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Using quality function deployment for collaborative product design and optimal selection of module mix

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A B S T R A C T

In response to fast-growing and rapidly-changing markets, launching new products faster than competitors cannot only assist firms in acquiring larger market share but also reducing development lead time, significantly. However, owing to its intrinsically uncertain properties of managing NPD (new product development), manufacturing companies often struggle with the dilemma of increasing product variety or controlling manufacturing complexity. In this study, a fuzzy MCDM (multi-criteria decision making) based QFD (quality function deployment) which integrates fuzzy Delphi, fuzzy DEMATEL (decision making trial and evaluation laboratory), with LIP (linear integer programming) is proposed to assist an enterprise in fulfilling collaborative product design and optimal selection of module mix when aiming at multi-segments. In particular, Fuzzy Delphi is adopted to gather marketing information from invited customers and their assessments of marketing requirements are pooled to reach a consensus; fuzzy DEMATEL is utilized to derive the priorities of technical attributes in a market-oriented manner; and LIP is used to maximize product capability with consideration of supplier's budget constraints of manufacturing resources. Furthermore, a real case study on developing various types of sport and water digital cameras is demonstrated to validate the proposed approach.

1. Introduction

In an era of customer-oriented global economy, dominating the majority market with a single product line becomes very challenging and almost infeasible for most companies (Hsiao & Liu, 2005). Traditionally, to satisfy market majorities, companies considered providing products with high quality, low cost, fast delivery and courteous after-sales service at most. Nowadays, owing to fiercely competitive environments and rapidly changing demand, the capability and the speed of developing niche products and launching them into the niche segments gradually dominate the competition paradigm, particularly when a transition has been shifting from "supply push" to "demand pull" (Jiao, Ma, & Tseng, 2003). To put it another way, "mass customization" embarks a new paradigm for modern manufacturing industries since it treats each customer as an individual and attempts to provide "tailor-made" featured products that was only offered in the pre-industrial "craft" era.

Over the past two decades, numerous publications originated from different disciplines have witnessed in the field of customer requirement management (Jiao & Chen, 2006). For example, various fields such as marketing research, consumer behavior, collaborative design, and concurrent engineering, attempt to contribute to different stages for new product development (NPD). Among them, marketing research and consumer behavior emphasize the front issues relevant to collecting the information of customer preference via specific channels. In contrast, collaborative design and concurrent engineering focus on utilizing a systematic and parallel approach for integrating a wide spectrum of product design and related manufacturing processes (Lin, Wang, Chen, & Chang, 2008). Although high product variety does stimulate product sales, companies still inevitably face the trade-offs between the diversity of customer needs and numerous adverse effects, such as larger inventory cost, longer cycle time and expensive research investment.

As a result, it is very imperative for companies to keep high flexibility while incurring limited manufacturing cost, concurrently. In practice, two common techniques have been proposed to tackle the above-mentioned issue, including product family architecture (Jiao & Tseng, 1999; Moon, Simpson, & Kumara, 2010) and modular product or product family design (Hsiao & Liu, 2005; Kreng & Lee, 2004). Modular product design offers a feasible way by developing a product architecture, in which physical relationships across modules are limited while functional relationships among components within a module are coherent. Furthermore, product family design based on a standard platform usually provides a cost-effective way to develop highly related but differentiated

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products. By sharing/reusing physical manufacturing resources and intangible human capitals, companies can efficiently balance the benefit and cost for NPD.

Based on previous studies, most of them are deficient in constructing a systematic approach to assist companies in achieving mass customization while keeping reasonable manufacturing cost. In this study, a fuzzy MCDM based QFD (quality function deployment) is proposed to fulfill collaborative product design and optimal selection of module mixes when aiming at multi-segments. Moreover, this paper contributes to this domain by presenting the following merits:

- QFD provides a communication platform to gather different opinions between industrial experts and even among customer individuals.
- QFD is capable to transform intangible marketing requirements (MRs) into measurable technical attributes (TAs) and to accommodate the dependences between MRs and TAs and the correlations among themselves.
- In additional to deriving the weights of MRs and TAs, the proposed fuzzy MCDM based QFD could further identify the optimal module mix (product variety) for a specific market segment.

The remaining of this paper is organized as follows. Section 2 overviews the related works and Section 3 introduces the proposed framework which integrates fuzzy Delphi, fuzzy DEMATEL with LIP (linear integer programming). A real example regarding collaborative design for various sport & water digital cameras is illustrated in Section 4. Conclusions are drawn in Section 5.

