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Optimization tools for design and marketing of new/improved products using the house of quality

George L. Vairaktarakis

Department of Operations Research and Operations Management, Weatherhead School of Management, Case Western Reserve University, 10900 Euclid Avenue, Cleveland, OH 44106-7235, USA

Abstract

Quality function deployment (QFD) has helped many firms realize significant reduction in product design costs and development time. The QFD process includes ranking customer preferences, rating the competitors, and parts deployment for the new/improved product. Prior to this research, such activities have been performed based on expert opinion, or the ''best-in-class'' approach. We develop and solve optimization models for the identification of consensus rankings and ratings, that take into account the priorities and perceptions of all the customers in a target market. Then, based on the consensus rankings, we identify a parts mix for the new/improved product that satisfies a budget constraint and matches or exceeds the performance expectations of all customers surveyed in the target market. Finally, we show how the QFD charts can be used to identify competitors that are falsely perceived as superior, as well as areas where the firm's marketing strategies have had the desired effects. Such insights are useful in developing the future marketing strategy of the firm.
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1. Introduction and literature review

QFD originated in 1972 at Mitsubishi's Kobe shipyard site. Toyota began to develop the concept shortly thereafter, and has used it since 1977 with impressive results. Xerox and Ford initiated the use of QFD in the United States in 1986. Today, QFD is used successfully by manufacturers of electronics, appliances, clothing, and construction equipment, by firms like General Motors, Ford, Mazda, Motorola, Xerox, Kodak, IBM, Procter and Gamble, Hewlett-Packard, and AT&T (see Jebb et al., 1992). Two organizations, the American Supplier Institute (ASI), a nonprofit organization, and GOAL/QPC, a Massachusetts consulting firm, have publicized and developed the concept in the United States. The ASI uses a basic four-matrix method developed by Macabe, a Japanese reliability engineer. GOAL/QPC advocates a multiple matrix method developed by Akao and incorporates many disciplines in a less structured format consisting of a matrix of matrices. Akao, 1990 has collected into a book the multiple matrix applications from many Japanese practitioners (see also Day, 1993).

We should make clear that QFD is concerned mostly with the proccess of improving an existing product so that it captures customer expectations. In this sense, QFD is concerned with the development of products that are ''best-in-class'', i.e., they are superior to any known existing product in a particu-

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lar and well established market segment. This philosophy contrasts the concept of *breakthrough product development* which is primarily concerned with ''first-in-class'' products, i.e., superior products that define new market segments and have no precedence in the market. Due to the large amounts of information required, QFD is not amenable to breakthrough product development simply because the required data are mostly unavailable. Having done this important distinction, QFD has been used by many firms to introduce dramatically improved products. Xerox has used QFD to develop the latest generation of office equipment. Canon used QFD to develop the last generation of cameras that support intelligent microchips for autofocus, focus based on eye movement, red eye reduction, etc. Ford used QFD in the 1980s to develop the concept of ''best-in-class''. The outcome of this concept was the Taurus model that dominated the car market for mid-sized cars for over a decade. Subsequently, the Ford Sable model was also developed using QFD. For more applications of QFD on breakthrough technologies refer to Akao (1990).

Due to its exposure, QFD is gaining broad acceptance as a design methodology for the design and manufacturing stages (Kupparaju et al., 1985; Sullivan, 1986; Hauser and Clausing, 1988) of new/improved products. Value measurement techniques are presented in Shillito and DeMarle, 1992. They are used to plot the relative importance and relative cost of items. Once plotted each graph can be used to locate areas for cost reduction and importance improvement. Case-based reasoning methods for QFD have been proposed by Araya and Ibrahim, 1994, and Lee and Lai, 1991. Case-based operations allow for the identification of relevant cases or aspects of cases to obtain a new case from which to initiate a design using artificial intelligence (Riesbeck and Schank, 1989; Slade, 1991; Kolodner, 1993). Variations of the QFD process are presented in Shillito, 1994. In Chap. 4 of that book the author presents a methodology called *customer-oriented product concepting*. In Chap. 5 of the same book the QFD process is extended to relate business plans to the corporate mission. This extended QFD framework is termed PQFD for *Planning* QFD.

To the best of our knowledge not much research is done on quantitative models for QFD. The proposed methodologies use mathematical programming to evaluate customer preferences, identify perceptual gaps, and select parts while adhering to budget constraints. A brief summary of the QFD methodology follows.

Four sets of matrices are used to relate the voice of the customer to a product's technical requirements, component requirements, manufacturing operations, and quality control plans. The tabulation of the data needed by each of the four matrices, utilizes a matrix format called *house of quality* (HOQ; see Fig. 1). The first HOQ matrix is the *customer requirements planning matrix*; see Evans and Lindsay, 1996. Building the first HOQ consists of 6 basic steps:

1. Identify customer requirements.
2. Identify technical requirements.
3. Relate the customer requirements to the technical requirements.
4. Conduct an evaluation of competing products.
5. Evaluate technical requirements and develop targets.
6. Determine which technical requirements to deploy.

Based on the findings of the first HOQ matrix, the design process continues with the three matrices indicated in Fig. 1.

The second HOQ matrix helps to identify parts and subsystems to be deployed, the third identifies specific processes to be used during the manufacturing stage, and the last HOQ matrix builds specific quality controls into the manufacturing process.

This research concentrates on optimization tools that facilitate the first two stages of the QFD process. More specifically, we develop tools for the ordering of customer preferences, rating of the competitors, and parts selection. The current literature on the first two stages of the QFD process focuses on an all-inclusive tabulation of the data regarding a new/improved product that accounts for customer desires and engineering concerns, without suggesting an objective way to manipulate this data.

Important decisions such as customer rankings, competitor ratings, and parts selection are currently made mostly based on expert opinion. Or, such decisions are based on the ''best-in-class'' competitor. In the former case, decisions regarding the new/improved product may be myopic since they

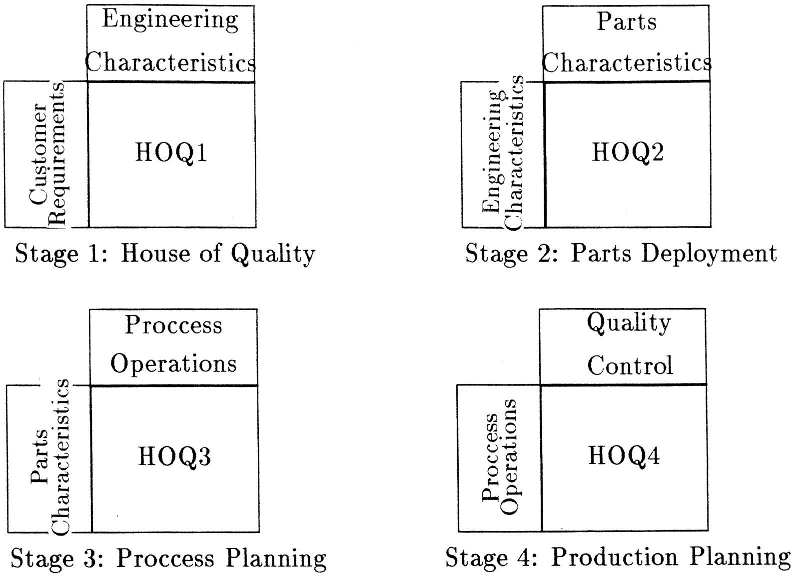

Fig. 1. The 4 stages of the QFD proccess.

account for only a small group of experts. In the latter, the decisions made attempt to improve current product offerings without accounting explicitly for actual customer expectations. Hence, such decisions are by design imitative, rather than innovative. Moreover, choosing the best features among existing products may result in excessive costs and does not guarantee meeting customer expectations.

Existing literature assumes that customer rankings and competitor ratings are readily available. It is generally true, however, that customers within the same target market have different preference priorities. We provide optimization models that use the data collected through customer surveys to compute consensus preferences for the customers and consensus ratings for the competitors. Based on the consensus rankings and ratings, we develop optimization models that identify the product parts and features that optimize the performance of the new/improved product, while satisfying the firm's budget limitations.

Evidently, in this article, we assume that the customer preferences as well as the product's engineering characteristics are known in advance. This usually involves interpreting customer information and product features and measures with the use of a set of seven quality control (QC) tools developed in Japan by the society of QC Techniques Development (see Guinta and Praisler, 1992). These tools are structural techniques used to analyze and structure qualitative data. Examples of such tools include affinity, tree, and matrix diagrams. The QFD analysis considered in this paper cannot be done without prior use of the above mentioned tools to design the QFD matrices. In this sense, the great advantage (and at the same time limitation) of QFD analysis is the ability to rationalize the use of large amounts of customer and engineering information regarding the product. On the other hand, if the product development team cannot acquire sufficient data (even through estimation), then QFD analysis cannot proceed. For this reason, QFD is of limited use for very new products.

Except for the availability of customer preferences and the product's engineering characteristics, in this article, we assume that the necessary studies have been performed to identify the target market as well as the existing competitors in this market. Using these data, in this paper, we present a methodology for identifying the competitors that enjoy the greatest perceptual benefits, i.e., competitors whose marketing strategies have led the customers to believe that their products (or particular characteristics thereof) are superior even though the actual performance of these products does not justify this belief. From a marketing viewpoint, such competitors are important because they can serve either as benchmarks of marketing performance, and/or as a source of proven winning marketing strategies.

The rest of this article is organized as follows. In Section 2, we present the main assumptions of this research, and introduce some notation. We also present an integer programming model for the identification of a parts mix for the new/improved product. In Section 3, we present optimization models for the identification of a single ‘‘consensus’’ ranking of customer preferences for the product. Also, we discuss current practices on this issue. In Section 4, we show how the information stored in the HOQ charts can be used to identify perceptual gaps, i.e., cases where one competitor is falsely perceived to perform better than another. In Section 5, we provide a comprehensive example using the models developed in the article. We conclude in Section 6. All proofs are included in Appendix A.

2. Assumptions, notation and basic results

For the models presented in this article we make the following assumptions.

