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PRODUCT ATTRIBUTE FUNCTION DEPLOYMENT (PAFD) FOR DECISION–BASED CONCEPTUAL DESIGN

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ABSTRACT

Quality Function Deployment (QFD) is a method that links the "Voice of the Customer" to product planning activities within design, production and marketing. It utilizes weighting factors and relationship matrices to rank order the importance of product attributes. However, fundamental flaws have been identified in using QFD, which result in irrational and unrealistic results when used for design concept selection and setting target levels of attributes for a design team. In this paper, based on the principles of Decision-Based Design (DBD), a new tool called the Product Attribute Function Deployment (PAFD) is introduced as an improvement to the QFD process. The PAFD method extends the qualitative matrix principles of QFD and utilizes the quantitative decision making processes of DBD, which incorporates the needs from both the producer and consumers in a rigorous decision making framework. The DBD method takes an enterprise view in problem formulation and optimizes a single criterion to avoid the difficulties associated with weighting factors and multi-objective optimization. In addition to the quantitative improvement, the definition of engineering attributes in the QFD method is formalized to include corporate, regulatory, manufacturing and other technical requirements to facilitate conceptualization of design alternatives and constraints. The conceptual design of the automotive Manifold Absolute Pressure (MAP) sensor is used as a case study to demonstrate the benefits of the PAFD method.

1. INTRODUCTION:

The Quality Function Deployment (QFD) process was developed in the 1960's as a means to link product planning directly to the "Voice of the Customer". The key element of the process, called the House of Quality (HoQ) was introduced in the US in the 1980's [1]. In addition to identifying the key engineering aspects in product design, the HoQ has also been used to set target levels of performance considering competitors' products and to study the correlation among the engineering characteristics. Much literature has demonstrated both successes and issues with the methodology [2]. In recent years, there has been increasing criticism on using QFD for ranking the importance of engineering characteristics and using it for decision making.

In the engineering research community, there is a growing recognition that decisions are the fundamental construct in engineering design (Marston et al. [3]; Shah and Wright [4]; Dong and Wood [5]; Schmidt and Herrmann [6]; Gu et al. [7]). The Decision-Based Design (DBD) approach [8] has been developed to model design as a decision-making process that seeks to maximize the value of a designed artifact through the use of optimization. Recent efforts in DBD research resolve trade-offs among technical objectives by utilizing models of the producer's financial objective, such as net revenue or profit (Hazelrigg [8]; Li and Azarm [9]; Wassenaar and Chen [10]; Michalek et al. [11]). Although the DBD approach provides a rigorous mathematical framework for decision making, it has not been applied widely due to the complexity of integrating *product planning* and *engineering product development* into an optimization formulation that involves various types of product design attributes with different levels of abstraction. *To manage the complexity of implementing the DBD approach, there is a need to develop design tools that can effectively guide the process of executing the method.* Such qualitative tools are especially useful in conceptual design when the design concepts are not fully developed and the quantitative descriptions are not completely available.

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While the flaws associated with the QFD approach limit its use as a quantitative tool for decision making, the QFD analysis does provide an effective visual tool and promote a rigorous thinking process for qualitatively linking product attributes to ensure that product planning activities are conducted while considering the voice of the customer. Also, it facilitates a multidisciplinary design process among marketing, engineering, and production. In this work, a Product Attribute Function Deployment (PAFD) method is introduced which extends the QFD mapping matrix concept to qualitatively identify relationships and interactions while employing the principles of Decision-Based-Design (DBD) to provide quantitative assessments for concept selection and attribute target setting. Our research development leads to a product design tool that overcomes the limitations of the QFD method and facilitates the implementation of the DBD approach.

2. QFD PROCESS AND ITS LIMITATIONS

The primary feature of the QFD process is the use of a House of Quality to provide inter-functional product planning mapping to link engineering decisions to customer desires. The relative importance of each engineering characteristic determines the product planning priorities of the enterprise. The House of Quality with major features is shown in Figure 1.

Based on the survey of the literature and our own views, the limitations of the QFD method are summarized into the following five main categories.

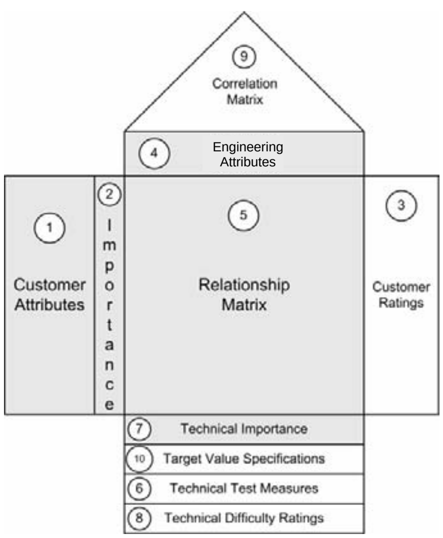


Figure 1: House of Quality, 1st House [12]

Limitation 1: Irrational Importance Rankings. Hazelrigg [13,14] has shown through the use of Arrow's Impossibility Theorem (AIT) that the importance weightings for ranking the importance of engineering attributes can be irrational when more than two attributes are ordered. Olewnik and Lewis [12] have demonstrated through the use of designed experiments that the QFD rating scale used in the relationship matrix yields results comparable to inserting random variables, or completely different scales in its place.

Limitation 2: Incorrect Aggregation of Customer Preferences. With the QFD approach, the importance ranking assumes that all customers' preferences are the same and can be represented by a group utility. But based on AIT, Hazelrigg has shown that group utility cannot exist: utility only exists at the individual, or disaggregate level [13]. *Each customer has a specific preference, and the demand for a product can only be determined by aggregating individual choices.*

Limitation 3: Unrealistic Settings of Target Values. According to Aungst et al. [15], targets that are set based on the information contained in the HOQ alone are unrealistic. Using only customer and competitor information without the consideration of other product objectives such as market share, contribution margin, or potential profit to set targets can result in targets that can never be achieved in practice.

Limitation 4: Biased Towards Meeting Customers' Requirements. Due to its philosophy, the QFD method is overly biased towards meeting customers' requirements. Gershenson and Stauffer [16] developed a taxonomy for design requirements for corporate stakeholders. They consider not only end-user requirements as in conventional QFD analysis, but also corporate, regulatory and technical requirements. This set of requirements is used as a basis for the Engineering Attributes **E** utilized in our proposed PAFD method.