2. Related works

Quality function deployment (Akao, 1990) originated in Japan in the 1970s has been widely applied to various industries for product development, concept evaluation, service design, and competitor benchmarking. Basically, customers' desires on a specific product or service can be represented by a set of intangible marketing requirements (MRs). Thereafter, a series of technical attributes (TAs) that impact on MRs need to be determined and realized for product development or service design. Typically, the conventional QFD consists of the following four phases (Chan, Kao, Ng, & Wu, 1999; Lin, Cheng, Tseng, & Tsai, 2010): phase one translates marketing requirements into technical attributes; phase two translates technical attributes into part characteristics; phase three translates part characteristics into manufacturing operation, and phase four translates manufacturing operations into production requirements. Specifically, at phase one of QFD, the so-called HoQ (house of quality) provides a communication platform to fuse diverse opinions among cross-functional team members (see Fig. 1).

To fast understand the research trend regarding QFD, representative publications are reviewed and listed below. First, to determine the importance degrees of MRs, AHP (analytical hierarchy process)/fuzzy AHP (Kwong & Bai, 2002, 2003), fuzzy Delphi (Chen & Ko, 2008; Karsak, 2004), and fuzzy group decision (Büyüközkan, Feyzioğlu, & Ruan, 2007; Sein, Ho, Lai, & Chang, 1999) have been suggested, respectively. Second, to improve the weakness of AHP/fuzzy AHP, numerous papers adopt ANP (analytical network process)/fuzzy ANP to consider the dependences between MRs and TAs and the correlations among themselves, such as Karsak, Sozer, and Alptekin (2002), Büyüközkan, Ertay, Kahraman, and Ruan (2004), Kahraman, Ertay, and Büyüközkan (2006), Lin et al. (2010), and Lee, Kang, Yang, and Lin (2010). Recently, various optimization schemes with consideration of budget cost or resource

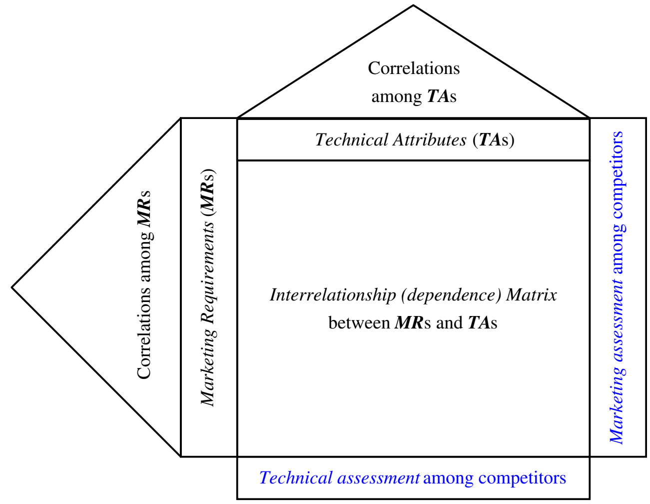

Fig. 1. A general framework for the conventional HoQ (house of quality).

constraints have been incorporated into the QFD. For example, zero-one goal programming or fuzzy goal programming is formulated to determine the level or a mix of design requirements (Chen & Weng, 2006; Karsak, 2004; Karsak et al., 2002). A two-phase QFD which combines ANP/fuzzy ANP with goal programming is utilized to determine the optimal varieties of product attributes for distinct market segments (Lee et al., 2010; Liu & Hsiao, 2006; Park, Shin, Insun, & Hyemi, 2008).

After reviewing the above-mentioned studies, several critical shortcomings are found and listed below:

- A systematic approach to efficiently identify the causal impacts of MRs on TAs and the correlations among themselves is imperative, yet, rarely addressed and incorporated into the entire decision-making process.
- AHP/fuzzy AHP (Saaty, 1980) are capable to determine the weights of "independent" criteria, but they are limited to handle a scenario in which the interdependences exist among criteria or the number of criteria is over a reasonable threshold.
- ANP/fuzzy ANP (Saaty, 1996) are commonly adopted to accommodate the complicated interdependences among criteria, but they might be infeasible in processing a scenario in which numerous criteria appear on a hierarchy.

Suppose that there are n mutually interdependent criteria (associated with an n-order matrix), to completely describe their interrelationships among all criteria, we might need to conduct up to $n^2(n-1)/2(n \times C_2^n)$ times of pair-comparisons for obtaining

Table 1
An overall comparison among AHP, ANP, DEMATEL and proposed method.