(i) A target market has been identified

(ii) The competitors competing in the same target market have also been identified

(iii) Product design is limited to the base model; not the possible options that may become available to attract secondary markets

(iv) Customer surveys have been elicited to collect the customer related input data required by our models.

Several marketing techniques (such as conjoint analysis) are available for market segmentation. In this article, we assume that such studies have been employed, and that a target market has been identified, as well as existing competitors for this market. Within a well defined target market, however, the expectations of prospective customers are different due to the environment in which the product is going to be used. For instance, a portable compact disk player may be used outdoors, or in the car. In each of these two cases, the expectations regarding the sensitivity and durability of the laser beam of the disk player are different. Still, the firm has to determine the characteristics of the laser beam that can satisfy all prospective customers in the target market. As a result, we assume that all customer surveys used to collect the input data required in our analyses, have been administered to customers of our target market only. In many cases, a product is accompanied with a variety of options that are designed to capture secondary markets. This research does not address the problem of determining optional offerings. It only focuses on the base model that can best capture a well defined target market.

Below, we summarize the notation used in the rest of the paper. These pieces of notation are also depicted in Table 1 in the HOQ1 and HOQ2 charts. For the HOQ1 chart we use the following notation.

n: number of customer requirements

req_i: the ith customer requirement

r_i: the customer's preference rating of req_i

m: number of engineering characteristics

e_j: the jth engineering characteristic of the product

a_{ij}: the intensity with which e_j affects req_i, $1 \le i \le n$, $1 \le j \le m$

u_j: the weight with which e_j affects product performance

Table 1
The HOQ1 and HOQ2 charts

	HOQ1 chart						
	e_1	e_2	$\cdots$	e_j	$\cdots$	e_m	
req_1				a_{1j}			r_1
req_2				a_{2j}			r_2
$\vdots$			$\ddots$	$\vdots$	$\ddots$		$\vdots$
req_i				a_{ij}			r_i
$\vdots$			$\ddots$	$\vdots$	$\ddots$		$\vdots$
req_n				a_{nj}			r_n
	u_1	u_2	$\cdots$	u_j	$\cdots$	u_m	
	HOQ2						
	p_1	p_2	$\cdots$	p_k	$\cdots$	p_{n_0}	
e_1				b_{1k}			u_1
e_2				b_{2k}			u_2
$\vdots$			$\ddots$	$\vdots$	$\ddots$		$\vdots$
e_j				b_{jk}			u_j
$\vdots$			$\ddots$	$\vdots$	$\ddots$		$\vdots$
e_m				b_{mk}			u_m
	w_1	w_2	$\cdots$	w_k	$\cdots$	w_{n_0}	

The intensities a_{ij} are determined by the product design team that draws heavily from the understanding of the marketing group on customer expectations. These expectations are determined through a number of marketing tools including surveys (by phone, mail or comment cards), interviews (group, individual, or by phone), focus groups, commercially prepared stock reports, panels, conjoint analysis, etc. The a_{ij}'s indicate importance and strength of qualitative relationships between customer requirements and engineering characteristics, and assist in making dialogue among design team members more convergent. We assume that $a_{ij} \geq 0$, with $a_{ij} = 0$ indicating negligible or no relationship between req_i and e_j.

Ideally, the weights u_j should be induced by the customer ratings r_i and the intensities a_{ij}. For this reason, throughout this paper we assume that

$$u_j = \sum_{i=1}^{n} r_i a_{ij} \quad j = 1,2,\ldots,m.$$

Alternatively, we could use the percentage weights $u_j = (\sum_i r_i a_{ij})/(\sum_j \sum_i r_i a_{ij})$. In our experience with QFD practitioners, there is no universal way of determining the u_j's. In fact, in the majority of cases they are determined arbitrarily by the design team, thus altering the intended effect of customer ratings. The additional notation used in the HOQ2 chart is as follows.

n_0: number of parts in the product
p_k: the kth part of the product
n_k: number of alternative choices for part p_k
p_{kl}: the lth alternative part choice for p_k
c_{kl}: the cost of p_{kl}
$\mathscr{P}_k(c_{kl})$: the performance rating of p_{kl} (that costs c_{kl})
b_{jk}: the intensity with which p_k affects e_j
w_k: the weight with which p_k affects product performance
W: the total available budget for the parts and components of the new/improved product.

The parts p_k that go into a product are determined by the engineering group so as to address the product's engineering characteristics. After knowing what parts should be used, one has to determine a parts mix. For every p_k, we assume that $p_{k1}, p_{k2}, \ldots, p_{k,n_k}$ are the available options at costs $c_{k1}, c_{k2}, \ldots, c_{k,n_k}$ respectively. Precisely one of these options has to be selected for building the product. These options correspond to different levels or grades for the part. For instance, tire rims could be selected among a variety of metal alloys. The base lens used in a camera could be selected among various millimeter options. The length of a lawn mower blade could be selected among different specified values. The amount of limestone in a tile may be selected among different levels of content percentage.

To each part option p_{kl} (that costs c_{kl}), we assign a numerical value that indicates how well it performs in comparison to the alternatives. This numerical value is denoted by $\mathscr{P}_k(c_{kl})$ and is chosen from a scale $[0,U]$ (e.g., 0 to 5). In our experience, manufacturing and engineering group members with knowledge on the characteristics of each part option, in the majority of cases can easily assign such a numerical attribute to each option. Consider, for instance, the tire rim to be used in a car. The design team has a choice among 3 different metal alloys, each of which has known performance and cost. It is easy for the design team to grade the performance of the 3 alternatives in a scale from 0 to 5. In general, for each $k = 1,2,\ldots,n_0$, the pairs $(c_{kl}, \mathscr{P}_k(c_{kl}))$ for $l = 1,2,\ldots,n_k$ determine the performance function $\mathscr{P}_k$. We assume that the functions $\mathscr{P}_1, \mathscr{P}_2, \ldots, \mathscr{P}_{n_0}$, are known discrete strictly increasing nonnegative functions of cost that take on values in a common range $[0,U]$, i.e.,

$$\mathscr{P}_k : [\mathbf{0},\infty] \rightarrow [0,U], \text{ for } k = 1,2,\ldots,n_0.$$

The domain $[0,\infty]$ of the functions $\mathscr{P}_k$ captures all possible cost values that a particular part or product component may cost. The rationale for using a common range for all performance functions $\mathscr{P}_k$ follows the description of the w_k weights below. The assumption that every $\mathscr{P}_k$ is strictly increasing stipulates that a part option p_{kl} is considered for inclusion into the product, if and only if all less costly options p'_{kl} (i.e., $c'_{kl} < c_{kl}$) are attributed inferior performance (i.e., $\mathscr{P}_k(c'_{kl}) \leq \mathscr{P}_k(c_{kl})$).

In the same spirit as for the u_j weights of HOQ1, the weights w_k should incorporate how significant is the effect of each e_j on product performance, as well as the intensities b_{jk}. Hence, in this paper we use

$$w_k = \sum_{j=1}^{m} u_j b_{jk} \quad k = 1,2,\ldots,n_0,$$

or alternatively the percentage weights $w_k = (\sum_j u_j b_{jk})/(\sum_k \sum_j u_j b_{jk})$. Again, in practice the w_k weights are often determined arbitrarily. Now, consider an arbitrary parts mix $p_{1l_2}, p_{2l_1}, \ldots, p_{n_0,l_{n_0}}$ with corresponding costs $c_{1l_1}, c_{2l_2}, \ldots, c_{n_0,l_{n_0}}$. Then the performance of this mix is given by

$$\sum_{k=1}^{n_0} w_k \mathscr{P}_{kl_k}(c_{kl_k}), \text{ and its cost is } \sum_{k=1}^{n_0} c_{kl_k}.$$

It now becomes evident that the role of the w_k weights in the performance of a parts mix can be distorted by using a different scale for each performance function $\mathscr{P}_{kl}$. For this reason, we use the common range $[0,U]$ for all $\mathscr{P}_k$'s. However, an arbitrary scale $[a,b]$ $(a \geq 0)$ can be used. Our choice $[0,U]$ is made for simplicity, and all subsequent analyses hold for the scale $[a,b]$.

The comments made earlier on the significance of the a_{ij} values extend to b_{jk}. Similarly, $b_{jk} \geq 0$. Finally, a comment on the cost values W and c_{kl}. W is the target per unit materials cost that makes the product economically viable. Usually, a great deal of input about W is provided by the finance group members. Note that the design team may have to experiment with various W values prior to choosing a product design. Iterative use of the models presented in this article allow for such experimentation. The cost W of the final design does not have to be the same as the corresponding cost of the products that compete in the same target market. W is merely the materials cost per unit of the offering with which the firm has decided to compete in the target market. For instance, if the firm is the ''high end'' provider in the target market, then W will (in most cases) be higher than the corresponding costs of competitors. In the rest of this paper we assume that a single budget constraint W is given. Our models do not capture the impact of different unit cost levels on product performance.

Finally, the costs c_{kl} are primarily provided by accounting team members with experience in procurement of materials.

With the above stipulations, the following model identifies a parts mix (if one exists) that maximizes product performance without exceeding the budget W for the materials. For $1 \leq k \leq n_0$ and $1 \leq l_k \leq n_k$, consider the binary variables

$$x_{kl_k} = \begin{cases} 1 & \text{iff } p_{kl_k} \text{ is selected among the alternatives for } p_k \\ 0 & \text{otherwise,} \end{cases}$$

and the model

$$(\mathbf{P}) \ \max \sum_{k=1}^{n_0} \sum_{l=1}^{n_k} w_k \mathscr{P}_k(c_{kl}) x_{kl} \quad (1)$$

$$\text{s.t.} \sum_{l=1}^{n_k} x_{kl} = 1 \quad k = 1,2,\ldots,n_0 \quad (2)$$

$$\sum_{k=1}^{n_0} \sum_{l=1}^{n_k} c_{kl} x_{kl} \leq W \quad (3)$$

$$x_{kl_k} \in \{0,1\} \quad 1 \leq k \leq n_0, \quad 1 \leq l_k \leq n_k. \quad (4)$$

The set (2) of constraints corresponds to the assignment of part options in the parts mix, constraint (3) is the budget constraint, and Eq. (4) corresponds to the integrality constraints. In our experience with QFD practitioners, model (**P**) is widely acceptable, regardless of the way the various input parameters are calculated.