Limitation 5: Ignorance of Uncertainty. Although the consideration of various sources of uncertainty is imperative in engineering design, the QFD analysis only offers a deterministic approach to ranking importance and setting target performance. It lacks a mathematical framework to incorporate uncertainty into decision making.

Other significant limitations are the over–simplification of attribute coupling in the "roof" of the QFD; an inadequate reflection of real design tradeoffs due to the subjective nature of ranking; a lack of well defined hierarchical structure of attributes; and a lack of methodology for considering manufacturing/production constraints. In the following section, introduction to the Decision-Based Design is provided to illustrate how in principle the DBD approach can be used to overcome the aforementioned limitations of the QFD method.

3. THE DBD APPROACH AND ITS STRENGTHS

The framework for the DBD method considered in this paper follows that of Wassenaar and Chen [10], Figure 2. When applied to conceptual design, the DBD approach can be used to select a preferred system concept and determine the target levels $\mathbf{E}^T$ of engineering attributes as opposed to specific values of design variables.

Single-Objective Utility optimization

In the DBD method, a single selection criterion, typically profit (net revenue), is employed to maximize the expected utility of a designed artifact. This single-objective approach avoids the difficulties associated with weighting factors and multi-objective optimization. It should be noted that uncertainty is considered explicitly and the objective is expressed as the maximization of the expected utility $E(U)$, considering decision maker's risk attitude.

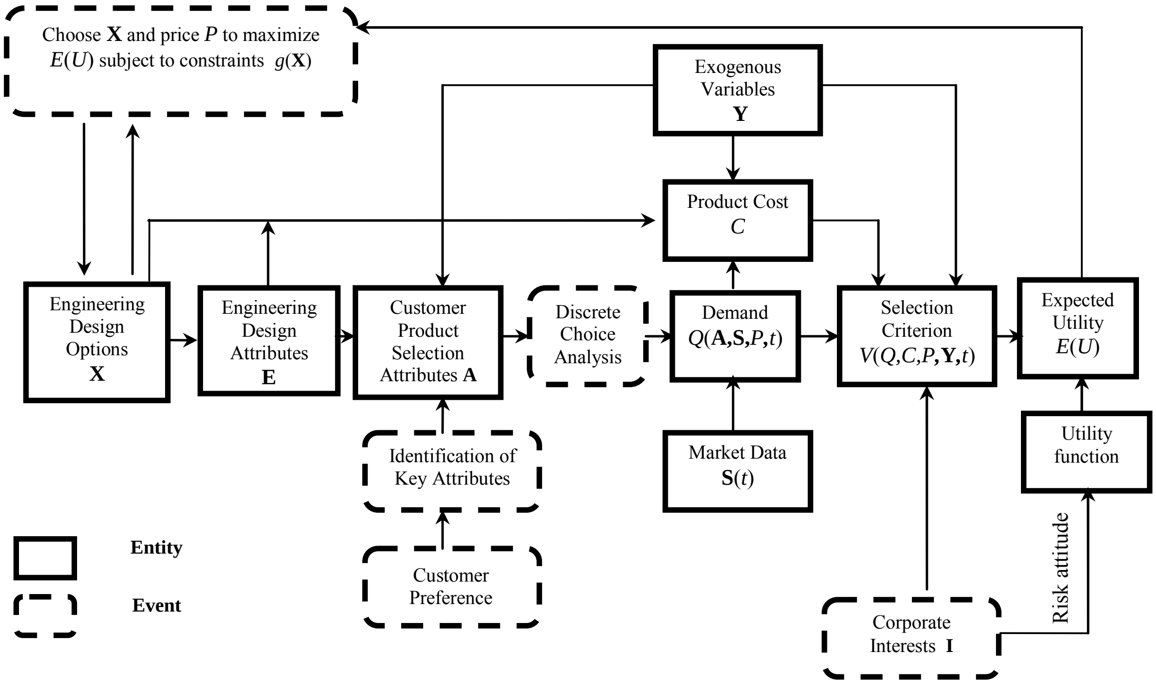


Figure 2: The Decision Based Design Framework [21]

Enterprise-Driven Design Formulation

The DBD approach takes an enterprise view in formulating a design problem and addresses several limitations of the QFD method described earlier. In this work, the *enterprise* is defined as the organization that designs and produces an artifact to maximize its utility (e.g., profit). The selection criterion V is typically net profit, Π, for the enterprise and is expressed as a function of product demand Q, price P, cost C, exogenous variables **Y** (the sources of uncertainty in the market), and time t. Based on these relationships, demand Q, is expressed as a function of customer product selection (CPS) attributes **A**, customer demographic attributes **S**, price P, and time t. Similar to "customer attributes" in QFD, **A** are product characteristics that a customer typically considers when purchasing the product. Engineering design attributes **E** are described as performance functions **E**(**X**) of engineering design options **X** through engineering analysis. In the proposed PAFD process (see Section 4), **E** can be put into several categories including those directly related to the product selection $\mathbf{E}_A$, and those resulting from corporate $\mathbf{E}_C$, regulatory $\mathbf{E}_R$ and physical requirements $\mathbf{E}_P$ which a customer does not consider explicitly in product selection. Qualitative CPS attributes **A** need to be expressed in terms of quantitative engineering attributes $\mathbf{E}_A$ in demand modeling to assist engineering decision-making.

$$
\begin{aligned}
V &= Q(\mathbf{A},\mathbf{S},P,t)\times P - C \\
&= Q(\mathbf{E_A},\mathbf{S},P,t)\times P - C(\mathbf{X},\mathbf{Y},Q,t) \\
&= \Pi(\mathbf{E_A},\mathbf{X},\mathbf{S},P,\mathbf{Y},t)
\end{aligned} \tag{1}
$$

As seen in Figure 2, by specifying the risk attitude, the optimization approach can be used to determine the optimal design options **X**, as well as optimal levels (targets) of engineering design attributes **E** to maximize the expected utility $E(U)$, subject to constraints $g(\mathbf{E}, \mathbf{X})$.

Modeling Customers' Preference using Discrete Choice Analysis (DCA)

To estimate the effect of design changes on a product's market share and consequently on the firm's revenues, Discrete Choice Analysis (DCA) [17] is used for demand modeling in DBD [10]. The use of DCA method to capture individual customers' choice behavior while considering the performance of the designed artifact versus competitors' products overcomes the incorrect aggregation of customer preferences with the QFD method. It should be noted that the customers could be either individual consumers or industrial customers. One of the primary motivations behind the use of DCA techniques is *their ability to model customer preferences at the individual customer level*. While there are a number of DCA techniques popular in literature (e.g., Multinomial Logit, Nested Logit, Mixed Logit), they are distinguished from each other by the degree of sophistication with which they model the unobserved error and heterogeneity in customer preferences. In the Multinomial Logit (MNL) model, the *coefficients of the choice utility function* (β) *for the product attributes are identical across all customers*. However, heterogeneity is modeled by considering demographic attributes (e.g., customer's age, income, etc.) in the choice utility function. Additional details on the use of MNL model for engineering design applications can be found in [10,20].

