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NEXT GENERATION QFD: DECISION-BASED PRODUCT ATTRIBUTE FUNCTION DEPLOYMENT

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ABSTRACT
The critical product planning phase, early in the product development cycle, requires a design tool to set engineering priorities, capable of selecting the preferred design concept and setting target levels of engineering performance to guide the later product development stages, while considering the needs of both the consumer and producer. The Quality Function Deployment (QFD) method was developed to transfer customer needs into engineering characteristics; however, limitations have been identified in using QFD, which can result in irrational and unrealistic results when used to set engineering priorities and target levels of product performance. In this paper, based on the principles of Decision-Based Design (DBD), a new design tool called the Product Attribute Function Deployment (PAFD) is demonstrated as a decision-theoretic, enterprise-wide process tool to guide the conceptual design phase. The PAFD method extends the qualitative matrix principles of QFD while utilizing the quantitative decision making processes of DBD to create a new process specifically for translating qualitative customer needs into quantitative engineering attributes and making early product design decisions. It is built upon established methods in engineering, marketing, and decision analysis to eliminate the need for subjective user ratings. In addition, the technical attributes considered are expanded beyond those typically considered to include requirements from the producer and regulators. The differences between QFD and PAFD are compared and the conceptual design of an automotive Manifold Absolute Pressure sensor is used to demonstrate the benefits of the PAFD method.

Keywords: Quality Function Deployment (QFD), Decision-Based Design, Conceptual design, Target setting, Sensor design, Decision making, Product attribute function deployment (PAFD)

1. INTRODUCTION
In the early stages of product design there is a need to set engineering priorities, primarily through the selection of a preferred design concept, identification of key product attributes, and establishment of performance targets for the artifact or *product* under design. Because product decisions made in the early or *conceptual* design phase can account for up to 75% of the committed manufacturing cost [1], it is essential that these decisions be rigorous and consistent with the objectives of the firm or *enterprise*. A design process tool utilized to guide these critical product planning activities must consider the needs of both the consumer and the producer in order to select concepts and set targets which will maximize the benefit to the enterprise as a whole. While design freedom is at a maximum in this phase, design knowledge is at a minimum, requiring that decisions made in this phase also explicitly consider uncertainty.

Within the engineering research community, there is a growing recognition that decisions are the fundamental construct in engineering design [2]. Traditionally, discipline specific decision-making methodologies, utilizing mathematical behavioral models such as those used in marketing (*e.g.*, conjoint analysis) and engineering (*e.g.*, differential equations), have been adopted based upon the specific needs of the individual discipline. These methods have used domain specific objectives as the decision criterion, biased towards either consumer product acceptance or producer performance metrics. These methods in isolation cannot achieve the necessary enterprise-level decision process required during the product planning phase, which has been acknowledged by the development of various process tools to bridge different enterprise domains to support product design activities [3].

Quality Function Deployment (QFD) was developed to bridge the marketing and engineering domains using a much simplified, consensus-driven qualitative analyses. This process was developed as a means to link product planning directly to the “Voice of the Customer”, and remains the leading tool for setting engineering priorities, determining target levels of product performance through benchmarking and, when supplemented with Pugh’s Method [4], selecting a design concept. The primary feature of the QFD process is the House of Quality (HoQ) [5], which provides inter-functional product planning mapping to link engineering attributes to customer desires, which are ranked in importance. In addition to identifying the key engineering aspects in product design, the HoQ has been used to document consumers’ rating of competitors’ products and to study the correlation among the engineering characteristics. The HoQ utilizes a weighted-sum multi-objective decision criterion, entailing technical test measures (benchmarking) analysis, technical importance rankings and estimates of technical difficulty to enable a decision maker to set performance targets for a designed artifact. The use of the HoQ will be demonstrated in Section 3. Pugh’s Method provides a method to compare alternative design concepts against customer requirements, with evaluations made relative to a base or favored concept, a process independent from the HoQ analysis.