	AHP	ANP	DEMATEL	Proposed
Handling an independent hierarchy structure	Yes	Yes	Yes	Yes
Handling an interdependent network structure	No	Yes	Yes	Yes
Conducting pairwise comparisons among criteria	Limited	Tedious	Not necessary	Not necessary
Deriving the importance weights of criteria	Yes	Yes	No	Yes
Handling numerous criteria within the same decision level	Limited	Limited	Yes	Yes
Identifying causal relationships among criteria	No	No	Strong	Strong

the importance weights of all elements. Obviously, when n becomes larger than a reasonable threshold, its running time of ANP might be quite tedious and result in a serious problem of efficiency or consistence for an evaluator. To overcome the difficulties incurred by the ANP, fuzzy Delphi is combined with fuzzy DEMATEL to construct a fuzzy MCDM based QFD. For convenience, an overall comparison among the aforementioned techniques is described in Table 1.

3. The proposed techniques

As indicated by Fig. 2, a hybrid research framework consisting of fuzzy Delphi, fuzzy DEMATEL, and LIP (linear integer programming) is presented to realize two critical issues: collaborative product design and optimal selection of module mixes. In particular, the concept of fuzzy set theory is incorporated into the conventional QFD to accommodate linguistic properties of human judgment (see Table 2). For clarity, their details are simply outlined as follows:

- Fuzzy Delphi is used to gather customers' assessments of initial weights of MRs and to fuse experts' opinions on the initial values of dependences and correlations.
- Fuzzy DEMATEL is utilized to incorporate the dependences between MRs and TAs and the correlations among themselves and the priorities of TAs could be further derived.
- With consideration of cost constraints for multi-segments, LIP is employed to determine the optimal combinations of module mix for the purpose of target marketing.

Based on previous studies (Chen & Weng, 2003; Delice & Güngör, 2009; Wasserman, 1993), the final weights of MRs and TAs are derived as follows:

$$Wt_{MRi} = Wt^0_{MRi} + \frac{1}{m-1}\sum_{i\neq k}^{m}\lambda_{ik} \times Wt^0_{MRk}, \tag{1}$$

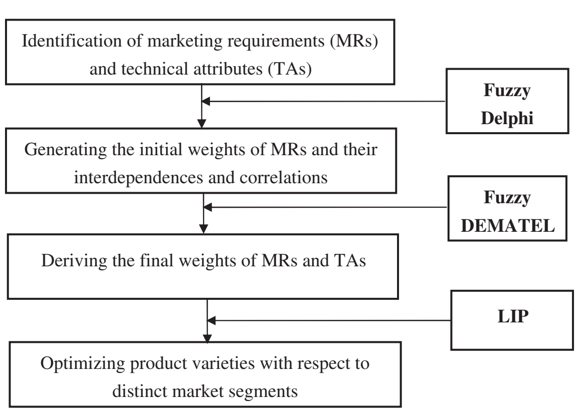

Fig. 2. The proposed research framework.

Table 2
Linguistic rating scale used in fuzzy MCDM methods.

	Triangular fuzzy number	Delphi/DEMATEL
$\tilde{1}$	(1, 1, 3)	VL (very low)
$\tilde{3}$	(1, 3, 5)	L (low)
$\tilde{5}$	(3, 5, 7)	M (medium)
$\tilde{7}$	(5, 7, 9)	H (high)
$\tilde{9}$	(7, 9, 9)	VH (very high)

$$R'_{ij} = \frac{\sum_{k=1}^{n} R_{ik} \times \gamma_{kj}}{\sum_{j=1}^{n}\sum_{k=1}^{n} R_{ik} \times \gamma_{kj}}, \tag{2}$$

$$Wt_{TAj} = \sum_{i=1}^{m} Wt_{MRi} \times R'_{ij}, \tag{3}$$

where Wt_{MRi}/Wt_{TAj} represent the weight of MR_i and TA_j, respectively. Meanwhile, we assume that m marketing requirements and n technical attributes exist in the QFD, R'_{ij} is the normalized dependences between MR_i and TA_j, and λ_{ik}/γ_{kj} denote the correlations among MRs/TAs, respectively. In view of Eqs. (1)–(3), the dependences between MRs and TAs and the correlations among themselves have been appropriately incorporated to generate their importance degrees.