The input parameters in (**P**) include W, the performance functions $\mathscr{P}_k(c_{kl})$, and the w_k's. The former two are decided by the design team based on knowledge of the technologies involved with the product and the associated costs. The w_k's are outside the control of the design team and incorporate the voice of the customer through the ratings r_i, which in turn are used for the calculation of the u_j's which are the engineering weights involved in the calculation of the w_k's. Evidently, the r_i values used for the calculation of the w_k's determine to a great extent the parts mix that solves (**P**). In this model, $\vec{r} = (r_1, r_2, \ldots, r_n)$ is assumed to be the *consensus ratings vector* that can satisfy various product users in the target market.

In reality, the identification of $\vec{r}$ is an exercise left for the design team based on the responses of the customers surveyed. In the next section we relax the assumption that $\vec{r}$ is known, and present models for determining the consensus ratings vector.

3. Consensus rankings and parts mix

Preferences among different customers vary for any particular product, due to personal taste and individual use. As a result, if a pool of customers that belong to the same target market is asked to prioritize its requirements for an existing or prospective product, it submits different or even conflicting priorities. In this case, it is appropriate to identify a consensus prioritization of preferences so that the resulting product captures the requirements of all customers in the target market to a satisfactory level. In Section 3.1 we present two approaches for finding consensus rankings, and subsequently consensus parts mix. In Section 3.2 we model the approach most often used in practice today, and discuss its differences with the proposed ones.

3.1. Consensus preference rankings and parts mix

To formulate the consensus rankings problem, we assume that a number of customers from the target market are surveyed, and that their individual preference rankings are available. The collection of these data is mainly done by the marketing group. We introduce the following notation.

s_0: number of customers surveyed

$\vec{r}_s = \{r_{is}\}_{i=1}^{n}$: the preference rankings of the sth customer

$w_{ks} = \sum_{j=1}^{m} u_{js} b_{jk}$: the weight attributed to p_k by the preference rankings of the sth customer, where $u_{js} = \sum_{i=1}^{n} r_{is} a_{ij}$

(P_s): the integer program that results by replacing $\{r_i\}_{i=1}^{n}$ in (P), by $\vec{r}_s = \{r_{is}\}_{i=1}^{n}$

Z_s: the optimal objective value of (P_s).

Evidently, for every customer, the vector $\vec{r}_s = \{r_{is}\}_{i=1}^{n}$ induces a model (P_s) that determines an optimal parts mix for the preferences of the sth customer. The performance of this parts mix (using the weights w_{ks} induced by $\vec{r}_s$) is Z_s. Without loss of generality, we assume that

$$\sum_{i=1}^{n} r_{is} = S \quad \text{for every } 1 \le s \le s_0,$$

otherwise we can normalize the vectors $\vec{r}_s$ to satisfy this property. Given that the preference ratings $\vec{r}_s$ of the customers may differ significantly, the parts mix resulting from the (P_s) models for $s = 1,2,\ldots,s_0$ may also be very different.

To resolve the problem of which parts mix to use, we turn our attention to finding a consensus ranking $\vec{r} = \{r_i\}_{i=1}^{n}$. Towards this end, let c_k^s, $k = 1,2,\ldots,n_0$, be the costs of the parts of the optimal parts mix determined by (P_s). Then, consider the model

$$\text{(LP)} \ \max_{r_i} \ \min_s \sum_{k=1}^{n_0} \sum_{j=1}^{m} \sum_{i=1}^{n} r_i a_{ij} b_{jk} \mathscr{P}_k(c_k^s) - Z_s \tag{5}$$

$$\text{s.t.} \ \sum_{i=1}^{n} r_i = S \tag{6}$$

$$L_i \le r_i \le U_i \quad 1 \le i \le n \tag{7}$$

where $[L_i, U_i]$ is the scale utilized by the customers to rank their priorities. A reasonable choice for this range could be $[\min_s r_{is}, \max_s r_{is}]$. The constraint $\sum_{i=1}^{n} r_i = S$ ensures that the consensus rankings vector will be normalized in the same manner as the vectors $\vec{r}_s$. Note that (LP) is equivalent to

$$\begin{aligned} \max \quad & Z \\ \text{s.t.} \quad & \sum_{k=1}^{n_0} \sum_{j=1}^{m} \sum_{i=1}^{n} r_i a_{ij} b_{jk} \mathscr{P}_k(c_k^s) \ge Z + Z_s \quad \forall 1 \le s \le s_0 \\ & \sum_{i=1}^{n} r_i = S \\ & L_i \le r_i \le U_i \quad 1 \le i \le n \end{aligned}$$

which is a linear programming problem. Thus, (LP) identifies a consensus ranking that benchmarks against the most demanding (with respect to performance) customer, say s (i.e., a customer that attains $\max_s Z_s$). Let $\vec{r}^* = (r_1^*, r_2^*, \ldots, r_m^*)$ be the consensus rankings vector obtained by (LP), and $(P(\vec{r}^*))$ denote the application of (P) when the rankings $\{r_i\}_{i=1}^{n}$ are replaced by $\vec{r}^*$. Then, the above suggested approach utilizes the models

$$(P_s): s = 1,2,\ldots,s_0, \ \text{LP}, \ \text{and} \ \big(P(\vec{r}^*)\big)$$

in this sequence. The advantage of this approach is that (LP) is easily solvable. The disadvantage is that (LP) singles out a particular customer to use as benchmark, and hence it is implicitly assumed that the expectations of all other customers are uniformly exceeded by the selected customer. This assumption may not be true for customers that have significantly different priorities in their product requirements. For these cases we suggest the alternative model presented below.

Consider the model

$$(\mathrm{P}') \max_{r_i, x_{kl}} \min_{1 \le s \le s_0} \sum_{k=1}^{n_0} \sum_{j=1}^{m} \sum_{i=1}^{n} (r_i - r_{is}) a_{ij} b_{jk} \sum_{l=1}^{n_k} \mathscr{P}_k(c_{kl}) x_{kl} \quad \text{s.t.} \quad (2),(3),(4),(6),(7). \tag{8}$$

Model (P') allows simultaneous identification of the consensus rankings and the parts mix. Moreover, by using the rankings r_{is}, model (P') benchmarks against the most demanding customer for each parts mix over all possible mixes (i.e., feasible assignments). Note that the most demanding customer, changes with the parts mix. Another advantage of this alternative approach is that it only involves solving (P') as opposed to the previous approach that involves solving $s_0 + 1$ integer programs and one linear.

3.2. Current practice

In a survey administered by the American Quality Foundation and Ernst and Young (1991), only 22% of US firms stated that they develop new products and services based on customer expectations always or almost always. The corresponding figures for German and Japanese firms were 40% and 58%, respectively. In the rest of this section, we present a model for parts deployment that is most often used for product design. According to this, a firm minimizes the deviation of its parts mix performance from the performance of the part mixes used by competitor products. The actual performance of the competitors' part mixes is recorded in the *tester* room of the expanded HOQ2 chart; also depicted in Table 2. We first introduce the following notation.

Q: number of competitors considered by the design team

comp_q: the qth competitor

β_{qk}: the performance of the part p_k used by comp_q.

Ideally, the β_{qk}'s are obtained from the performance functions $\mathscr{P}_k(c_k)$ for $k = 1,2,\ldots,n_0$ using reverse engineering. Namely, the engineering team analyzes each competitor product into its building blocks/parts. Assuming that the part p_k used by comp_q is one of the possible part options for our new/improved product, the function $\mathscr{P}_k$ identifies its performance β_{qk}.

Table 2
The expanded HOQ2 chart

	HOQ2						
	p_1	p_2	$\cdots$	p_k	$\cdots$	p_{n_0}	
e_1				b_{1k}			u_1
e_2				b_{2k}			u_2
$\vdots$			$\ddots$	$\vdots$	$\ddots$		$\vdots$
e_j				b_{jk}			u_j
$\vdots$			$\ddots$	$\vdots$	$\ddots$		$\vdots$
e_m				b_{mk}			u_m
	w_1	w_2	$\cdots$	w_k	$\cdots$	w_{n_0}	
comp_1				β_{1k}			
comp_2				β_{2k}			
$\vdots$			$\ddots$	$\vdots$	$\ddots$		
comp_q				β_{qk}			
$\vdots$			$\ddots$	$\vdots$	$\ddots$		
comp_Q				β_{Qk}			

Let

$$u_j = \sum_{i=1}^{n} a_{ij} r_i, \quad \text{and} \quad w_k = \sum_{j=1}^{m} u_j b_{jk},$$

where $\vec{r}$ is the consensus rankings vector determined by the method of choice of the firm (very often firms use rankings that built consensus among design team members rather than the customers. Consensus customer rankings can be developed using the models of Section 3.1). Then, the formulation

$$(\mathrm{P}_C) \max_{x_{kl}} \min_{1 \le q \le Q} \sum_{k=1}^{n_0} \sum_{l=1}^{n_k} w_k (\mathscr{P}_k(c_{kl}) x_{kl} - \beta_{qk}) \quad \text{s.t.} \quad (2),(3),(4) \tag{9}$$

identifies a parts mix with minimum performance deviation from the parts mixes used by the competitors. More specifically, if the quantity $Y = \max \min_{1 \le q \le Q} \sum_{k=1}^{n_0} \sum_{l=1}^{n_k} w_k (\mathscr{P}_k(c_{kl}) x_{kl} - \beta_{qk})$ is positive, then the model (P_C) identifies a parts mix with maximum possible performance. Else, $Y < 0$ and (P_C) identifies a mix that minimizes the performance difference from any of the competitors. Note that (9) is equivalent to

$$\max \sum_{k=1}^{n_0} \sum_{l=1}^{n_k} w_k \mathscr{P}_k(c_{kl}) x_{kl} - \max_{1 \le q \le Q} \sum_{k=1}^{n_0} w_k \beta_{qk} n_k$$

which is equivalent to benchmarking the parts mix against that of the ''best in class'' competitor whose weighted actual performance is $\max_{1 \le q \le Q} \sum_{k=1}^{n_0} w_k - \beta_{qk} n_k$.