Latent Variable Modeling to Capture Perceptual Attitudes and Attributes Hierarchy

Latent variable modeling [18,19] can be included as part of the demand model to capture customer perceptual attitudes toward a designed artifact. Latent variables **L** (e.g., vehicle performance), are product attributes that cannot be measured directly; however, latent variables do influence customer's choice behavior, and can be measured by observing indicators **I** of these psychological factors (e.g., through survey ratings that reflect individual's perceptions). Latent variables account for the fact that customers do not always select a product based on the actual values of a set of attributes (e.g., horsepower,), but rather on perceived qualities (e.g., performance). With latent variable modeling, the structural model expresses the latent variables **L** (e.g., performance) as a function of the customer attributes **A** (e.g., horsepower, turning radius, steering effort, torque) and the customer background **S** (e.g., age, income, education, household size); the measurement model measures the relationship between the latent variables **L** and the indicators **I** (e.g., customer ratings for passing power at highway speeds, overall feeling about the engine). As indicated in Figure 3, combining the latent variable model with the Discrete Choice Analysis forms the integrated discrete choice latent variable model. The latent variable approach separates attributes into groups, i.e., **L** form the set of high-level customer's desires and **A** form the specific CPS attributes. Further details of this method can be found in Wassenaar and Chen [20].

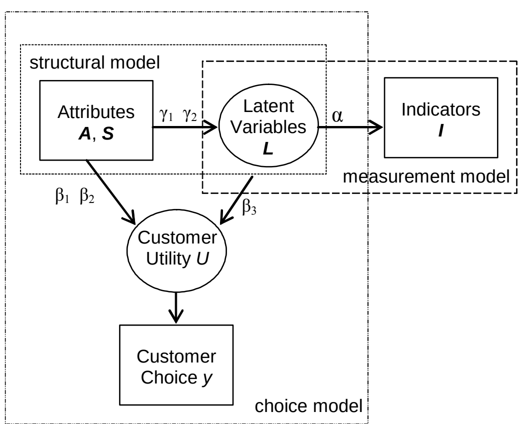


Figure 3: Description of Latent and Indicator Variables [20]

While DBD provides quantitative selection analysis, it does not include a formal process of mapping various types of attributes at various levels of abstraction to determine relationships and interactions, a feature that can be offered by the QFD Method with certain extensions.

4. PAFD METHOD

Combining the strengths of the QFD and the DBD methods, the PAFD method is developed in this work as a multiple–stage process that utilizes two "houses" to establish the qualitative attribute mapping and further formulate a DBD problem for optimal decision making. When applied to conceptual design, the goal of the PAFD method is to select the preferred design concept and determine target values $\mathbf{E}^T$ for the Engineering Design Attributes. The three-stage PAFD process is shown schematically in Figure 4.

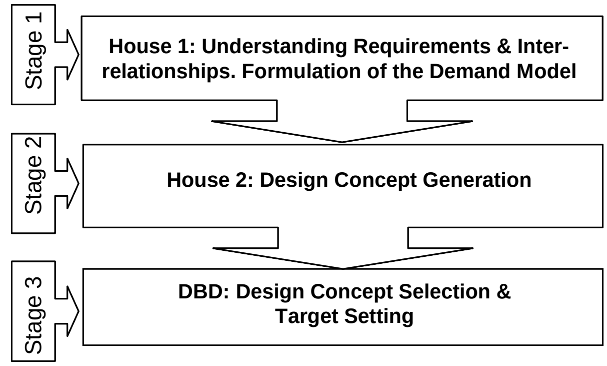


Figure 4: Three Stages of PAFD Methodology

Significant improvements and additions have been made to the fundamental QFD process. In the following descriptions, *elements of the PAFD method common with the QFD methodology have been shaded in gray* in the two houses shown in Figure 5 and Figure 9. The remaining elements are newly added to improve the QFD process; details are provided as follows for each stage.

Stage 1: Understanding of Requirements and Inter-Relationships

The first house of the PAFD method is used to accomplish the Stage 1 processes. Similar to the conventional QFD analysis is the deployment of mapping between engineering design attributes and customer attributes, as well as the determination of engineering attribute levels from competitors' products (competitive analysis). The Engineering Design Attributes determined in this matrix are the $\mathbf{E}_A$ related to product selection attributes **A** as described in Section 2.

Also expanded are several other matrices that establish the relationships between Customer Product Selection Attributes **A**, Latent Variables **L**, and Indicators **I**. Customer Demographic Attributes **S** are considered and interactions ($\mathbf{A}\times\mathbf{S}$) are identified to account for the heterogeneity of individual customers. This part of the expansion facilitates the construction of the DCA demand model to capture the impact of engineering design (engineering attributes) on customers' purchase behavior. As shown in Figure 5, House 1 is composed of 4 relationship matrices (labeled 1–4):

- **Matrix 1**: Mapping of CPS Attributes, **A**, to Engineering Design Attributes, $\mathbf{E}_A$.
- **Matrix 2**: Identifying interactions between demographic attributes **S** and **A**.
- **Matrix 3**: Mapping of **A** to customer perceptual Latent Variables **L**.
- **Matrix 4**: Mapping of **L** to the appropriate Indicators **I**.

Additionally, a table is provided for tabulating competitive alternatives:

- **Table A**: Table of competitive alternatives J with corresponding levels of $\mathbf{E}_A$.