3.1. Use of fuzzy Delphi method to determine the initial weights of MRs

Delphi method has been widely applied to various industries as a group-decision based forecasting technique. It normally requires a group of partially or completely anonymous experts responding their opinions via the preset questionnaires and involves several rounds of iterations to reach a consensus. In the first round, all experts respond to the questionnaire and the results are evaluated and returned to experts through a feedback process. In reality, Delphi method often suffers from low convergence among experts, high execution cost and tedious operating process. Besides, because linguistic human judgments are usually imprecise, evaluation terms expressed in fuzzy sense might be more feasible in practice. Instead of using crisp values in the conventional Delphi, Murry, Pipino, and Gigch (1985) proposed a hybrid scheme which intends to incorporate the concept of fuzzy set into the conventional Delphi to overcome the above-mentioned flaws. Cheng and Lin (2002) present fuzzy Delphi method to achieve a consensus of experts' opinions which are denoted by fuzzy numbers. Followed by Karsak (2004), fuzzy Delphi method is slightly modified to generate the weights of MRs. The whole process is operated as follows:

- The invited evaluators, who act as domain experts, are responsible to rate the importance degrees of marketing requirements. In particular, the rating scale is measured in terms of a triangular fuzzy number as:

$$\tilde{w}_{ij} = (w_{ija}, w_{ijb}, w_{ijc}), \quad 1 \leqslant i \leqslant m, 1 \leqslant j \leqslant p, \tag{4}$$

where m denotes the number of MRs, p represents the number of invited evaluators, and $\tilde{w}_{ij}$ is the importance rating of MR_i assigned by evaluator j.

- Aggregate the importance rating to attain its mean value of MR_i:

$$\tilde{w}_{im} = \frac{1}{p}\left(\sum_{j=1}^{p} w_{ija}, \sum_{j=1}^{p} w_{ijb}, \sum_{j=1}^{p} w_{ijc}\right) = (w_{ima}, w_{imb}, w_{imc}), \tag{5}$$

Then, the differences between $\tilde{w}_{ij}$ and $\tilde{w}_{im}$ are calculated and sent back to the evaluators for reconsideration.

- For later rounds, all evaluators are required to revise their fuzzy rating and the process is repeated in a similar way until the gaps between successive mean values are reasonably converged. To calculate the distance between two fuzzy numbers, the following is adopted (Geng, Chu, Xue, & Zhang, 2010):

$$d(\tilde{w}^t_{im}, \tilde{w}^{t+1}_{im}) = \frac{1}{\sqrt{3}}\left[\sqrt{(w^t_{ima} - w^{t+1}_{ima})^2 + (w^t_{imb} - w^{t+1}_{imb})^2 + (w^t_{imc} - w^{t+1}_{imc})^2}\right], \tag{6}$$

where $\tilde{w}^t_{im}/\tilde{w}^{t+1}_{im}$ represent fuzzy mean value at iteration $t/t+1$.

- Based on "the center of area" approach (Yager, 1978), the process of defuzzification can be applied to the fuzzy rating of each marketing requirement and its defuzzified crisp value is represented as:

$$w_{im} = \frac{w_{ima} + w_{imb} + w_{imc}}{3}, \tag{7}$$

- Generating the initial weight for each marketing requirement via the normalization process:

$$Wt^0_{MRi} = \frac{w_{im}}{\sum_{i=1}^{m} w_{im}}, \tag{8}$$

where Wt^0_{MRi} denotes the initial weight of MR_i.

3.2. Use of fuzzy DEMATEL to derive the final weights of MRs and TAs

DEMATEL (*decision making trial and evaluation laboratory*), developed by the science and human affairs program of the Battelle Memorial Institute of Geneva Research Centre (Fontela & Garbus, 1976), is able to visualize the complex interdependent relationship among all evaluation criteria through converting the causal relationship into a visible structure of the whole system. Suppose that p experts are invited to assess m marketing requirements (MRs) and n technical attributes (TAs). Followed by Lin and Wu (2008), fuzzy DEMATEL is applied to our problem and its details are described as follows:

- Assigning a fuzzy rating scale to measure the direct-relation matrix:

As seen in Fig. 3, a $(m + n) \times (m + n)$ fuzzy matrix $\widetilde{X}$ with an element of $\tilde{x}^k_{ij} = (l^k_{ij}, m^k_{ij}, u^k_{ij})$ is evaluated by expert k, which represents the impact of MR_i on TA_j and all the diagonal elements of matrix $\widetilde{X}$ will be set as zero ($\tilde{x}^k_{ii} = (0, 0, 0)$). By averaging all experts' scores, the direct-relation matrix $\widetilde{A}$ can be characterized with an element of $\tilde{a}_{ij}$:

$$\tilde{a}_{ij} = \frac{1}{S}\sum_{k=1}^{S}\tilde{x}^k_{ij} = (al_{ij}, am_{ij}, au_{ij}), \tag{9}$$