The ''best-in-class'' approach, although insightful, does not account for the performance expectations Z_s of the customers; rather it strives for products that ''outperform'' the products of the competitors. This notion exemplifies current practice, where competition focuses more on beating a competing design rather than closely matching or exceeding the expectations of the customers in the target market.

4. Consensus ratings and perceptual gaps

The problems encountered when customers are asked to rate various competitors in a target market are similar to those presented in Section 3.1. Since these ratings are heavily dependent on personal product use, customer interactions with the producer, word of mouth, exposure to marketing campaigns, etc., it is expected that customer ratings vary widely. To evaluate how each competitor is perceived, we need to identify consensus ratings for each competitor, based on rating surveys. We need the following additional notation (see also Table 3).

s'_0: number of customers surveyed on competitor ratings

t^s_{iq}: the rating comp_q received on req_i by the sth customer surveyed

$\vec{t}_q = \{t_{iq}\}_{i=1}^n$: the consensus ratings vector for comp_q

For consensus ratings we can use similar analysis as for the case of consensus rankings. In this case there is no justification in normalizing $\sum_{i=1}^n t_{iq}$, because for instance a particular competitor may be perceived to outperform all others with respect to every single customer requirement. However, if $[L_i, U_i]$ is the scale used to rate the perceived performance of the competitors on req_i, it is required that $L_i \le t_{iq} \le U_i$ for every $1 \le i \le n$ and $1 \le q \le Q$. The following linear program identifies the consensus rating of competitor comp_q; namely $\vec{t}_q = \{t_{1q}, t_{2q}, \dots, t_{nq}\}$.

$$\left(LP\left(\vec{t}_q\right)\right) \quad \min Z \tag{10}$$

$$\begin{aligned} \text{s.t.} \quad & -Z \le \sum_{i=1}^{n} r_i^* \left(t_{iq} - t^s_{iq}\right) \le Z \quad && \forall\, 1 \le s \le s'_0 \\ & L_i \le t_{iq} \le U_i && 1 \le i \le n \end{aligned} \tag{11}$$

Note that in $(LP(\vec{t}_q))$ the ratings t^s_{iq} are weighted by the corresponding consensus rankings r_i^*. The resulting vector $\vec{t}_q$ minimizes the maximum deviation of the weighted ratings $\sum_{i=1}^n r_i^* t^s_{iq}$ from $\sum_{i=1}^n r_i^* t_{iq}$ over all customers. In the rest of this article we assume that the consensus ratings $\vec{t}_q$ are already determined through the use of $(LP(\vec{t}_q))$, for every $q = 1,2,\dots,Q$.

Table 3
The expanded HOQ1 chart

	e_1	e_2	$\cdots$	e_j	$\cdots$	e_m	$\vec{r}*$	comp_1	comp_2	$\cdots$	comp_q	$\cdots$	comp_Q
req_1				a_{1j}			r_1^*				t_{1q}		
req_2				a_{2j}			r_2^*				t_{2q}		
$\vdots$			$\ddots$	$\vdots$	$\ddots$		$\vdots$			$\ddots$	$\vdots$	$\ddots$	
req_i				a_{ij}			r_i^*				t_{iq}		
$\vdots$			$\ddots$	$\vdots$	$\ddots$		$\vdots$			$\ddots$	$\vdots$	$\ddots$	
req_n				a_{nj}			r_n^*				t_{nq}		
	u_1^*	u_2^*	$\cdots$	u_j^*	$\cdots$	u_m^*							
comp_1				α_{1j}									
comp_2				α_{2j}									
$\vdots$			$\ddots$	$\vdots$	$\ddots$								
comp_q				α_{qj}									
$\vdots$			$\ddots$	$\vdots$	$\ddots$								
comp_Q				α_{Qj}									

In Section 4.1 we show how the consensus competitor ratings can be used to identify gaps in the perceived performance of competitors. We do this by developing graphs whose nodes represent competitors, and arcs represent perceptual gaps between competitors. After developing such graphs, the firm's marketing group can identify the competitors that have been most successful in marketing the product, or specific product features. Also, in the case where the firm is already one of the competitors, the above mentioned graphs indicate how the current marketing strategy of the firm is perceived in the target market. The managerial significance of these graphs is evident. A firm can reformulate its marketing strategy by emulating or innovating upon proven competing strategies, and can reinforce its own strategies that have proved successful. Moreover, the firm is allowed to take a micro look in the product by focusing not only on the product as a whole, but also on specific customer requirements as well as specific engineering characteristics.

4.1. The networks of perceptual gaps

The HOQ1 chart starts by relating customer requirements to the engineering characteristics e_j. These characteristics are chosen by the design team and are measured through testing. As a result, the lower part of Table 3 is known as *tester room*. Let,

α_{qj} = actual performance rating of comp_q with respect to e_j $(\alpha_{qj} \geq 0)$.

The α_{qj}'s record the actual performance of each competitor comp_q with respect to e_j, as exhibited during product testing. In many cases, such test results are available in product manuals in which case testing is unnecessary. In the rest of this article we assume that

$$u_j^* = \sum_{i=1}^{n} a_{ij} r_i^*, \text{ and } w_k^* = \sum_{j=1}^{m} u_j^* b_{jk},$$

where $\vec{r}^*$ is the consensus rankings vector determined by any of the methods suggested in Section 3.1. Consider two competitors comp_{q_1} and comp_{q_2}, where $1 \leq q_1, q_2 \leq Q$. In what follows we provide a definition for the perceptual gap g_{q_1,q_2} between these two competitors.

Definition 1 *If* $\sum_{k=1}^{n_0} w_k^* \beta_{q_1,k} \geq \sum_{k=1}^{n_0} w_k^* \beta_{q_2,k}$, *then the perceptual gap* g_{q_1,q_2} *between* comp_{q_1} *and* comp_{q_2} *is*

$$g_{q_1,q_2} = \max\left\{ \sum_{i=1}^{n} r_i^* \left(t_{i,q_2} - t_{i,q_1} \right), 0 \right\}.$$

In the above definition, $\sum_{k=1}^{n_0} w_k^* \beta_{q_1,k}$ and $\sum_{k=1}^{n_0} w_k^* \beta_{q_2,k}$ correspond to the actual performance of competitors comp_{q_1}, and comp_{q_2}, weighted by the weights u_j^* that incorporate the consensus rankings r_i^*. The condition $\sum_{k=1}^{n_0} w_k^* \beta_{q_1,k} \geq \sum_{k=1}^{n_0} w_k^* \beta_{q_2,k}$ indicates that the actual performance of competitor comp_{q_1} is no worse than the performance of comp_{q_2}. The perceptual gap g_{q_1,q_2} is zero if comp_{q_1} is perceived to perform at least as well as comp_{q_2} (i.e., $\sum_{i=1}^{n} r_i^* t_{i,q_1} \geq \sum_{i=1}^{n} r_i^* t_{i,q_2}$). In case that comp_{q_2} is perceived to perform better than comp_{q_1}, we have a perceptual gap $g_{q_1,q_2} = \sum_{i=1}^{n} r_i^* (t_{i,q_2} - t_{i,q_1}) > 0$.

To depict the perceptual gaps among competitors, we construct a directed network $\mathcal{N}$ whose node set consists of the Q competitors comp_1, comp_2, ..., comp_Q. In $\mathcal{N}$, two nodes comp_{q_1} and comp_{q_2} are connected by an arc, if $g_{q_1,q_2} > 0$. Moreover, to each arc $(\text{comp}_{q_1}, \text{comp}_{q_2})$ of $\mathcal{N}$ we associate the weight g_{q_1,q_2}. The arc $(\text{comp}_{q_1}, \text{comp}_{q_2})$ indicates that the competitor comp_{q_1} suffers a perceptual gap over comp_{q_2}. Using the network $\mathcal{N}$ we can identify those competitors that enjoy the greatest benefits from customer perceptions. The marketing strategies of those competitors can serve as benchmarks for our marketing strategy towards a new/improved product.

In the case of an existing product, one of the nodes of $\mathcal{N}$, say comp_1, corresponds to our product. Then, the competitors comp_q with the greatest ''distance'' from comp_1 correspond to a reasonable choice of competitors to serve as benchmarks for shaping the firm's marketing strategy. This is because by construction of $\mathcal{N}$, the greater the distance from comp_1, the greater the perceptual benefits of competitors over comp_1. In Section A.1 we describe the properties of $\mathcal{N}$ for two simple distance measures. More sophisticated measures could be used by the firm, however, the relevant analysis would be similar.

4.1.1. Perceptual gaps for individual characteristics

The perceptual gap g_{q_1,q_2} utilizes the expression $\sum_{i=1}^{n} r_i^*(t_{i,q_2} - t_{i,q_1})$ when $g_{q_1,q_2} > 0$; see Definition 1. This expression corresponds to the perception gains of competitor q_2 over the entire set of customer requirements. Similarly, in Definition 1 the expression $\sum_{k=1}^{n_0} w_k^* \beta_{q_1,k}$ captures the performance of comp_{q_1} over the entire set of engineering characteristics. Given that every characteristic affects (in general) only a small number of customer requirements, it is possible that there exists a perceptual gap between two competitors for an individual characteristic, which is nullified when summed up over all the characteristics. Such finer analysis of perceptual gaps is facilitated by the following definition.