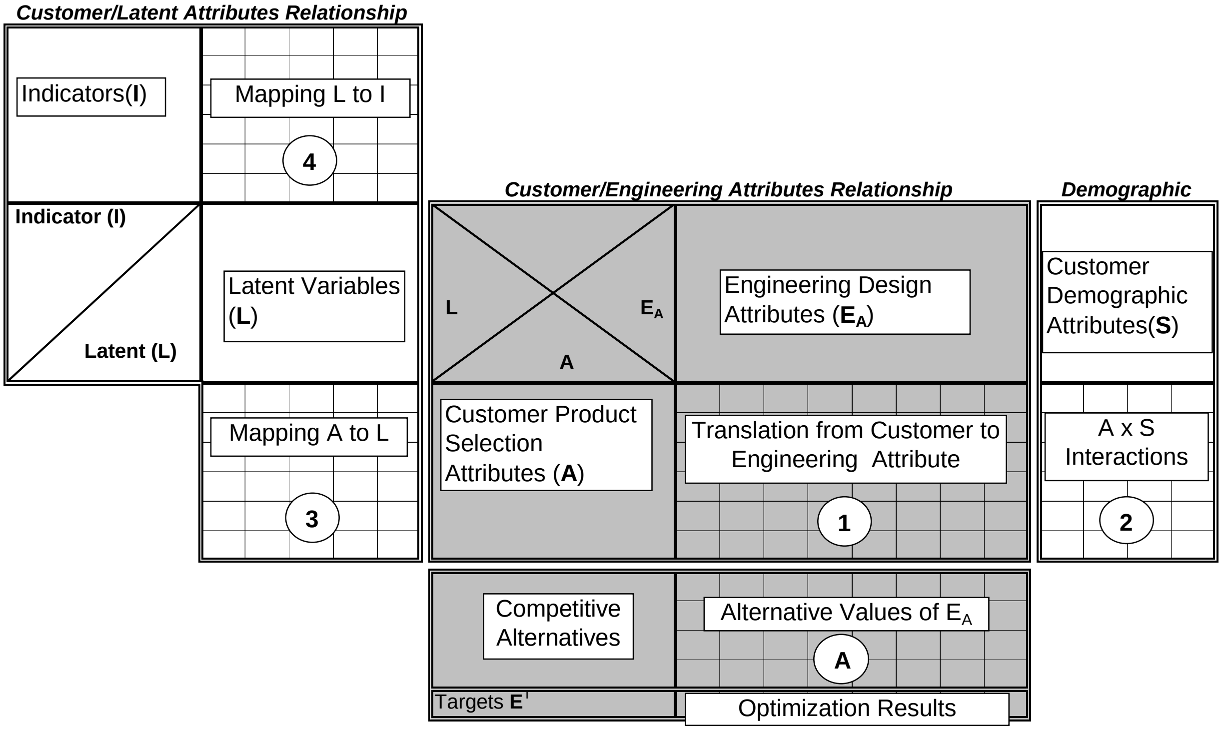


Figure 5: House 1 of the PAFD Method

The “roof” which identifies the coupling of Engineering Attributes has been eliminated in this house. The roof will be incorporated in the 2nd House in which specific design alternatives are generated. As noted in Section 2 and illustrated in the Example in Section 5, the coupling of multiple engineering attributes **E** largely depends on the chosen design concept, with **E** coupling in different ways for different design concepts. The relationship matrices in PAFD only show qualitative linking between attributes. A rating scale (i.e. 1, 3, 9) is not utilized to characterize the strength of the relationship; however, an “x” is placed to indicate the presence of a relationship. The purpose of completing these relationship matrices is to ensure that each of the **A** has a corresponding $\mathbf{E}_A$ and **S**, and that inter–relations between latent variables **L** and both **A** and **I** are clearly identified.

The demand model $Q(\mathbf{E}_A, \mathbf{S}, P, t)$ is estimated using the $\mathbf{E}_A$ and **S** (and optionally **L** and **I**) identified in House 1 as explanatory variables, with J comprising the set of choice alternatives based on competitors’ products. The form of the parameters in the demand model requires insight into customer choice behavior, with potentially several model iterations needed to maximize the goodness of fit. Linear (e.g. E_i) and transformed (e.g. E_i^2) forms of the variables are explored during the modeling process based upon expected customer demand behavior. The relationship matrices are used to guide the modeling of $A_i \times S_i$ interactions in terms of $\mathbf{E}_A$ and **S** necessary for the optimization formulation. Alternative Specific Constants (ASC) are utilized to represent preferences that are inherent and independent of specific attribute values.

Stage 2: Design Concept Generation

The $\mathbf{E}_A$ established in House 1 now become one set of product attributes, with the $\mathbf{E}_C$, $\mathbf{E}_R$, and $\mathbf{E}_P$ attributes added in the 2nd House to form the complete set of **E**. With a comprehensive set of **E** determined, design concepts can now be generated to fulfill the requirements. A design concept is defined as a high–level system configuration, composed of multiple subsystems and corresponding key design features **F**. Each design feature F_i is modeled by either continuous or discrete design options **X**, such as material type, dimension, etc. The number of design concepts that can be evaluated in PAFD is not fixed, with the house structure repeated for each additional concept to be evaluated. The key design features **F** associated with each concept are tabulated first in the Engineering–Design House structure (Figure 9), and then repeated in the Manufacturing–Design House structure (Figure 10) to facilitate the identification of manufacturing attributes **M**. The design options **X** selected *are the minimum, high–level set necessary to calculate the cost C_i of each feature* and to represent the coupling of the design features in the optimization problem to select a preferred concept and set targets $\mathbf{E}^T$; the specific form of the X_i are established in the detailed design process. The specific attribute mapping matrices provided in House 2 are shown in Figures 9 and 10 as:

- **Matrix 5:** Attribute Relationship Mapping of **F** to **E**.
- **Matrix 6**: Interactions among the individual Design Features F_i w.r.t. **E**.
- **Matrix 7:** Attribute Relationship mapping of **F** to **M**.
- **Matrix 8:** Interactions among the individual Design Features F_i w.r.t. **M**.

Additionally, a table is included for key design options:

- **Table B:** High-level design options **X** associated with the design features to be determined in optimization.

The key design features can be generated using several methods available in the design literature. Brainstorming and functional decomposition techniques [21,22] can be utilized to generate the design concepts and corresponding design features, while TRIZ (Theory of Inventive Problem Solving) principles [23] can be employed to aid in the creative process. Optionally, Suh's axiomatic design method [24] can also be employed with PAFD, enforcing an un-coupled or de-coupled relationship among the **E** and **X** and the **M** and **X**. After establishing the set of design alternatives and specific high-level design features, preliminary manufacturing process attributes **M** are identified for each concept. The **M** establish the material and process costs C_D of each option, identify additional constraints on **X** to include in the optimization problem, and ensure appropriate manufacturing processes are identified for each design alternative. Using the identified **X** and **M**, the cost total, C^k, for each design concept, k, is calculated by:

$$C^k(\mathbf{X}^k, Q) = \sum_N C_D^k(\mathbf{X}^k, Q) + C_{CC}^k + C_{CO}^k \quad (2)$$

where $C_D^k(\mathbf{X}^k, Q)$ is the material and processing cost for each design option, N is the number of design options, C_{CC}^k is the cost of capital, and C_{CO}^k is corporate overhead cost for each design concept.