- Normalizing the direct-relation matrix:

The normalized matrix $\widetilde{B}$ can be obtained by normalizing the matrix $\widetilde{A}$:

$$\tilde{b}_{ij} = \frac{1}{\Omega}\tilde{a}_{ij} = (bl_{ij}, bm_{ij}, bu_{ij}), \quad \text{where} \tag{10}$$

$$\Omega = Max\left(\max_{1\leqslant i\leqslant n}\sum_{j=1}^{n} u_{ij}, \max_{1\leqslant j\leqslant n}\sum_{i=1}^{n} u_{ij}\right), \tag{11}$$

- Deriving the total-relation matrix:

Once the normalized matrix $\widetilde{B}$ has been obtained, the total-relation matrix $\widetilde{T}$ can be derived based on Eqs. (12)–(15):

	MR_1 .... MR_m	TA_1 .... TA_n
MR_1 . MR_m	$m \times m$ correlation matrix	$m \times n$ dependence matrix
TA_1 . TA_n	$n \times m$ zero matrix	$n \times n$ correlation matrix

Fig. 3. Input of the direct-relation matrix for fuzzy DEMATEL.

$$\widetilde{T} = \widetilde{B} + \widetilde{B}^2 + \widetilde{B}^3 + \cdots = \widetilde{B}(I - \widetilde{B})^{-1}, \tag{12}$$

where $\tilde{t}_{ij} = (tl_{ij}, tm_{ij}, tu_{ij})$ and the amount of three matrix elements are list below:

$$\text{matrix}[tl_{ij}] = B_l(I - B_l)^{-1}, \tag{13}$$

$$\text{matrix}[tm_{ij}] = B_m(I - B_m)^{-1}, \tag{14}$$

$$\text{matrix}[tu_{ij}] = B_u(I - B_u)^{-1}, \tag{15}$$

where I denotes an identity matrix and $B_l/B_m/B_u$ represents the crisp matrix composed of lower/medium/upper values of the normalized matrix, respectively.

- Defuzzifying the total-relation matrix $\widetilde{T}$ (Yager, 1978) and computing a causal diagram through the dispatcher group D and the receiver group R, where D is the sum of rows in crisp matrix T and R is the sum of columns:

$$T_{ij} = \frac{tl_{ij} + tm_{ij} + tu_{ij}}{3}, \tag{16}$$

$$D_i = \sum_{j=1}^{n} T_{ij}, \tag{17}$$

$$R_j = \sum_{i=1}^{n} T_{ij}. \tag{18}$$

After a crisp matrix T is obtained via Eq. (16), the dependences between MRs and TAs (R'_{ij}) and the correlations among themselves (λ_{ik}/γ_{kj}) will be automatically extracted from the matrix T for deriving the weights of TAs (see Eqs. (1)–(3)). A causal diagram can be visualized by displaying ($D + R$, $D - R$): the horizontal axis "$D + R$" named "prominence" reveals how much important the criterion is and the vertical axis "$D - R$" named "influence" categorizes the criterion into either the cause group or the effect group.

3.3. Use of linear integer programming for optimal selection of module mixes

As indicated by Fig. 4, based on different affordable prices, the entire market is partitioned into three segments, like the low-end, middle-end, and high-end. Here, the company attempts to configure various types of digital cameras for multi-segments through considering the optimal product varieties and the constraints of manufacturing cost (relevant to pricing policies), simultaneously. Hence, the primary goal of a company is to maximize its product capability, or state this equivalently, to maximize its customer satisfaction because the latter is proportional to the former, positively. For convenience, we describe the objective, decision variables, and constraints as follows (see Eqs. (19)–(22)).