Much literature has demonstrated both successes and issues with the QFD methodology [6]. Based on the survey of the literature and our own views, while QFD provides a useful attribute mapping methodology, it suffers from several limitations which can lead to sub-optimal or irrational early product decisions. Firstly, according to Aungst et al. [7], using only customer and competitor information to set targets without consideration of the physics of engineering attribute interactions or other product objectives such as market share and potential profit, can result in targets that can never be achieved in practice. Several proposed improvements to the QFD have been presented in the literature. Aungst et al. [7] have presented the Virtual Integrated Design Method which uses a quantitative, rather than qualitative, link between the conventional four HoQ matrices. Brackin and Colton [8] have proposed a method in which analytical relations between the engineering attributes and customer attributes are created and real values of engineering attributes are searched from an appropriate database to ensure targets are achievable. Locascio and Thurston [9] have combined the QFD ratings and rankings into a design utility function to determine performance targets using multi-objective optimization. Although these methods improve upon the target setting methodology of QFD, they utilize customer group importance rankings and engineering rankings which have been shown to be problematic [10].

In 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 Arrow’s Impossibility Theorem (AIT), Hazelrigg has shown that utility only exists at the individual, or disaggregate level [10]. *Each customer has a specific preference, and the demand for a product can only be determined by aggregating individual choices.* Although the Analytical Hierarchy Process (AHP) was introduced [11] to aid in the determination of importance rankings, Hazelrigg [10],[12] has shown through the use of AIT that the importance weightings for ranking the importance of engineering attributes can be irrational when more than two attributes are ordered. Further, Olewnik and Lewis [13] have demonstrated through the use of designed experiments that the HoQ rating scale used in the relationship matrix yields results comparable to inserting random variables, or completely different scales in its place. Additionally, due to its philosophy, the QFD method is overly biased towards meeting customers’ requirements. Prasad [14] presented an expanded QFD methodology called Concurrent Function Deployment (CFD) that expands upon the customer attributes to consider other corporate objectives, such as cost and manufacturing. Similarly, Gershenson and Stauffer [15] 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. These methods still employ conventional weighting and ratings techniques.

The limitations above point to the need for a design planning tool which is supported by a rigorous decision-making framework to ensure that consumer preference is accurately represented and targets set by the process are achievable in engineering design. The Decision-Based Design (DBD) method, an emerging design paradigm [2],[16],[17] provides such a desired rigorous decision making framework which models design as a decision-making process that seeks to maximize the value of a designed artifact through the use of utility optimization. Combining the strengths of DBD and QFD, the Product Attribute Function Deployment (PAFD) method was introduced in a previous work [18] as a comprehensive product planning process tool for the conceptual design phase, with preliminary results of the tool development provided. In this work, the PAFD process is fully developed and compared in detail to the QFD methodology. This comparison is conducted to demonstrate the parallels and differences between the two methods, and to illustrate how the PAFD method addresses the limitations described in this section which arise when conducting a QFD analysis on a real design problem.

2. PAFD DESIGN ASSESSMENT USING THE DBD FRAMEWORK

In this work, the DBD framework [2] has been formulated specifically for the conceptual design phase of a product or artifact for use in the PAFD method. A key feature of this method is the merging of separate marketing and engineering domains, described previously Section 1, into a single enterprise-level decision-making framework. In the DBD method, a single criterion, *V*, which represents economic benefit to the enterprise, typically profit, is employed as the selection criterion. This single-objective approach avoids the difficulties associated with weighting factors and multi-objective optimization [10]. A *utility function*, *U*, which expresses the value of a designed artifact to the enterprise, considering the decision maker's risk attitude, is created as a function of the selection criterion. A preferred concept and attribute targets are selected through the maximization of enterprise utility. The mathematical formulation of the DBD method, described in the following sub-sections, provides insight into the key parameters, attributes, and relationships which must be included in the proposed PAFD method to ensure rigorous decision making.

