0, 0 \cdot 5, 0 \cdot 0, 0 \cdot 0, 0 \cdot 0, 0 \cdot 0, 0 \cdot 0)$$

$$\begin{bmatrix} 1 \cdot 0 & 0 \cdot 5 & 0 \cdot 0 \\ 0 \cdot 5 & 0 \cdot 5 & 0 \cdot 0 \end{bmatrix}$$

	0.5	0.0	00	00	00	00	00	00
_	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
_	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

i.e. the condition matrix C_1 for Rule 1 can be obtained by taking the Cartesian product of the membership functions of the related fuzzy sets in the premise of the rule.

Similarly, the predicates of the *i*th fuzzy rule can be described by a condition matrix C_i . Furthermore, a conditions vector $\overline{C_i}$ can be derived from the matrix C_i with entries:

$$\overline{c}_i = c_{j_1 j_2 \dots j_N}$$

where $i = [\{[(j_1 - 1) * n_2 + (j_2 - 1)]^* n_3 + (j_3 - 1)\} * n_4 + \dots + (j_{N-1} - 1)] * n_N + j_N, \\ \forall j_1 = 1, 2, \dots, n_1; j_2 = 1, 2, \dots, n_2; \dots; j_N = 1, 2, \dots, n_N.$

Hence, the above conditions matrix, C_l can be transformed into a conditions vector, C_1 , i.e.

$$\bar{C}_1 = (1 \cdot 0, 0 \cdot 5, 0 \cdot 0, 0 \cdot 5, 0 \cdot 5, 0 \cdot 0, 0 \cdot$$

As a result, Rule 1 can be expressed in a rule matrix, Q_1 such that:

$$Q_{1} = C_{1} \times B_{1}$$

$$= (1 \cdot 0, 0 \cdot 5, 0 \cdot 0, 0 \cdot 5, 0 \cdot 5, 0 \cdot 0, 0$$

-

$$\times (1.0, 0.5, 0.0, 0.0, 0.0, 0.0)$$

_

	1.0	0.5	0.0	0.0	0.0	0.0	
	0.5	0.5	0.0	0.0	0.0	0.0	
	0.0	0.0	0.0	0.0	0.0	0.0	
	0.0	0.0	0.0	0.0	0.0	0.0	
	0.0	0.0	0.0	0.0	0.0	0.0	
	0.0	0.0	0.0	0.0	0.0	0.0	
=	0.0	0.0	0.0	0.0	0.0	0.0	
	0.0	0.0	0.0	0.0	0.0	0.0	
	0.5	0.5	0.0	0.0	0.0	0.0	
	0.5	0.5	0.0	0.0	0.0	0.0	
	0.0	0.0	0.0	0.0	0.0	0.0	
	::::					::::	
	0.0	0.0	0.0	0.0	0.0	0.0	48*6

This is a 48×6 matrix with its unspecified entries '....' taking a value of zero ('0.0'). For Rule 2: 'If the Top Speed is moderate and the Seating Capacity is medium, then the Engine Power is medium',

i.e. 'If
$$X_1 = x_{12}$$
 and $X_2 = x_{22}$, then $Y_1 = y_2$ '

and its conditions matrix can be expressed as:

 $C_2 = A_{12} \times A_{22} = (0.0, 0.0, 1.0, 0.0, 0.0, 0.0) \times (0.0, 0.5, 1.0, 0.5, 0.0, 0.0, 0.0, 0.0)$

and the corresponding conditions vector becomes:

Hence, the resulting rule matrix, Q_2 can be given by:

Similarly, for Rule 3: 'If the Seating Capacity is very large, then the Engine Power is high', i.e. "If $X_2 = x_{24}$, then $Y_1 = y_3$ ".

Since the 'Top Speed' does not appear in the premise of this rule, its membership function can be represented by a unit vector (1, 1, 1, 1, 1, 1), so that the corresponding conditions matrix can be given by:

$$C_3 = (1, 1, 1, 1, 1, 1) \times A_{24} = (1 \cdot 0, 1 \cdot 0) \times (0 \cdot 0, 0 \cdot 5, 1 \cdot 0)$$

and the corresponding conditions vector becomes:

Hence, the resulting rule matrix, Q_3 can be given by:

Assuming there are only three entries in the rule-base relevant to the current problem domain, their matrices can be combined into a single consolidated rule matrix through a series of fuzzy OR " \lor " operations, i.e. $Q = r_1 \cdot Q_1 \lor r_2 \cdot Q_2 \lor r_3 \cdot Q_3$, where r_i represents the certainty factor for the fuzzy proposition R_i , (i = 1, 2, 3).

Assuming all the $r_i = 1$ in this case, hence the consolidated rule matrix becomes:

<i>Q</i> =	$Q_1 + q_2$	$Q_2 + q_2$	Q_3			
	1.0	0.5	0.0	0.0	0.0	0.0]
	0.5	0.5	$0 \cdot 0$	0.0	0.0	0.0
	0.0	0.0	$0 \cdot 0$	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	$0 \cdot 0$	0.0	$0 \cdot 0$	0.0
	0.0	0.0	$0 \cdot 0$	0.0	$0 \cdot 0$	0.0
	0.0	0.0	0.0	0.5	0.5	0.5
	0.0	0.0	0.0	0.5	1.0	1.0
	0.5	0.5	0.0	0.0	0.0	0.0
	0.5	0.5	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	$0 \cdot 0$	$0 \cdot 0$	0.0	$0 \cdot 0$	0.0
	0.0	$0 \cdot 0$	$0 \cdot 0$	0.0	$0 \cdot 0$	0.0
	0.0	$0 \cdot 0$	$0 \cdot 0$	0.5	0.5	0.5
	0.0	$0 \cdot 0$	$0 \cdot 0$	0.5	$1 \cdot 0$	1.0
	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.5	0.0	0.0	0.0
	0.0	0.0	$1 \cdot 0$	0.0	0.0	0.0
	0.0	0.0	0.5	0.0	0.0	0.0
	0.0	0.0	$0 \cdot 0$	0.0	0.0	0.0
	0.0	0.0	$0 \cdot 0$	0.0	0.0	0.0
	0.0	0.0	0.0	0.5	0.5	0.5
_	0.0	0.0	0.0	0.5	$1 \cdot 0$	1.0
_	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.5	0.5	0.5
	0.0	0.0	0.0	0.5	1.0	1.0
	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.5	0.5	0.5
	0.0	0.0	0.0	0.5	1.0	1.0
	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.0	0.0	0.0
	0.0	0.0	0.0	0.5	0.5	0.5
	L 0.0	0.0	0.0	0.5	1.0	1.0

5.1.3. Processing specific customer attributes

Now, assuming the product engineers have to re-design an engine for a model of motor car in response to a specific set of customer attributes on 'Top Speed' X_1 and 'Seating Capacity' X_2 , they want to know the minimum output power that the engine has to deliver in order to meet these requirements.

The relevant linguistic variables for X_1 and X_2 are fuzzified and represented by the membership vectors,

$$A_{f} = (0.0, 0.1, 0.8, 0.2, 0.0, 0.0)$$

and

$$A_2 = (0.1, 0.6, 0.4, 0.2, 0.0, 0.0, 0.0, 0.0)$$
 respectively.

Hence, the conditions matrix representing these specific customer specifications can be expressed as:

$$C' = A_{f} \times A_{f} = (0.0, 0.1, 0.8, 0.2, 0.0, 0.0) \times (0.1, 0.6, 0.4, 0.2, 0.0, 0.0, 0.0, 0.0)$$

$$= \begin{bmatrix} 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.1 & 0.1 & 0.1 & 0.1 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.1 & 0.6 & 0.4 & 0.2 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.1 & 0.2 & 0.2 & 0.2 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \end{bmatrix}$$

and, the Conditions Vector becomes

5.1.4. Evaluating the fuzzy rule base

Then, the set of customer attributes represented by the conditions vector, $\overline{C'}$ is submitted to rule evaluation against the consolidated rule matrix, Q established in § 5.1.2. The corresponding output membership vector, B' can be worked out through max-min compositional inference on the condition vector and the consolidated rule matrix as follows:

$$B' = \bar{C}'^{\circ} Q = (0.1, 0.1, 0.5, 0.0, 0.0, 0.0)$$

where "o" is the max–min compositional operation; it works in a way similar to ordinary matrix multiplications, except that the addition operation '+ ' is replaced by the maximization operation ' \lor ', and the multiplication operation '*' is replaced by the minimization operation ' \land '.

This vector represents the membership function of the output fuzzy region after aggregating the sub-conclusions for the product attribute Y_1 , the 'Engine Power' in the universe of discourse P_1 .



Figure 11. Defuzzifying the singleton output region to yield the minimum engine power required.

5.1.5. Defuzzifying the output fuzzy region

The resulting target value y' for the model variable Y_1 can be determined by defuzzifying the singleton output fuzzy region using the centroid method, i.e.

$$y' = (0.1 * 0 + 0.1 * 25 + 0.5 * 50 + 0.0 * 75 + 0.0 * 100 + 0.0 * 125)$$

/(0.1 + 0.1 + 0.5 + 0.0 + 0.0 + 0.0)
= 27.5/0.7
= 39.3 hp (horsepower)

Hence, the minimum 'Engine Power' required to satisfy the set of customer attributes has been worked out to be 39.3 horsepower as illustrated in Fig. 11.

This case study demonstrates how the fuzzy inference process in the proposed hybrid model can be used to determine the design target for minimum power that the engine has to deliver in order to fulfil the specified customer requirements on *Top Speed* and *Seating Capacity* of a certain model of motor car using matrix computations. More complex problems can be processed in a similar manner.

Since definitive formulae for coping with fuzzy VoC are practically unavailable, without FCRIS the design engineers would have to resort to time-consuming procedures probably by rule of thumb to estimate the design targets which are liable to subjectivity and inconsistency.

6. Conclusions and further work

The approach proposed in this paper can decode the VoC more effectively through extending the basic applications of QFD and HoQ quantitatively towards a new horizon of determining the technical design targets with the help of artificial intelligence. The principles and applications of the intelligent hybrid model for customer requirements analysis and product design targets determination have been explained and discussed throughout this paper. The novel ideas of structuring the Focused HoQ with the use of AHP and the Affinity Diagram for particular categories of product attributes, and implementing the fuzzy inference process using matrix computations, have been expounded with the help of a number of examples and a practical case study. The proposed intelligent hybrid model is capable of effectively analysing and processing specific customer requirements to give quantitative design specifications which are essential for guiding the downstream activities in product planning and manufacturing. As a result, the fuzzy front end in the product design cycle can be compressed, hence the overall time to market can be substantially shortened.

Putting the research into future perspective, certain related areas can be further polished. They include automating the data manipulations in HoQ's, reducing the inter-dependency between the attributes, improving the method of knowledge representation and enhancing the user interfaces in FCRIS. With these additional efforts, the proposed hybrid model can be further strengthened to become an essential construct in the architecture of market-focused manufacturing.

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