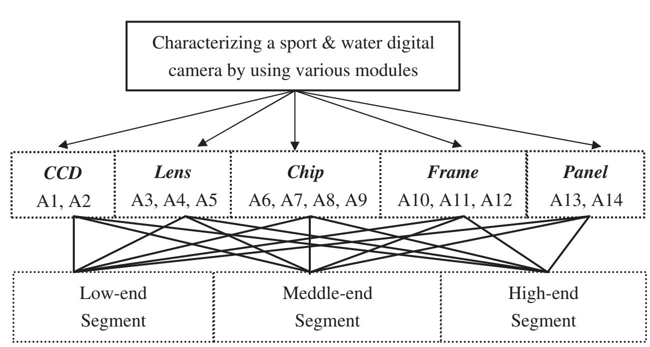

Fig. 4. Product configuration and module decomposition for three market segments.

$$\begin{aligned} &\text{Max}\sum_i\sum_j P_{ij}X_{ij} \\ &\quad \text{s.t.}\sum_j X_{ij} = 1, \quad \text{for } \forall i, \\ &\qquad \sum_i\sum_j C_{ij}X_{ij} \leqslant B_s, \quad \text{for } \forall s, \\ &\qquad X_{ij} \in \{0,1\}, \end{aligned} \tag{19}$$

$$P_{ij} = \sum_k Wt_{TA}(k) * \tilde{y}_{ij}(k), \tag{20}$$

$$\tilde{y}_{ij}(k) = \frac{y_{ij}(k) - \min_j y_{ij}(k)}{\max_j y_{ij}(k) - \min_j y_{ij}(k)}, \tag{21}$$

$$\tilde{y}_{ij}(k) = \frac{\max_j y_{ij}(k) - y_{ij}(k)}{\max_j y_{ij}(k) - \min_j y_{ij}(k)}, \tag{22}$$

where i is the module index of the product, j is the alternative index for the module, X_{ij} denoted by a zero–one integer means the selection of alternative j for module i, $y_{ij}(k)$ represents the kth attribute of alternative j for module i, P_{ij} and C_{ij} denote its functional performance and manufacturing cost, respectively. For simplification, we assume that the product is characterized by various functional modules and each module which is composed of specific attributes has limited alternatives. Meanwhile, the whole market is divided into several segments and each segment has a cost constraint of B_s for pricing the target product. In particular, functional performance P_{ij} (see Eq. (20)) is modeled by a weighted sum of various TAs. They are normalized by one of the following types: either the-larger-the-better (see Eq. (21) for the benefit set) or the-smaller-the-better (see Eq. (22) for the cost set).

4. A real case study

The market growth of digital camera has become much more saturated than before and Kodak's bankruptcy in 2011 has strongly impacted on the entire industry since several Taiwanese OEM/ODM camera manufacturers are now incurring huge loss of "accounts receivable". To take advantage of its great cost-controlling capability and large manufacturing capacity, a Taiwanese electronic company is planning to gradually change herself from an OEM/ODM firm into a brand company. To avoid fierce price competition, this company is now thinking the way to differentiate themselves from the other suppliers.

For fast acquiring market share, this company also focuses its core resources on aiming at recently emerging regions like East Europe, Middle-South America, and South-East Asia. In view of

Table 3
A sample denoting the correlations among MRs.

MRs	R1	R2	R3	R4	R5
R1 Photo quality		L			
R2 Video capability	L				
R3 Electronic function				H	
R4 Robust function			H		L
R5 User interface				L	

Table 6
Derived weights (priorities) of MRs and TAs.

MRs	Weights	Rank	TAs	Weights	Rank
R1	0.348	1	A1	0.090	4
R2	0.165	3	A2	0.093	3
R3	0.104	4	A3	0.117	2
R4	0.288	2	A4	0.076	7
R5	0.095	5	A5	0.118	1
			A6	0.049	12
			A7	0.054	11
			A8	0.038	13
			A9	0.037	14
			A10	0.079	6
			A11	0.066	8
			A12	0.080	5
			A13	0.052	9
			A14	0.052	9

Table 4
A sample denoting the correlations among TAs.

TAs	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14
A1 CCD mega pixels		H												
A2 CCD sensor area (inch)	H				VH									
A3 Optical zoom				H	H									
A4 Wide angle (mm)			H											
A5 Max aperture		H	M											
A6 Dynamic video resolution							H							
A7 High-speed shutter (Y/N)						H								
A8 GPS receiver (Y/N)									L					
A9 Wireless LAN (Y/N)								L						
A10 Water proof (m)													H	M
A11 Shock proof (m)												H		M
A12 Freeze proof (°C)												M	M	
A13 LCD size (inch)														M
A14 Screen resolution													M	

Table 5
A sample denoting the dependences between MRs and TAs.

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14
R1	H	M	VH	M	H									
R2						H	VH							
R3								H	H					
R4										VH	H	H		
R5													M	H

Table 7
Various types of scoring for visualizing a causal diagram of the QFD.