Stage 3: DBD: Design Alternative Selection & Target Setting

From Houses 1 and 2, the parameters necessary to form the DBD optimization problem as laid out in Section 3 are identified. For each design alternative (concept), the attribute mapping in House 2 provides the qualitative relationship between the **X** and **E**. From the qualitative relationship, the quantitative functional relationship $E_i = f(\mathbf{X})_i$ is established using engineering analysis.

The design variables which describe **X** can take the form of integer, discrete, or continuous values. In cases where design options are highly conceptual, and an analytical relationship cannot be estimated, the range of achievable levels of **E** can be estimated in the optimization formulation. Since each design concept may have a different relationship for a given E_i, the optimization algorithm must search each design concept branch for the optimal solution.

The optimization problem, as presented in the description of the DBD framework in Section 3, is formulated to maximize the expected utility E(U). Constraints are of the form $g(\mathbf{X}, \mathbf{E}) \leq 0$, and are estimated for each design concept based upon physical and manufacturing limitations upon the **X** identified in House 2. As the result of optimization, a preferred design concept, described by high-level design options **X,** and the target values for the Engineering Design Attributes $\mathbf{E}^T$ are determined for further engineering development.

5. AUTOMOTIVE SENSOR CASE STUDY

The design of an automotive pressure sensor is used as a case study to demonstrate the PAFD methodology. The specific example considered is to design a standard Manifold Absolute Pressure (MAP) Sensor for the automotive industry. The MAP Sensor measures the air pressure in the intake manifold for fuel and timing calculations performed by the engine computer. The customers are *industrial customers*, composed of both automobile manufacturers and engine system sub–suppliers. The targeted market is the mid-size sedan segment. A high level function diagram of a MAP sensor is shown in Figure 6.

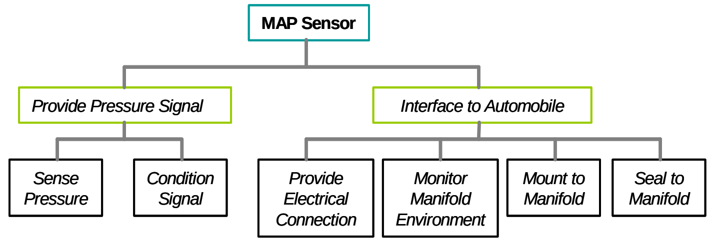


Figure 6: MAP Sensor Functions

Multiple sensing technologies exist for pressure measurement, and each technology drives specific corresponding high-level design features, resulting in differing levels of performance and cost structure for each design concept. *Therefore, before detailed design of the sensor, a decision on the conceptual design alternative must be made and target levels of performance must be established.*

Since this is an industrial application, it is assumed that customer perceptual attitudes are of minimal importance, i.e., the industrial customers can directly relate to the actual values of product attributes when making choices. Hence, Latent variable modeling is not considered and Matrices 3 and 4 in House 1 are not used in this particular example. Additionally, a risk neutral attitude is assumed for the enterprise, and the market is assumed to be constant over the time interval t. To complete the PAFD process, a cross-functional design team is assembled in the same manner as a QFD analysis. The team then completes the three stages of PAFD shown in Figure 4.

Stage 1: Understanding MAP Sensor Requirements and Interrelationships

As the first step in stage 1, key CPS attributes **A** (e.g. *High Accuracy* and *Wide Pressure Range*) and demographic attributes **S** (e.g. *Vehicle Selling Price*) are identified and tabulated in House 1 (Figure 7). Next, key Engineering Design Attributes for the sensor, such as Pressure *Span* (kPa) and *Temperature Range* (°C), are determined by the design team and listed in the $\mathbf{E}_A$ row. With **A**, $\mathbf{E}_A$, and **S** identified, matrix 1 identifying the linking of the $\mathbf{E}_A$ to **A**, and matrix 2 identifying the interaction among **S** and **A**, such as the interaction of *High Accuracy* and *Vehicle Selling Price*, are completed. To determine a set of choice alternatives for the DCA model, competitive analysis is conducted on 5 hypothetical sensors (based upon available data sheets) and their attribute values of the $\mathbf{E}_A$ are tabulated. The results are shown in Figure 7.

A MNL demand model is formulated as a function of the values of $\mathbf{E}_A$ for the new sensor design and each of the competitive sensors. The model parameters determined to create a demand model with good fit statistics are composed of linear (e.g. *Span*, *Temperature Range*, *Burst Pressure*), interaction (e.g. *Accuracy* × *Vehicle Selling Price*) and alternative specific variables (ASV) (e.g. *Alternative*$_j$ × *Vehicle Selling Price)*. These parameters establish the utility of each alternative as described in Section 3 and are summarized in Figure 7 as well.

Customer/Engineering Attributes Relationship										Demographic		
E_A / A	Sense Element Accuracy (%)	Span (kPa)	Temperature Range (°C)	Output shift Due to Contamination (mV)	Burst Pressure (MPA)	Housing Footprint (mm^2)	Natural frequency housing (hz)	Connector Mating Force (N)	Sensor Price ($)	Country of Origin	Vehicle Selling Price ($)	*Interaction Parameters*
High Accuracy	x	x	x							x	x	**3.2**
Wide Pressure Range	x	x										
Withstand Temperature Extremes			x								x	**2.1**
Withstand Chemical Environment				x							x	
Withstand Pressure Pulses		x			x							
Fits in dimensional envelope		x				x						
Withstand Manifold Vibration						x	x					
Low Connector Mating Force								x				
Sensor Price									x		x	
Competitor A	1.8	80	145	7.0	1.0	1800	1500	35	0.95	Base	Base	Base
Competitor B	1.0	240	150	5.0	2.5	1500	1500	40	1.09	**2.0**	**8.5**	**-1.8**
Competitor C	0.8	185	165	5.0	2.0	1725	1500	25	1.02	**-1.3**	**5.1**	**-1.1**
Competitor D	1.0	250	165	0.0	10.0	2650	2000	35	1.20	**1.6**	**24.0**	**1.4**
Competitor E	1.8	250	150	0.0	10.0	2400	2000	40	1.15	**0.1**	**18.2**	**0.6**
DCA Linear Parameters	**-14.2**	**2.3**	**5.1**	**-0.9**	**24.0**	**-40.0**	**-6.5**	**-1.5**	**-48.8**	*ASV*	*ASV*	*ASC*
Targets T*												