Definition 2 *If* $\alpha_{q_1,j} \geq \alpha_{q_2,j}$, *then the perceptual gap between* comp_{q_1} *and* comp_{q_2} *for the jth engineering characteristic is*

$$g_{q_1,q_2}^{j} = \max\left\{ \sum_{\substack{i=1 \\ a_{ij} \neq 0}}^{n} r_i^* \left(t_{i,q_2} - t_{i,q_1} \right), 0 \right\}.$$

The condition $\alpha_{q_1,j} \geq \alpha_{q_2,j}$ in Definition 2 indicates that comp_{q_1} performs no worse than $comp_{q_2}$ with respect to e_j. Also, when $g_{q_1,q_2}^{j} > 0$ the competitor q_2 is perceived to perform better than comp_{q_1} since $g_{q_1,q_2}^{j} > 0 \Rightarrow \sum_{\substack{i=1 \\ a_{ij} \neq 0}}^{n} r_i^* t_{i,q_2} > \sum_{\substack{i=1 \\ a_{ij} \neq 0}}^{n} r_i^* t_{i,q_1}$. Note that these perceptions are based solely on the requirements that affect the jth characteristic, i.e., $a_{ij} > 0$.

As we did with the network $\mathcal{N}$, we construct the networks $\mathcal{N}^j$ where the arc $(\text{comp}_{q_1}, \text{comp}_{q_2}) \in \mathcal{N}^j$ if $g_{q_1,q_2}^{j} > 0$. The properties of the networks $\mathcal{N}^j$, $1 \leq j \leq m$, are the same as those presented in Section A.1 for $\mathcal{N}$.

4.1.2. Perceptual gaps for individual customer requirements

The perceptual gap g_{q_1,q_2} uses the expression $\sum_i r_i^*(t_{i,q_2} - t_{i,q_1})$ which involves the entire set of customer requirements. It is desirable to measure the actual performance of competitors on each individual requirement req_i. This can be done by focusing only on those e_j's that affect req_i, i.e., those e_j's for which $a_{ij} > 0$. This motivates the following definition.

Definition 3 *If* $\sum_{k=1}^{n_0} \sum_{\substack{j=1 \\ a_{ij} \neq 0}}^{m} u_j^* b_{jk} \beta_{q_1,k} \geq \sum_{k=1}^{n_0} \sum_{\substack{j=1 \\ a_{ij} \neq 0}}^{m} u_j^* b_{jk} \beta_{q_2,k}$, *then the perceptual gap between* comp_{q_1} *and* comp_{q_2} *for* req_i *is* $g_{q_1,q_2}^{(i)} = \max\{ t_{i,q_2} - t_{i,q_1}, 0 \}$.

The condition $\sum_{k=1}^{n_0} \sum_{\substack{j=1 \\ a_{ij} \neq 0}}^{m} u_j^* b_{jk} \beta_{q_1,k} \geq \sum_{k=1}^{n_0} \sum_{\substack{j=1 \\ a_{ij} \neq 0}}^{m} u_j^* b_{jk} \beta_{q_2,k}$ in the above definition indicates that the weighted actual performance of comp_{q_1} is no worse than that of comp_{q_2}; note that $a_{ij} \geq 0$ and hence the terms contributing in each sum are only those with $a_{ij} > 0$. However, $g_{q_1,q_2}^{(i)} > 0$ indicates that comp_{q_2} is rated better than comp_{q_1}. Constructing the network $\mathcal{N}_i$ by including the arc $(\text{comp}_{q_1}, \text{comp}_{q_2})$ iff $g_{q_1,q_2}^{(i)} > 0$, we can identify perceptual gaps among competitors for the ith requirement req_i.

The design team of a new/improved product can use the networks $\mathcal{N}, \mathcal{N}^1, \mathcal{N}^2, \ldots, \mathcal{N}^m$ and/or $\mathcal{N}_1, \mathcal{N}_2, \ldots, \mathcal{N}_n$ to identify those competitors that score the best in customer perception. Based on these findings they can formulate marketing strategies for the newly designed product. In the appendix we present the properties of the network $\mathcal{N}$ for two common distance measures. All the results presented hold true for the networks $\mathcal{N}, \mathcal{N}^1, \mathcal{N}^2, \ldots, \mathcal{N}^m$ and $\mathcal{N}_1, \mathcal{N}_2, \ldots, \mathcal{N}_n$ and the associated gaps g_{q_1,q_2}^{j} and $g_{q_1,q_2}^{(i)}$. In Section 5 we present an example that illustrates the modeling methodology presented in this article for the design and marketing of new/improved products.

5. An example

In Table 4 we provide the expanded HOQ1 and HOQ2 charts of an imaginary product with 6 engineering characteristics $(m = 6)$, 5 customer requirements $(n = 5)$, and 5 competitors $(Q = 5)$ with comp_1 corresponding to our existing product. The intensities a_{ij} in this example utilize the scale [0,9] where 0 corresponds to negligible effect of e_j on req_i. The

Table 4
Example problem

A	Engineering characteristics						Preference rankings (R)				Consensus ranking $\vec{r}*$	Consensus competitor ratings (T)				
	e_1	e_2	e_3	e_4	e_5	e_6	1	2	3	4		comp$_1$	comp$_2$	comp$_3$	comp$_4$	comp$_5$
req$_1$	9	0	0	0	3	1	2	5	5	3	r_1^*	7	3	4	1	4
req$_2$	4	9	2	0	0	4	3	2	2	4	r_2^*	2	2	4	2	2
req$_3$	0	0	5	3	5	0	1	3	2	4	r_3^*	5	4	6	4	4
req$_4$	6	4	0	0	2	3	5	3	2	3	r_4^*	2	6	3	3	5
req$_5$	1	1	7	8	0	4	4	2	4	1	r_5^*	4	5	2	5	6
$\mathscr{A}$	u_1^*	u_2^*	u_3^*	u_4^*	u_5^*	u_6^*										
comp$_1$	2	8	15	16	5	30										
comp$_2$	7	8	9	20	15	12										
comp$_3$	5	6	12	24	35	24										
comp$_4$	6	4	15	4	25	30										
comp$_5$	4	2	6	12	20	36										

B	HOQ2					
	p_1	p_2	p_3	p_4	p_5	
e_1	3	4	2	0	7	u_1^*
e_2	0	0	7	5	2	u_2^*
e_3	0	5	3	2	0	u_3^*
e_4	9	0	0	4	5	u_4^*
e_5	1	0	4	1	8	u_5^*
e_6	0	2	0	6	6	u_6^*
$\mathscr{B}$	w_1^*	w_2^*	w_3^*	w_4^*	w_5^*	
comp$_1$	3	4	4	4	3	
comp$_2$	3	4	3	5	3	
comp$_3$	4	4	4	4	3	
comp$_4$	1	4	3	5	5	
comp$_5$	1	3	4	5	5	

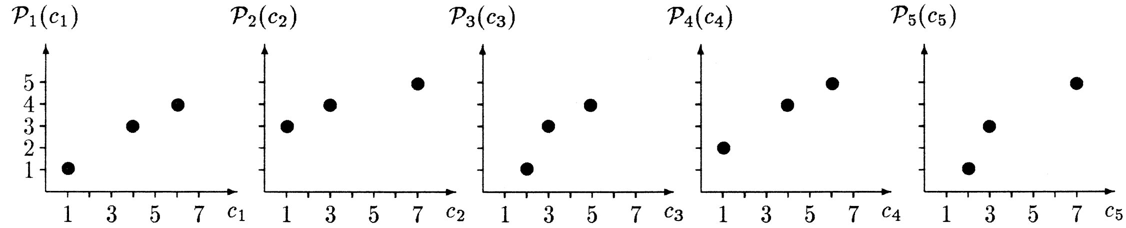

Fig. 2. Parts performance as a function of cost.

number of customers surveyed for their preferences is $s_0 = 4$, and the preference scale is [1,5]. We assume that the consensus ratings for the competitors are already computed using model $(\vec{t})$ for $q = 1,2,\ldots,5$. The consensus ratings are recorded in Table 4 and utilize the scale [1,7]. Moreover, the actual performance of the competitors for each engineering characteristic e_j $(1 \le j \le 6)$ is recorded in the tester room of HOQ1 in Table 4. This example will be used to illustrate all models presented so far in this paper. To simplify calculations, we will use matrix arithmetic using the matrices $A = \{a_{ij}\}$, $\mathscr{A} = \{\alpha_{qj}\}$, $B = \{b_{jk}\}$, $\mathscr{B} = \{\beta_{qk}\}$, $T = \{t_{iq}\}$, and $R = \{r_{is}\}$, also indicated in Table 4. Further, we will use the budget of $W = 18$ units, and the performance functions of Fig. 2 for the five parts.

Using the matrices $A = \{a_{ij}\}$, $R = \{r_{is}\}$ and $B = \{b_{jk}\}$, we have

$$\{u_{js}\} = A^T R = \begin{pmatrix} 64 & 73 & 69 & 62 \\ 51 & 32 & 30 & 49 \\ 39 & 33 & 42 & 35 \\ 35 & 25 & 38 & 20 \\ 21 & 36 & 29 & 35 \\ 45 & 30 & 35 & 32 \end{pmatrix} \text{ and}$$

$$\{w_{ks}\} = B^T A^T R = \begin{pmatrix} 528 & 480 & 578 & 401 \\ 541 & 517 & 556 & 487 \\ 686 & 613 & 590 & 712 \\ 764 & 542 & 625 & 622 \\ 1163 & 1168 & 1175 & 1104 \end{pmatrix}$$

5.1. The consensus rankings

Using the above matrices, the consensus ranking problem can be solved using the sequence

$$(P_s): s = 1,2,\ldots,s_0,\ LP,\ \text{and}\ \left(P(\vec{r}^*)\right)$$

of problems presented in Section 3.1. Solving (P_s) for each of the 4 customers, we get the cost vectors $\{c_k^1\} = (1,1,3,6,7)$, $\{c_k^2\} = (1,1,5,4,7)$, $\{c_k^3\} = (1,1,3,6,7)$, and $\{c_k^4\} = (1,1,5,4,7)$. Each of these vectors indicates the optimal parts mix according to the corresponding customer. We can make the following observations. The mix that maximizes the expectations of customers 1 and 3 coincide. Similarly with customers 2 and 4. There is general agreement with respect to parts p_1, p_2 and p_5. The different customer expectations from the product, drive the choice of parts p_3 and p_4. This scenario is typical for customers surveyed from a target market. As a result, our models are expected to identify those critical parts that drive different customer expectations.