	Active score D	Passive score R	Prominence score $D + R$	Influence score $D - R$
R1	1.516	0.052	1.567	1.464
R2	0.691	0.052	0.743	0.640
R3	0.917	0.271	1.187	0.646
R4	1.349	0.314	1.662	1.035
R5	0.529	0.065	0.594	0.465
A1	0.342	0.610	0.953	−0.268
A2	0.663	0.913	1.576	−0.250
A3	0.598	0.880	1.478	−0.281
A4	0.329	0.542	0.871	−0.213
A5	0.577	1.072	1.650	−0.495
A6	0.259	0.541	0.800	−0.281
A7	0.259	0.575	0.834	−0.316
A8	0.052	0.327	0.378	−0.275
A9	0.052	0.327	0.378	−0.275
A10	0.414	0.322	0.736	0.092
A11	0.414	0.271	0.684	0.143
A12	0.345	0.679	1.024	−0.334
A13	0.172	0.953	1.126	−0.781
A14	0.172	0.888	1.060	−0.715

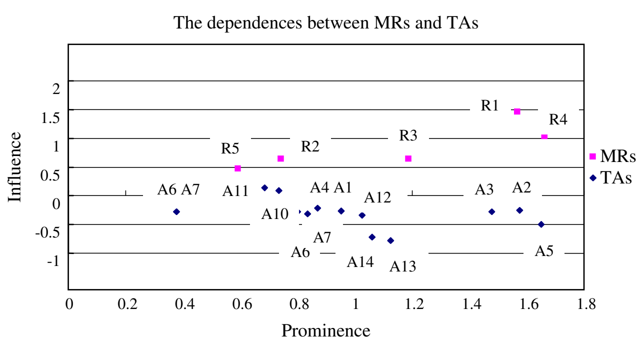

Fig. 5. A structural diagram to visual causal impacts inherent in the QFD.

Fig. 4 again, five basic modules that characterize a digital camera include CCD (charge couple device), lens, chip, frame, and panel and each module is composed of specific components and limited alternatives. Without loss of generality, the whole market is assumed to be divided into three segments that are based on customers' affordable price (relevant to supplier's manufacturing cost).

4.1. Marketing planning to derive the priorities of MRs and TAs

In the beginning, a common technique named "majority-voting" is employed to assist invited experts in determining representative MRs and TAs. Thereafter, fuzzy Delphi method is used to generate the initial weights of MRs (see Eq. (8)), the correlations among MRs/TAs (see Tables 3 and 4), and the dependences between MRs and TAs (see Table 5). Here, both the "majority-voting" scheme and fuzzy Delphi method are adopted to help evaluators efficiently reach a consensus during a group decision process.

Secondly, we input initial values of dependences and correlations into the direct-relation matrix $\widetilde{X}$. After processed by fuzzy DEMATEL, final values of dependences (R_{ij}) and correlations (λ_{ik}/γ_{kj}) could be extracted through the direct-relation matrix $\widetilde{T}$. Based on Eq. (1), the weights of MRs can be obtained and their priorities are presented as $R1 \succ R4 \succ R2 \succ R3 \succ R5$, as indicated by Table 6. Obviously, photo quality (R1), robust function (R4), and video capability (R2) are listed as the top three priorities for the sport & water digital camera.

Based on Eqs. (2), (3), the weights of TAs are derived and the top six priorities demonstrate an order of $A5 \succ A3 \succ A2 \succ A1 \succ A12 \succ A10$ (see Table 6 again). Apparently, significant TAs result from their strong dependences on dominant MRs. For example, "max aperture" (A5), "optical zoom" (A3), "CCD sensor area" (A2), and "CCD pixels" (A1) are closely related to "photo quality" (R1). Similarly, "freeze proof" (A12) and "water proof" (A10) are mainly affected by "robust function" (R4).

4.2. Visualization of their causal interrelationships between MRs and TAs

To identify the complicated relationships among all relevant factors inherent in the QFD, Table 7 depicts various types of scoring through using Eqs. (16)–(18). In brief, the active score "D" denotes the "*dispatched*" impact of the corresponding factor on the others while the passive "R" score represents the sum of "*received*" influence of the corresponding factor from the others. Moreover, the prominence score "$D + R$" defined by "adding the active score to the passive score" is regarded as its general degree of "importance". By contrast, the influence score "$D - R$" defined by "subtracting the active score from the passive score" indicates the intensity of "causality".