Figure 7: House 1 for MAP Sensor

Stage 2: MAP Sensor Design Concepts Identification

Stage 2 begins by transferring the $\mathbf{E}_A$ identified in House 1 to the **E** Column in House 2 (Figure 9) and identifying the design concepts. For this problem, two design concepts were identified: *Concept 1* utilizes a piezoresistive sensing element with a micro–machined sensing diaphragm and *Concept 2* utilizes a two–plate capacitive sense element, shown conceptually in Figure 8. The additional engineering design attributes, $\mathbf{E}_C$, $\mathbf{E}_R$, $\mathbf{E}_P$, are established by the design team and placed in the appropriate section of the **E** Column. For example, the design team has identified *UL Flammability Resistance* and *Recyclability* as $\mathbf{E}_R$, and *Minimum Trace Cross-sectional Area* of electrical connections and *Housing Stress* as $\mathbf{E}_P$; however, no $\mathbf{E}_C$ have been identified for this problem.

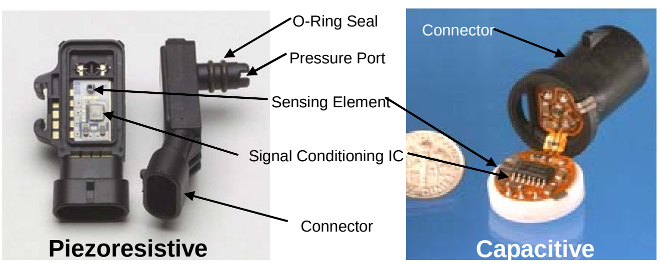


Figure 8: Comparisons of Concepts 1 and 2

The key design features for each concept are established and corresponding high-level design options **X** to model the concept performance and cost in the optimization problem are determined and tabulated in Table B of House 2. For example, $\boldsymbol{T}_E$ (Piezoresistive Sense Element Thickness) is a continuous variable to be determined based on the tradeoff between pressure *Span* and the current manufacturing limitation; $\boldsymbol{D}_{IC}$ (Integrated Circuit A/D Discretization Error) is a discrete variable to be determined based on the tradeoff between the resolution, pressure *Span*, and cost.

Key conceptual manufacturing process attributes **M** (e.g., silicon micro-machining, injection molding, etc.) are identified for each design concept, and placed in the corresponding **M** columns of Matrix 7 (Figure 10).

This case study demonstrates the key features of the PAFD method. As shown, the technology selection drives specific design features and the corresponding set of design options for a given design concept. For example, the packaging of each sensor is fundamentally different: concept 1 uses an injection–molded housing with integral pressure port and connector, whereas concept 2 requires a separate port and connector component, requiring a constraint to ensure their assembly.

Also noted, each set of high-level design options (**X**) for a given alternative has a different functional relationship with **E**. Concept 1 utilizes the piezoresistive sensing element with a resistance output given by the relation [25]:

$$Span \propto k(\Delta L_E / L_E) \qquad (3)$$

where the engineering attribute is Span, the design option is diaphragm length L_E, and the piezoresistive k-factor, k, is a constant. Concept 2 utilizes a capacitive output given by:

$$Span \propto \varepsilon_0 \varepsilon_r \left(A_E / D_E\right) \qquad (4)$$

where the engineering attribute is *Span*, the design options are the plate area A_E, and the plate separation distance D_E, with absolute and relative dielectric constants, ε_0, and ε_r.

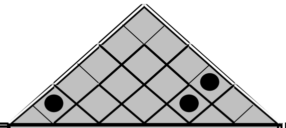
As seen in the roofs of Figures 9 and 10, the design features couple in different ways for each concept. Attributes which interact in one concept may have no interaction or a different coupling in another concept. Also shown, each concept requires a specific manufacturing process flow, and the different sets of **M** result in a differing cost structure and place different constraints upon the **X**. For example, the micro-machining process used to make the diaphragm of the piezoresistive sense element has a minimum manufacturable diaphragm thickness, and hence, places a constraint on the minimum size of the sense element, independent of engineering analysis.

Also confirmed by this study is that Engineering Design Attributes **E** resulting purely from CPS Attributes **A** are not sufficient to create an Engineering Specification (target setting). For the sensor, physical limitations on the current carrying capacity of the traces and stresses induced by the manufacturing process lead to key engineering requirements which would not result from customer desires.

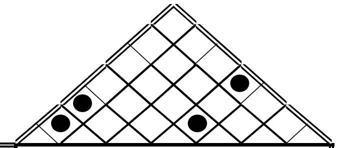
Stage 3: Design Concept Selection and Target Setting

Stage 3 is conducted by formulating, the optimization problem as shown in Table 1. A demonstration of uncertainty is also considered in this problem: the PRT Sense Element Thickness T_E and Capacitive Sense Element Plate Separation Distance D_E are normally distributed random variables due to known variation in the element manufacturing processes.

The results of the optimization problem are summarized in Table 2, showing target levels $\mathbf{E}^T$, and values of demand, price, and cost which maximize net revenue. The preferred design concept for this problem is Concept 1, resulting in highest net profit for the enterprise while considering uncertainty. A point to note is that concept 1 did not result in the highest market share, but due to cost structure, resulted in the highest profit *V*.

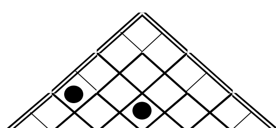


	Subsystem / Design Features (F) / Engineering Attribute (E)	Micromachined PRT Element	Signal conditioning IC	Die Encapsulent	Integral molded housing/connector	Housing Reinforcement Structure	Integral USCAR Connector Features
		Design Concept 1					
		Sensing			Packaging		
E_A	Sense Element Accurcacy (%)	x	x				
	Span (kPa)	x	x				
	Temperature Range (°C)		x		x		
	Output shift contamination (mV)			x			
	Burst Pressure (MPa)	x					
	Housing Footprint (mm^2)				x		
	Natural frequency housing (hz)					x	
	Connector Mating Force (N)						x
E_R	UL Flamability Resistance				x		
	Recyclablity				x		
E_T	Housing Stress (kPa)					x	
	Trace Min X sectional area (mm^2)				x		
	Design Options X	L_E	D_{IC}	D_F	W_H	H_R	F_C
		T_E	C_{IC}		L_H	T_R	
					A_T		
					P_H		