The observation that the optimal part mixes for various customers often contain several parts in common, can be used to reduce the size of our optimization models by eliminating those common parts from consideration. In the rest of this example however, we continue our analysis using all five parts considered initially.

The corresponding performance vectors $\{\mathscr{P}_k(c_k^s)\}$ of the part mixes $\{c_k^s\}$ are recorded as columns of the matrix $\mathscr{P} = \{\mathscr{P}_{ks}\}$ where $\mathscr{P}_{ks} = \mathscr{P}_k(c_k^s)$ below.

$$P = \begin{pmatrix} 1 & 1 & 1 & 1 \\ 3 & 3 & 3 & 3 \\ 3 & 4 & 3 & 4 \\ 5 & 4 & 5 & 4 \\ 5 & 5 & 5 & 5 \end{pmatrix}$$

Note that the performance attributed by customer s to his/her optimal parts mix is computed using the objective function (1) of (P). This can be calculated as the dot product of $\{w_{ks}\}$ and $\{\mathscr{P}_{ks}: k = 1,2,3,4,5\}$. Hence,

$$Z_s = \{w_{ks}\} \cdot \{\mathscr{P}_{ks}\}, \text{ and } \begin{pmatrix} Z_1 \\ Z_2 \\ Z_3 \\ Z_4 \end{pmatrix} = \begin{pmatrix} 13844 \\ 12491 \\ 13016 \\ 12718 \end{pmatrix}$$

Then, the problem (LP) of Section 3.1 can be written as

$$\begin{array}{lll} \max & Z & \\ \text{s.t.} & r_1+r_2+r_3+r_4+r_5=15 & \\ & \vec{r}AB\mathscr{P} \geq Z\begin{pmatrix}1\\1\\1\\1\end{pmatrix}+\begin{pmatrix}13844\\12491\\13016\\12718\end{pmatrix} & \\ & 1 \leq r_i \leq 5 & i=1,2,3,4,5 \end{array}$$

and yields $\vec{r}^* = (1,5,1,3,5)$ and $Z^* = 674$. Consequently, according to model $(P(\vec{r}^*))$, the consensus parts mix that satisfies our budget $W = 18$ has cost $\{c_k^*\} = (1,1,3,6,7)$ and the corresponding parts performance vector is $\{\mathscr{P}_k(c_k^*)\} = (1,3,3,5,5)$. Hence, the consensus parts mix coincides with the optimal mix for customers 1 and 3. In general however, the consensus mix may not be optimal for any of the customers surveyed. Along these lines, observe that $\vec{r}^*$ does not coincide with any of the preference rankings of the customers (see Table 4). The consensus ranking vector induces the consensus weights

$$u^* = \{u_j^*\} = (52,62,50,43,14,50) \text{ and}$$

$$w^* = \{w_j^*\} = (557,558,744,896,1115),$$

where $u_j^* = \sum_i a_{ij} r_i^*$ and $w_j^* = \sum_j u_j^* b_{jk}$. Hence, the performance of the consensus parts mix is $\sum_{k=1}^5 w_k^* \mathscr{P}_k(c_k^*) = 14518$ (note that $14518 = Z^* + Z_1$). This means that, given the budget of $W = 18$ units it is possible to develop a product that outperforms all competitors with respect to the consensus rankings.

As indicated in Section 3.1, an alternative consensus vector $\vec{r}^*$ can be obtained by solving model (P'). In the rest of this example however, we will use the consensus ranking and parts mix obtained above.

5.2. The ''current practice''

We now solve model (P_C) for the input data of Table 4 and the available part choices of Fig. 2. Recall that the fallacy of (P_C) stems from the use of a rankings vector $\vec{r}^*$ which is different than the customer consensus rankings $\vec{r}^*$. For simplicity, let us suppose that the rankings vector used by the design team is $\vec{r}^* = (5,2,3,3,2)$. Then, the associated w-weights are $\vec{w} = \{w_k\} = (480,517,613,542,1168)$, and hence the optimal parts mix according to (P_C) has cost $c^* = (1,1,5,4,7)$, and the associated performance of the parts is $\{\mathscr{P}_k(c_k^*)\} = (1,3,4,4,5)$. Note that this parts mix is different that the consensus parts mix obtained above. In fact, as we saw earlier, c^* is the cost vector of the optimal parts mix for customers 2 and 4.

Also, note that using the weights $\{w_k\}$, the performance of the 5 competitors is calculated to be $\vec{w}\mathscr{B}^T = (11632,11561,12112,12937,13033)$ as opposed to $\vec{w}*\mathscr{B}^T = (13808,13960,14365,15076,15262)$ for the consensus weights w_k^*. Evidently, using the rankings $\vec{r}$, the firm distorts the value attributed to each competitor for overall product performance. Moreover, using $\vec{r}$ it appears that the firm's product is superior to comp$_2$ (because $11632 > 11561$) while the consensus rankings $\vec{r}^*$ show that comp$_1$'s product is inferior to comp$_2$'s (because $13808 < 13960$).

Evidently, $\vec{r}$ directs the firm's decisions based on the perception of the design team about the competitive environment, while $\vec{r}^*$ directs decisions based strictly on customer preferences.

5.3. Consensus ratings

Having obtained $\vec{r}^*$, the linear programs $(LP(\vec{t}_q))$ yield the consensus ratings vector for each competitor. To do this, we assume that we have surveyed customers from the target market for their ratings on each competitor product. For brevity, in our example we assumed that such survey and the subsequent analysis have been performed, and that the t_{iq}'s in T are the consensus ratings obtained by model $(LP(\vec{t}_q))$.

5.4. Perceptual gap networks

The network $\mathscr{N}$ for the example of Table 4 is depicted in Fig. 3. To construct $\mathscr{N}$ we computed the values $\sum_{k=1}^{n_0} w_k^* \beta_{qk}$ and $\sum_{i=1}^{n} r_i^* t_{iq}$, for $1 \leq q \leq 5$. The resulting vectors are

$$\vec{r}^* AB\mathscr{B}^T = (13808,13960,14365,15076,15262) \text{ and}$$

$$\vec{r}^* T = (48,60,49,49,63).$$

Solid arcs (q,q') in $\mathscr{N}$ represent perceptual gaps between comp$_q$ and comp$_{q'}$, suffered by comp$_q$ (see Definition 1). The number associated with each arc (q,q') in $\mathscr{N}$ in Fig. 3 is the quantity $g_{q,q'}$.

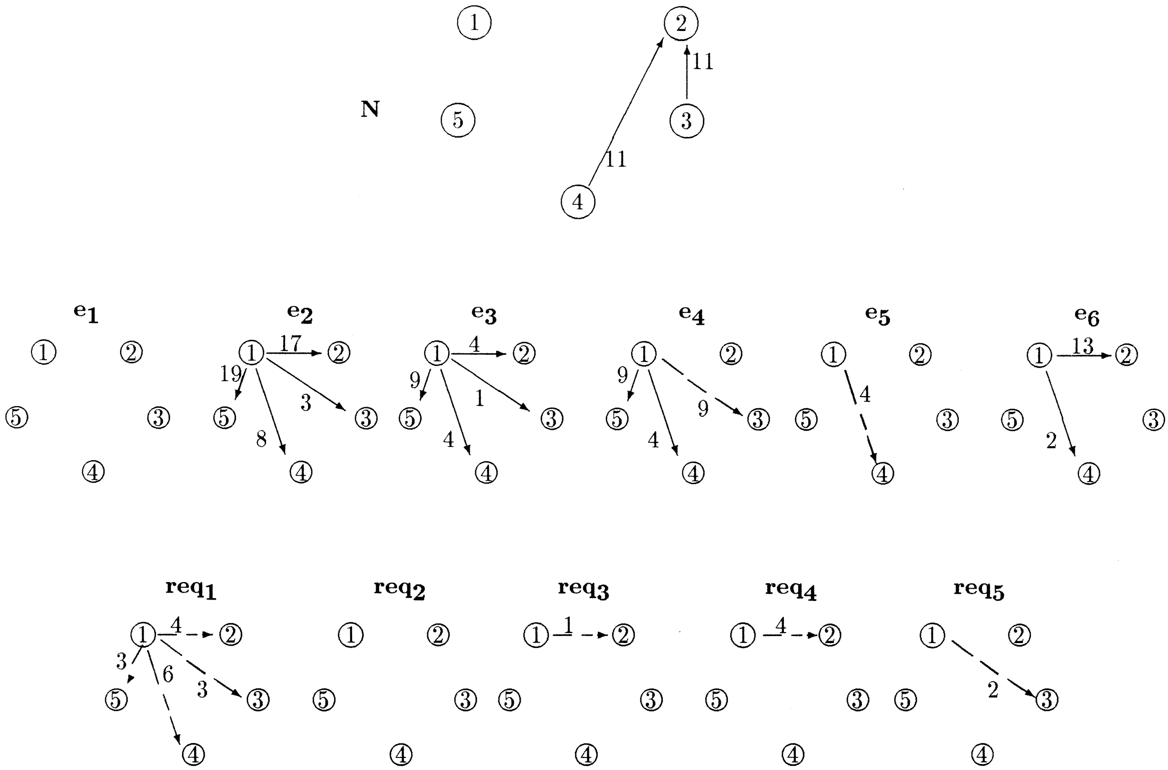

Fig. 3. The network $\mathscr{N}$ of perceptual gaps.