Based on Table 7, their relative influence (referred to the vertical axis) and absolute prominence (referred to the horizontal axis) are displayed in Fig. 5. Owing to "positive" influence, MRs (denoted by the symbol of "square") are classified into the "cause"

Table 8
Combinations of module mixes for configuring the sport & water digital camera.

	Module 1: CCD			Module 2: Lens			Module 3: Chip			Module 4: Frame			Module 5: Panel		
	M11	M12	M13	M21	M22	M23	M31	M32	M33	M41	M42	M43	M51	M52	M53
A1	1200	1400	1000												
A2	1/2.3	1/2.3	1/1.8												
A3				3	4	5									
A4				28	28	25									
A5				3.9	3.5	3.1									
A6							640 * 480	720 * 480	1080 * 720						
A7							0	0	1						
A8							0	1	1						
A9							0	0	1						
A10										3	5	10			
A11										1.5	2	3			
A12										−10	−10	−20			
A13													2.7	3.0	3.3
A14													23K	46K	92K
Cost ($TWD)	1050	1400	2100	1400	2000	2800	2100	3000	4200	1750	2500	3500	700	1000	1400

Table 9
Results of selected module mix for three market segments (asterisk symbols correspond to selected modules).

Segment (cost budget)	Module 1: CCD			Module 2: Lens			Module 3: Chip			Module 4: Frame			Module 5: Panel		
	M11	M12	M13	M21	M22	M23	M31	M32	M33	M41	M42	M43	M51	M52	M53
Low-end ($7000)	*			*			*			*			*		
Middle-end ($10,000)	*					*		*		*					*
High-end ($15,000)			*			*			*			*			*

(dispatcher) group. Conversely, TAs (denoted by the symbol of "diamond") are categorized into the "effect" (receiver) group due to "negative" influence. As a result, by virtue of fuzzy DEMATEL, product planners or project managers are capable to generate the priorities of TAs in a market-oriented manner and to visualize their complex interrelationships, concurrently.

4.3. Optimizing module mixes for distinct market segments

Theoretically, the principle of target marketing assumes that diverse customers should have different requirements for product capability and affordable price. Normally, higher purchasing price (manufacturing cost) will sustain better product specifications. According to its marketing survey, the marketing department of the consulted company offers an industrial dataset, as shown in Table 8. In this study, a sport and water digital camera is characterized by five functional modules and each module is composed of specific attributes which work collaboratively. Besides, each module has three alternatives that are associated with different manufacturing costs.

By virtue of linear integer programming (see Eqs. (19)–(22)), the optimal selection of various module mixes for multi-segments are described in Table 9. Here, an asterisk denotes the "selected" module for the corresponding segment. For instance, five specific modules are suggested (i.e. *M11 for CCD, M23 for lens, M32 for chip, M41 for frame, M53 for panel*) to be fabricated together when acquiring the middle-end segment. Similar explanations could be applied to the low-end and the high-end segments, respectively. Rather than using the roof of the QFD to indicate positive/negative correlations among TAs, specific alternatives of various functional modules are used to accommodate their complex correlations, including the extremely exclusive constraints among TAs.

5. Conclusions

In the era of global customization, to survive in a wide range of market segments, companies need to balance the trade-offs between enhancing product varieties and controlling manufacturing complexity. Consequently, numerous paradigms have received much attention, including product family architecture, platform-based development, and modular product design. In this paper, a fuzzy MCDM based QFD which integrates fuzzy Delphi, fuzzy DEMATEL, with LIP is presented to accomplish two fundamental tasks of NPD: collaborative product design and optimal selection of module mix with respect to distinct multi-segments. More importantly, this paper demonstrates the following merits:

- To reduce the gap between customer needs and product development, this study is capable to gather opinions between individual customers and industrial experts and then fuse their assessments to reach a consensus.
- To understand the causal impacts of marketing requirements on technical attributes, this study could visualize their complicated interrelationships and derive the priorities of technical attributes in a market-oriented manner.
- To assist an enterprise in optimizing product varieties with respect to multi-segments, this study utilizes linear integer programming to maximize product capability with consideration of budget constraints on manufacturing costs, concurrently.

For simplification, this study assumes that the entire market is partitioned into three segments which are based on the pricing policy of an enterprise. Future study might extend our current framework to a more general scenario in which market segmentation is based on customer preference. In addition, other classical techniques like conjoint analysis (Luce & Tukey, 1964) or Kano model (1984) might be further incorporated into the proposed framework to fulfill sufficient customer involvement.

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