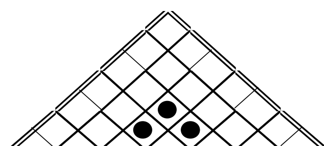


Subsystem / Design Features (F) / Engineering Attribute (E)	MicroMachined Capacitive Element	Signal conditioning IC	Housing	Pin Connector	Interconnection circuit	Assembly Reinforcement Structure	USCAR Connector Features
	Design Concept 2						
	Sensing		Packaging				
Sense Element Accurcacy (%)	x	x					
Span (kPa)	x	x					
Temperature Range (°C)		x	x	x			
Output shift contamination (mV)	x						
Burst Pressure (MPa)	x						
Housing Footprint (mm^2)			x	x			
Natural frequency housing (hz)						x	
Connector Mating Force (N)							x
UL Flamability Resistance							
Recyclablity							
Housing Stress (kPa)						x	
Trace Min X sectional area (mm^2)					x		
Design Options X	D_E	D_{IC}	W_H	D_C	A_T	H_R	F_C
	A_E	C_{IC}	L_H	L_C		T_R	
			P_H				

Figure 9: Engineering–Design House 2 for the MAP Sensor



Subsystem / Design Features (F) / Manufacturing Attribute (M)	Process Cost ($/hr)	Micromachined PRT Element	Signal conditioning IC	Die Encapsulent	Integral molded housing/connector	Housing Reinforcement Structure	Integral USCAR Connector Features
		Design Concept 1					
		Sensing			Packaging		
Micromachining PRT Element	120	x					
Ceramic board population	60		x				
Digital Calibration	100						
Encapsulent Dispense	40			x			
Insert Mold Housing	40				x	x	x
Assemble housing components	40				x		
Final Test	60	x	x				



Subsystem / Design Features (F) / Manufacturing Attribute (M)	Process Cost ($/hr)	MicroMachined Capacitive Element	Signal conditioning IC	Housing	Pin Connector	Interconnection circuit	Assembly Reinforcement Structure	USCAR Connector Features
		Design Concept 2						
		Sensing		Packaging				
Micromachining Cap. Element	140	x						
Flex circuit population	80		x					
Laser Trim	100							
Machine Port	70			x				
Connection to Pressure Port	80	x		x				
Interconnection to Connector	60				x	x		x
Final test	60	x	x					

Figure 10: Manufacturing–Design House 2 for the MAP Sensor

Table 3 shows the market share distribution before and after introduction of the new MAP sensor. The target levels identified for the preferred concept are not simply the best values of $\mathbf{E}_A$ identified from competitive analysis, but reflect the actual achievable levels of $\mathbf{E}_A$ for this design concept, based upon the constraints imposed in the optimization problem. This is further illustrated by noting that concept 2 has a different set of $\mathbf{E}^T$ corresponding to the maximum profit for that alternative. In summary, the PAFD method has provided a clear conceptual direction and engineering targets necessary to begin the detailed design of the MAP sensor.

Table 1: Pressure Sensor Optimization Problem

Given

Mid-Size Sedan Market Size 1,000,000 [sensors/year]

Demographic data of targeted industrial customers **S**

Engineering Attributes $\mathbf{E}_A$ (PAFD: House 1)

$\mathbf{E}_A$ determined as a function of the high-level design options **X**

Design Concept (PAFD: House 2)

2 Design Concepts considered (piezoresistive & capacitive sensing)

Sources of Uncertainty Y

Normal Distribution of T_E and D_E $\sigma = (0.1)\ \mu$

Cost Model (PAFD: House 2)

Cost of each alternative given by Equation 2.

Demand Model *Q* (PAFD: House 1)

Obtained from the MNL model of the competitive alternative attribute data.

Single criterion $V = QP$-C

FIND:

Design Options **X**, Target Engineering Levels $\mathbf{E}^T$ (PAFD: House 1) and Price *P*

MAXIMIZE:

E(*V*), assuming an enterprise risk neutral attitude

SUBJECT TO (PAFD: House 2):

$g(\mathbf{X}, \mathbf{E}) \leq 0$ Constraints on **X, E** due to design & manufacturing requirements

$g(\mathbf{X}, \mathbf{E}) \leq 0$ Constraints on **X , E** due to coupling relationships

$g(\mathbf{X}, \mathbf{E}) \leq 0$ Constraints on **X , E** due to physical, regulatory, or corporate attributes

Table 2: Optimization Results–Preferred Concept (shaded)

Engineering Attribute E	**Concept 1 ($\mathbf{E}^T$)**	**Concept 2 ($\mathbf{E}^T$)**
Sense Element Accuracy (%)	1.0	1.3
Full Scale Span (kPa)	100.0	100.0
Temperature Range (°C)	145.0	145.0
Output shift contamination (mV)	3.0	0.0
Burst Pressure (MPa)	1.0	6.0
Housing Footprint (mm^2)	1500.0	1800.0
Natural frequency housing (Hz)	1000.0	1250.0
Connector Mating Force (N)	25.0	25.0
Demand / year (# sensors)	**325,000**	**362,000**
Unit Price (USD)	**$10.25**	**$10.50**
Expected(*V*) / year (USD)	***$597,000***	***$488,000***

Table 3: Market Share Comparison with New Sensor

	Initial ***Market Share***	**Concept 1** ***Market Share***	**Concept 2** ***Market Share***
Competitor A	9.9%	5.1%	4.6%
Competitor B	29.4%	16.8%	15.4%
Competitor C	12.6%	6.8%	6.2%
Competitor D	30.7%	26.2%	25.6%
Competitor E	17.4%	12.6%	12.0%
New Sensor		32.5%	36.2%

6. CONCLUSION

In this work, the Product Attribute Function Deployment (PAFD) method is developed to guide the process of executing the Decision-Based Design (DBD) approach. The need for developing such a method results from a close examination of the limitations of the QFD method and the advantages that the Decision–Based Design approach offers. The PAFD method extends the QFD mapping matrix concept to qualitatively identify relationships and interactions of product design attributes, while employing the DBD principles to provide rigorous quantitative assessments for design alternative decisions. In conceptual design, the PAFD method can be used to determine the optimal system concept and set targets for engineering design attributes. Alternatively, the PAFD method can be implemented, with minor modification, to work with other enterprise–driven design approaches which provide necessary quantitative assessments.