Using Definition 2, we construct the networks $\mathscr{N}^j$ corresponding to the engineering characteristics e_j. In Fig. 3, we only include arcs (q,q') where either $q=1$ or $q'=1$. These arcs indicate the perceptual gains/losses of comp_1 (recall that we have assumed that comp_1 represents the firm's existing product). More specifically, in the networks $\mathscr{N}^j$ corresponding to the e_j's, solid arcs correspond to perceptual losses (according to Definition 2), and dotted arcs correspond to gains. The labels used in the $\mathscr{N}^j$'s correspond to the associated $g^j_{q,q'}$ values. Quite similarly, and using Definition 3, we constructed the networks $\mathscr{N}_i$ corresponding to the customer requirements req_i (see Fig. 3). To obtain the quantities $\sum_{k=1}^{n_0}\sum_{j=1,\, a_{ij}\neq 0}^{m} u^*_j b_{jk} \beta_{qk}$ we used the product $B\mathscr{B}^T$ of matrices.

Assuming that comp_1 is the firm's existing product, we make the following observations for the perceptions of customers in comparison to other competitors. The firm's product has the worst actual performance when weighted with the w^*_k weights that incorporate the consensus rankings r^*_i (this may indicate that the design efforts for the existing product focused on entering the market without proper consideration of customer expectations). As a result, no unfavorable perceptual gap is possible. Also, no favorable gap is present, since no arc in $\mathscr{N}$ points to comp_1. $\mathscr{N}$ also indicates that even though comp_2's product is among the worse performers, comp_3 and comp_4 are perceived as worse by customers; this suggests a closer analysis of the marketing strategies of these competitors. For such closer analysis, let us first look at the networks corresponding to engineering characteristics. With respect to e_1, no competitor enjoys unfair advantages over comp_1 because there is no arc emanating from comp_1. In contrast, all 4 competitors of comp_1 are unfairly perceived better with respect to e_2 and e_3. Similarly, competitors 3, 4 and 5 are wrongly perceived better than comp_1 on e_4, and competitors 2 and 4 on e_6. These observations mean that the firm's marketing strategy has not been successful in promoting the product's engineering characteristics. A first step in improving the current situation may be to analyze $comp_4$'s marketing strategy, because $comp_4$ has proved successful in convincing customers that $comp_4$ is better than $comp_1$ in 5 of the 6 engineering characteristics of the product.

Similarly, for the networks associated with the req_i's we only depict in Fig. 3 arcs (q,q') where $q=1$ or $q'=1$. According to Definition 3, the performance of $comp_q$ with respect to req_i is given by the element in the ith row and qth column of the matrix $\mathbf{M}=\{\mathbf{M}_{iq}\}$ where $\mathbf{M}_{iq}=\sum_{k=1}^{n_0}\sum_{\substack{j=1\\ a_{ij}\neq 0}}^{m} u_j^* b_{jk}\beta_{qk}$,

$$M=\begin{pmatrix} 5966 & 6120 & 6136 & 7332 & 7184\\ 10656 & 10678 & 10812 & 11942 & 12072\\ 5152 & 5232 & 5553 & 5084 & 5040\\ 9314 & 9344 & 9484 & 10804 & 11090\\ 13150 & 13344 & 13693 & 14264 & 14394 \end{pmatrix}.$$

As seen, the performance of $comp_1$ is the worst among competitors for the customer requirements req_1, req_2, req_4 and req_5. Hence, it is impossible for $comp_1$ to suffer perceptual losses for these requirements. The dotted arcs in the networks N_i indicate the unfair perceptual advantages enjoyed by $comp_1$. Most notably, $comp_1$ is wrongly perceived as being the most satisfactory with respect to req_1. To identify competitors with successful marketing strategies, one can draw the networks where $q,q'\neq 1$.

In summary, the imaginary product and data given in Table 4 does not capture customer requirements satisfactorily, and as a result it is perceived as having the worst overall performance. Moreover, customers unfairly perceive the firm's product as inferior, even for the characteristics e_2, e_3, e_4, e_5 and e_6 where the product's actual performance is among the top contenders. The only notable success of the firm's marketing strategy appears to be with req_1. In conclusion, the firm needs to upgrade their product (as seen this is possible for the allowable budget), and promote its engineering superiority. Possible ways for improving the current marketing strategy is by analyzing the strategy followed by $comp_2$ who is unfairly perceived better than $comp_3$ and $comp_4$.

As shown by this example, the perceptual networks can be used as ''control charts'' to evaluate the competitive environment, and guide, focus, and benchmark the firm's marketing strategy.

6. Conclusion and future research directions

Quality function deployment offers a blueprint for new/improved product design. In this article we presented optimization modeling techniques for some of the decisions involved with the first 2 stages of QFD that have been traditionally made based on expert opinion. This effort helps to more fully and objectively consider the voice of the customers, engineers, marketeers, and accountants in the design phase. We presented an approach for parts deployment that accounts for affordability. Finally, we exploited information available in the QFD charts to provide marketing insights and identify winning marketing strategies of competitors.

In our experience the development of optimization models for an objective use and interpretation of the data collected during the QFD process is a very useful and needed exercise. In our future research we intend to consider modeling approaches for the stages 3 and 4 of QFD, as well as the development of a link between parts deployment (considered in this article) and the latter two stages. As mentioned in Section 2, our models assume that the unit cost W is known exactly. Clearly, the available budget can greatly affect product performance and hence the design itself. Also, the elasticity of demand to the selling price for the product has ramifications on the acceptable unit cost level and hence the design. Therefore, extending our methodology to incorporate the impact of pricing and demand elasticity on product design is a worthwhile task. Finally, except for problem (P') the formulations presented in this article are relatively simple as the goal is to demonstrate the feasibility of using optimization to resolve consensus issues more objectively. Research towards identifying alternative model formulations and the corresponding solution procedures will allow the members of product design teams to choose the most appropriate objective for their application.

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Appendix A

In Section A.1, this appendix includes properties of the network $\mathcal{N}$ of perceptual gaps constructed in Section 3.1. These properties result from Definition 1. Using $\mathcal{N}$, we identify the competitor(s) that enjoy the greatest benefits over comp_1 in customer perceptions. To do this, we utilize 2 simple measures for the ‘‘distance’’ among competitors. More appropriate measures are possible depending on the application, however, relevant analysis should be similar. In Section A.2 we discuss solution procedures for the models (P) and (P') of Sections 2 and 3, respectively.

A.1. Properties of perceptual gap networks

In what follows we examine two measures that can be used for the distance between an arbitrary pair $(\text{comp}_{q_1}, \text{comp}_{q_2})$ of competitors. Namely,

- $l(\text{comp}_{q_1}, \text{comp}_{q_2})$: the longest length of any directed path from $comp_{q_1}$ to $comp_{q_2}$, and
- $wl(\text{comp}_{q_1}, \text{comp}_{q_2})$: the longest weighted directed path from comp_{q_1} to comp_{q_2}, where the weight associated with an arc $(\text{comp}_q, \text{comp}_{q'}) \in \mathcal{N}$ is $g_{q,q'}$.

The following proposition states that the network $\mathcal{N}$ does not contain directed cycles. This observation is important, since otherwise one could reach erroneous conclusions stemming from the resulting associativity of perceptual gaps (e.g., competitor x is perceived better than y, y better than z, and z better than x).

Proposition 1 *The network $\mathcal{N}$ of perceptual gaps is acyclic.*

Proof: By contradiction. Without loss of generality, let us assume that $\text{comp}_1, \text{comp}_2, \ldots, \text{comp}_q$ is a directed cycle in $\mathcal{N}$. By construction of $\mathcal{N}$, we have

$$\sum_{k=1}^{n_0} w_k^* \beta_{1k} \geq \sum_{k=1}^{n_0} w_k^* \beta_{2k} \geq \ldots \geq \sum_{k=1}^{n_0} w_k^* \beta_{qk},$$

and

$$\sum_{i=1}^{n} r_i^* t_{i1} < \sum_{i=1}^{n} r_i^* t_{i2} < \ldots < \sum_{i=1}^{n} r_i^* t_{iq},$$

which imply that

$$\sum_{k=1}^{n_0} w_k^* \beta_{1k} \geq \sum_{k=1}^{n_0} w_k^* \beta_{qk}, \text{ and } \sum_{i=1}^{n} r_i^* t_{i1} < \sum_{i=1}^{n} r_i^* t_{iq}.$$

The latter inequalities indicate that there is an arc $(\text{comp}_1, \text{comp}_q)$ in $\mathcal{N}$; contradiction to the assumption that $\text{comp}_1, \text{comp}_2, \ldots, \text{comp}_q$ form a directed cycle. This completes the proof of the proposition. □

In case of a new product, comparative perceptual performance among competitors can be used to decide which competitors should serve as benchmarks. In case of an existing product, one of the nodes of $\mathcal{N}$, say comp_1, corresponds to our product. Then, the competitors comp_q with the greatest ‘‘distance’’ from comp_1 correspond to a reasonable choice of competitors to serve as benchmarks for shaping the firm’s marketing strategy. This is because by construction of $\mathcal{N}$, the greater the distance from comp_1, the greater the perceptual benefits of competitors over comp_1. Note that we could use any graph theoretic distance measure $d(\cdot,\cdot)$ in place of the two measures described above. For the particular distance measures described above however, the following proposition shows that for any competitor comp_q, maximizing the distance from comp_q is equivalent to maximizing the perceptual gap over comp_q. Let $P(q,q')$ denote a directed path from comp_q to $\text{comp}_{q'}$. Then, if $(\text{comp}_{q_1}, \text{comp}_{q_2})$ is an arc in $P(q,q')$, it holds by definition that $l(\text{comp}_{q_1}, \text{comp}_{q_2}) = 1$, and $wl(\text{comp}_{q_1}, \text{comp}_{q_2}) = g_{q_1,q_2}$. The distance measure $l(\cdot,\cdot)$ is a special case of $wl(\cdot,\cdot)$ where $g_{q_1,q_2} = 1$ for every $(\text{comp}_{q_1}, \text{comp}_{q_2}) \in \mathcal{N}$ such that $\max\{\sum_{i=1}^{n} r_i^*(t_{i,q_2} - t_{i,q_1}), 0\} > 0$. For this reason, we present the next proposition for the measure $wl(\cdot,\cdot)$ only.