PAFD is presented as a multistage process that utilizes two “houses” to establish the qualitative attribute mapping and further formulate a DBD problem for optimal decision making. While keeping the functional deployment spirit of the QFD method, the PAFD method considerably extended and reconfigured the HoQs from traditional QFD methods. House 1 is used to capture the hierarchy of customer desires, perceptual attitudes, and explore the interactions between customers’ demographic attributes (e.g., age, income) and product attributes (e.g. accuracy, price) for the demand model formulation. House 2 is used to generate design concepts capable of meeting the set of engineering requirements, and identify design options, costs, and constraints to be included in the optimization problem formulation. In the final stage of alternative selection & target setting, the DBD method takes an enterprise view in problem formulation and optimizes a single criterion to avoid the difficulties associated with weighting factors and multi-objective optimization in QFD. The use of single-objective utility optimization provides a rigorous mathematical framework for decision making under uncertainty. The use of profit as a single criterion better captures the real design tradeoffs, incorporates the needs from both producer and consumers, and leads to more realistic settings of target values.

A case study involving the conceptual design of a Manifold Absolute Pressure (MAP) sensor is used to illustrate the benefits of the PAFD method. Complex trade-offs among engineering, manufacturing, and customer considerations in conceptual design which were treated unsatisfactorily in the traditional QFD analysis are resolved effectively by the PAFD approach. It should be noted that, in addition to conceptual design selection, the method can be applied repeatedly throughout the design process to lower levels in the design hierarchy to identify optimal design alternatives and set target levels of performance, subject to the specific constraints identified in the analysis.

Future research includes providing a more rigorous guide for creating the demand model in House 1 and providing more detail for the determination of costs and constraints in House 2. Also, expanding the design option definition to include enterprise-financial planning decisions that have a direct impact on those non-engineering related customer attributes (e.g., warranty and APR rate) can be explored. Different types of design problems can be solved with PAFD to better assess the feasibility of this method as a general design tool.

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REFERENCES

1. Hauser, J. and Clausing, D., “The House of Quality”, *Harvard Business Review*, **66**(3), pp. 63–74, May–June, 1988.

2. Chan, L., Wu, M., “Quality function deployment: A literature review”, *European Journal of Operational Research*, **143**, pp. 463–497, 2002

3. Marston, M., Allen, J., and Mistree F., “The Decision Support Problem Technique: Integrating Descriptive and Normative Approaches in Decision Based Design”, *Engineering Valuation & Cost Analysis, special edition on “Decision-Based Design: Status & Promise”*, **3**(2/3), pp. 107-130, 2000.

4. Shah, J.J. and Wright, P.K., “Developing Theoretical Foundations of DFM”, *Proceedings of DETC 2000 ASME Design Engineering Technical Conference*, Baltimore, MD, Sept. 10–13, 2000.

5. Dong, H. and Wood, W.H., "Integrating computational synthesis and decision-based conceptual design", *Proceedings of ASME 2004 Design Engineering Technical Conference*, Salt Lake City, Utah, Sept. 28–Oct. 2, 2004.

6. Schmidt, L.C. and Herrmann, J.W., "Viewing Product development as a decision production problem", *Proceedings of ASME 2002 Design Engineering Technical Conference*, Montreal, Canada, Sep 29–Oct 2, 2002.

7. Gu, X., Renaud, J., Ashe, L., Batill, S., Budhiraja, A., and Krajewski, L., “Decision-Based Collaborative Optimization,” *Transactions of ASME: Journal of Mechanical Design*, **124**(1), pp. 1–13, 2002.

8. Hazelrigg, G.A., “A Framework for Decision based Engineering Design”, *ASME Journal of Mechanical Design*, **120**, pp. 653-658, 1998.

9. Li, H., and Azarm, S., "Product Design Selection under Uncertainty and with Competitive Advantage", *Transactions of ASME: Journal of Mechanical Design*, **122**, pp. 411–418, 2000.

10. Wassenaar, H. J. and Chen, W., “An approach to Decision-Based Design with Discrete Choice Analysis for Demand Modeling”, *Transactions of ASME: Journal of Mechanical Design*, **125**(3), pp. 490-497, September, 2003.

11. Michalek, J., Feinberg, F. and Papalambros, P.Y., “Linking marketing and engineering product design decisions via analytical target cascading,” *Journal of Product Innovation Management*, **22**, pp. 42–62, 2005.

12. Olewnik, A. and Lewis, K., “On Validating Engineering Design Decision Support Tools”, *Concurrent Engineering: Research and Applications*, **13**, pp. 111–122, June 2005.

13. Hazelrigg, G.A., “The implication of Arrow’s impossibility theorem on approaches to optimal engineering design”, *J. Mech. Design*, **118**, pp. 161–164, 1996.

14. Hazelrigg, G.A., “Validation of Engineering Design Alternative Selection Methods”, *Engineering Optimization*, **35**, pp. 103–120, 2003.

15. Aungst, S., Barton, R., Wilson, D., “The Virtual Integrated Design Method”, Quality Engineering, **15**, pp. 565–579, 2003.

16. Gershenson, J.K., Stauffer, L.A., “A taxonomy for design requirements from corporate customers”, *Research in Engineering Design*, **11**, pp. 103–115, 1999.

17. Ben-Akiva, M. and Lerman, S.R., *Discrete Choice Analysis*, The MIT Press, Cambridge, MA, 1985.

18. Everitt, B.S., *An Introduction to Latent Variable Models*, Monographs on Statistical and Applied Probability, Chapman and Hall, 1984.

19. Loehlin, J.C., *Latent Variable Models, an introduction to factor, path, and structural analysis*, 3rd ed., Mahwah, NJ: L. Erlbaum Associates, 1998.

20. Wassenaar, H.J., Chen, W., Cheng, J., and Sudjianto, A., “An Integrated Latent Variable Modeling Approach for enhancing Product Demand Modeling*”, Proceedings of DETC 2004 ASME Design Engineering Technical Conference*, Salt Lake City, Utah, Sept. 28–Oct. 2, 2004.

21. McAdams, D., Stone, R., Wood, K., “Functional Interdependence and Product Similarity Based on Customer Needs”, *Research in Engineering Design,* **11**, pp. 1–19, 1999.

22. Stone, B. R. and Wood, K.L., “Development of a Functional Basis for Design”, *ASME Journal of Mechanical Design*, **122**, 359–370, 2000.

23. Altshuller, G.S., *Creativity as an Exact Science: The Theory of the Solution of Inventive Problems*, New York: Gordon and Breach Science Publishers, 1984.

24. Suh, N., *The Principles of Design*, New York: Oxford University Press, 1990.

25. Hauptmann, P., *Sensors: Principles and Applications*, Prentice Hall, Hertfordshire, 1993.