Proposition 2 *If* $wl(\text{comp}_{q_0}, \text{comp}_{q_1}) > wl(\text{comp}_{q_0}, \text{comp}_{q_2})$ *then*

$$\sum_{(\text{comp}_q, \text{comp}_{q'}) \in P(q_0,q_1)} g_{q,q'} > \sum_{(\text{comp}_q, \text{comp}_{q'}) \in P(q_0,q_2)} g_{q,q'}.$$

Proof: The proof follows trivially from the definition of $wl(\cdot,\cdot)$. □

In what follows we use the notation $d(\cdot,\cdot)$ to denote either $l(\cdot,\cdot)$ or $wl(\cdot,\cdot)$. In light of Proposition 2, and assuming that the node comp_1 corresponds to our product, we are interested in solving the model:

$$(\boldsymbol{D}) \ \max_{1 \le q \le Q} \quad d(\text{comp}_1, \text{comp}_q) \qquad (12)$$
$$\text{s.t.} \quad P(1,q) \text{ is a directed path in } \mathscr{N}.$$

To solve (D) we need to gain more insight on the structure of $\mathscr{N}$. Recall from the proof of Proposition 1, that for every directed path $P(q,q')$ on more than two nodes, the arc (comp_q, $\text{comp}_{q'}$) belongs to $\mathscr{N}$. Then, if $P(1,q) = \text{comp}_1, \text{comp}_2, \ldots, \text{comp}_q$ is a longest path starting from comp_1, the directed subgraph G_B of $\mathscr{N}$ with node set $B = \{\text{comp}_1, \text{comp}_2, \ldots, \text{comp}_q\}$ must have an orientation of arcs like the one in Fig. 4 where the indegree of comp_k is $\text{indegree}(\text{comp}_k) = k\text{-}1$ for $1 \le k \le q$. Also, note that G_B is a complete subgraph of $\mathscr{N}$; such subgraph is referred to as a clique of $\mathscr{N}$. The following result from graph theory holds true for directed complete graphs (i.e., graphs every two nodes of which are connected by a directed arc).

Theorem 1 Redei, 1934 *Every directed complete graph on q nodes contains a directed path of length* $q-1$.

According to the preceding discussion, $\text{indegree}(\text{comp}_1) = 0$ which means that comp_q (i.e., a competitor with maximum distance from comp_1) must be the starting node of the directed path implied by Theorem 1. Hence, we have the following corollary.

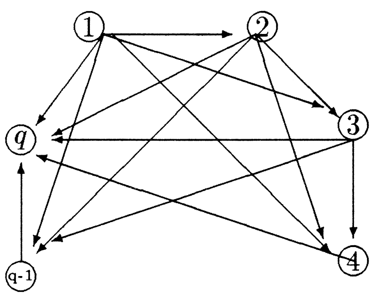

Fig. 4. The clique induced by a longest path.

Corollary 1 $\max_{\text{comp}_q \in \mathscr{N}} \ l(\text{comp}_1, \text{comp}_q) = k(\mathscr{N}) - 1$, *where* $k(\mathscr{N})$ *is the number of nodes of a maximum clique of* $\mathscr{N}$ *that includes* comp_1.

In most applications, the number Q of competitors is expected to be small and hence the corresponding network $\mathscr{N}$ is expected to be manageable. In these cases, Corollary 1 along with Fig. 4 can be used to visually identify a longest path from comp_1. Else, Dijkstra's algorithm can be used (see Dijkstra, 1959, or Papadimitriou and Steiglitz, 1982, p. 128) to identify a longest path from comp_1, in $\mathscr{O}(Q^2)$ time.

The above observations characterize the longest paths of $\mathscr{N}$ that start from comp_1. These longest paths use the distance function $l(\cdot,\cdot)$. The characterization of longest weighted paths utilize the distance function $wl(\cdot,\cdot)$, and is much simpler.

Proposition 3 *Let* $\text{comp}_1, \text{comp}_2, \ldots, \text{comp}_q$ *be a directed path of maximum weighted length. Then,* $wl(\text{comp}_1, \text{comp}_q) = g_{1,q}$.

Proof: By definition of $\mathscr{N}$ and the fact that $\text{comp}_1, \text{comp}_2, \ldots, \text{comp}_q$ forms a directed path, we have

$$\sum_{k=1}^{n_0} w_k^* \beta_{1k} \ge \sum_{k=1}^{n_0} w_k^* \beta_{2k} \ge \ldots \ge \sum_{k=1}^{n_0} w_k^* \beta_{qk}$$

and

$$\begin{aligned} wl(\text{comp}_1, \text{comp}_q) &= g_{1,2} + g_{2,3} + \ldots + g_{q-1,q} \\ &= \sum_{i=1}^{n} r_i^* (t_{i2} - t_{i1}) \\ &\quad + \sum_{i=1}^{n} r_i^* (t_{i3} - t_{i2}) + \ldots \\ &\quad + \sum_{i=1}^{n} r_i^* (t_{iq} - t_{i,q-1}) \\ &= \sum_{i=1}^{n} r_i^* (t_{iq} - t_{i1}) > 0. \end{aligned}$$

Hence, $\sum_{k=1}^{n_0} w_k^* \beta_{1k} \ge \sum_{k=1}^{n_0} w_k^* \beta_{qk}$ and $g_{1,q} = \sum_{i=1}^{n} r_i^* (t_{iq} - t_{i1}) > 0$ which means that the arc (comp_1, comp_q) is included in the arc set of $\mathscr{N}$ and has weight $g_{1,q}$. This completes the proof of the proposition. □

According to Proposition 3, there exists a longest weighted path that consists of a single arc. To identify such an arc it is enough to check all arcs emanating from comp_1. This takes no more than $\mathscr{O}(\triangle)$ time, where Δ denotes the maximum degree of the nodes of $\mathscr{N}$. Finding this arc, identifies a competitor with largest distance (according to measure $wl(\cdot,\cdot)$) from comp_1.

A.2. Solution methods for optimization models

In this subsection, we discuss solution procedures for models (P) and (P'). Model (P_C) has the same form as (P); the two models differ only in the coefficients of the objective function. All other models used in the body of the paper are linear programs.

Model (P) can be solved optimally using the following simple dynamic program (DP).

$f_k(w)=$ the maximum objective function value for the parts $p_1, p_2, \dots, p_k$, and a budget of w units.

Recurrence relation: $f_k(w)=\max_{1\le l\le n_k}\{f_{k-1}(w-c_{kl})+w_k\mathscr{P}_k(c_{kl})\},\ k=1,2,\dots,n_0$.

Boundary conditions: $f_0(w)=0$ if $0\le w\le W$; $-\infty$ otherwise.

Solution: $f*=\max_{0\le w\le W} f_{n_0}(w)$.

Further, to identify the smallest budget w that maximizes the objective function of (P), we search for $\min_{f_{n_0}(w)=f*} w$. The state space of DP is of order $\mathscr{O}(n_0W)$ and hence the computational complexity is $\mathscr{O}(n_0^2W)$.

This completes our presentation for (P).

Problem (P') is significantly harder than (P) because it considers the parts mix and rankings subproblems simultaneously. In particular, for a given parts mix (i.e., a given assignment), (P') is equivalent to model (LP). For given rankings, (P') reduces to (P) and hence the previous DP algorithm applies. These facts indicate that an efficient branch and bound algorithm is possible for (P'), that uses (P) and (LP) as subroutines. Developing such an algorithm for (P') is beyond the scope of this article which focuses more on a modeling framework for QFD rather than algorithmic development. Developing a dynamic programming algorithm for (P') is possible, however the usefulness of such algorithm would be limited due to its high computational complexity.

References

Akao, Y. (Ed.), 1990. Quality Function Deployment. Productivity Press, Cambridge, MA.

Araya, A.A., Ibrahim, N.A., 1994. Advancing quality function deployment with case-based capabilities. Journal of Design and Manufacturing 4, 265–280.

Day, R.G., 1993. Quality Function Deployment: Linking a Company with its Customers. ASQC, Milwaukee, WI.

Dijkstra, E.W., 1959. A note on two problems in connection with graphs. Numerische Mathematik 1, 269–271.

Evans, J.R., Lindsay, W.M., 1996. The Management and Control of Quality. West Publishing, Saint Paul, MN.

Guinta, L., Praisler, N., 1992. The QFD Book. AMA Press, New York.

Hauser, J., Clausing, D., 1988. The house of quality. Harvard Business Review 3, 63–73.

Jebb, A., Sivalaganthan, S., Edney, R., Evbuomwan, N., Wynn, H., 1992. Design function deployment. Engineering Systems Design and Analysis 1, 251–256.

Kolodner, J., 1993. Case-Based Reasoning. Morgan Kaufmann, San Mateo.

Kupparaju, N., Ittimakin, P., Mistree, F., 1985. Design through selection: a method that works. Design Studies 2, 91–106.

Lee, J., Lai, K., 1991. What's in design rationale? Human–Computer Interaction 6, 251–280.

Papadimitriou, C.H., Steiglitz, K., 1982. Combinatorial Optimization: Algorithms and Complexity. Prentice-Hall, Englewood Cliffs, NJ 07632.

Redei, L., 1934. Ein kombinatorischer Satz. Acta Litt. Sci. Szeged 7, 39–43.

Riesbeck, C.K., Schank, R.C., 1989. Inside Case-Based Reasoning. Lawrence Erlbaum Associates, NJ.

Shillito, M.L., 1994. Advanced QFD: Linking Technology to Market and Company Needs. Wiley, New York.

Shillito, M.L., DeMarle, D.J., 1992. Value: Its Measurement, Design, and Management. Wiley, New York.

Slade, S., 1991. Case-based reasoning: a research paradigm. AI Magazine 12, 42–55.

Sullivan, L.P., 1986. Quality function deployment. Quality Progress 19, 39–50.