2.1 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 our formulation, utilizing profit, Π, as the selection criterion (*V*) captures the needs of both the consumer and the producer stakeholders, resulting in maximum benefit to the enterprise when utility is maximized. Profit is expressed as a function of product demand *Q*, price *P*, and cost *C*, where demand *Q*, is expressed as a function of *customer desired attributes* **A**, customers' *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. To enable engineering decision-making, qualitative customer desired attributes **A** must be expressed in terms of quantitative *engineering attributes* **E** in the demand modeling phase. The **E** can be described as performance functions **E**(**X**) of engineering design concepts and variables **X** through engineering analysis, to capture technical trade-off behavior among the attributes. Cost, *C*, is a function of the design concepts and variables, **X**, exogenous variables **Y** (the sources of uncertainty in the market), demand, *Q*, and time *t*. Price, *P*, is an attribute whose value is determined explicitly in the utility optimization process. Based upon these functional relationships, the selection criterion can be expressed as:

$$V = \Pi = Q(\mathbf{E}(\mathbf{X}), \mathbf{S}, P, t) \times P - C(\mathbf{X}, \mathbf{Y}, Q, t) \quad (1)$$

It should be noted that uncertainty is considered explicitly and the objective is expressed as the maximization of the expected enterprise utility *E*(*U*), considering the enterprise risk attitude:

$$\mathbf{max}: \ E(U) = \int_V U(V)\,pdf(V)\,dV \quad (2)$$

where *V* is the single selection criterion in Eq. (2).

2.2 Modeling Demand using Discrete Choice Analysis (DCA)

Unlike QFD analysis which may unrealistically treat customers as a "group" with a single, aggregate preference, Discrete Choice Analysis (DCA) [19] is used to model product demand by capturing *individual* customers' choice behavior, in which performance of a given product is considered versus that of competitive products. It should be noted that in this formulation, the customers could be either individual consumers or industrial customers. DCA is based upon the assumption that individuals seek to maximize their personal *customer choice utility*, *u*, (not to be confused with enterprise utility, *U*) when selecting a product from a choice set. The concept of choice utility is derived by assuming that the individual's true choice utility *u* consists of an observed part *W*, and an unobserved random disturbance *ε*:

$$u_{in} = W_{in} + \varepsilon_{in} \quad (3)$$

While there are a number of DCA techniques popular in literature, Multinomial Logit (MNL) is used in this work, resulting in a model in which the *coefficients* (β) *of the observed customer choice utility function* (W) *for the product attributes are identical across all customers*. However, heterogeneity is modeled by considering demographic attributes **S** (e.g., customer's age, income, etc.) in the customer choice utility function. Assuming this utility function can be expressed as a linear combination of attributes, W follows the form:

$$W = \beta_1 \mathbf{E} + \beta_2 \mathbf{S} + \beta_3 (\mathbf{E} \times \mathbf{S}) \tag{4}$$

Estimation of the customer choice utility function allows the demand, Q, for a choice alternative i to be determined by summing over the market population, N, all probabilities, $\Pr_n(i)$, of a sampled individual, n, choosing alternative i from a set of J competitive choice alternatives:

$$Q(i) = \sum_{n}^{N} \Pr_n(i) = \sum_{n}^{N} \frac{e^{W_{in}}}{\sum_{k=1}^{J} e^{W_{kn}}} \tag{5}$$

The set of choice alternatives J may include both the new designed artifact and the existing competitive alternatives available. Additional details on the use of MNL models for engineering design applications can be found in [2],[17].

While this section describes the mathematical foundation of PAFD using DBD principles, the formal process for mapping the various types of attributes at various levels of abstraction to determine relationships and interactions is based upon concepts from the QFD method with certain extensions.

3. PAFD METHOD WITH COMPARISON TO QFD

In comparing the new PAFD to the existing QFD, both methods are categorized into three primary stages as shown in Figure 1.

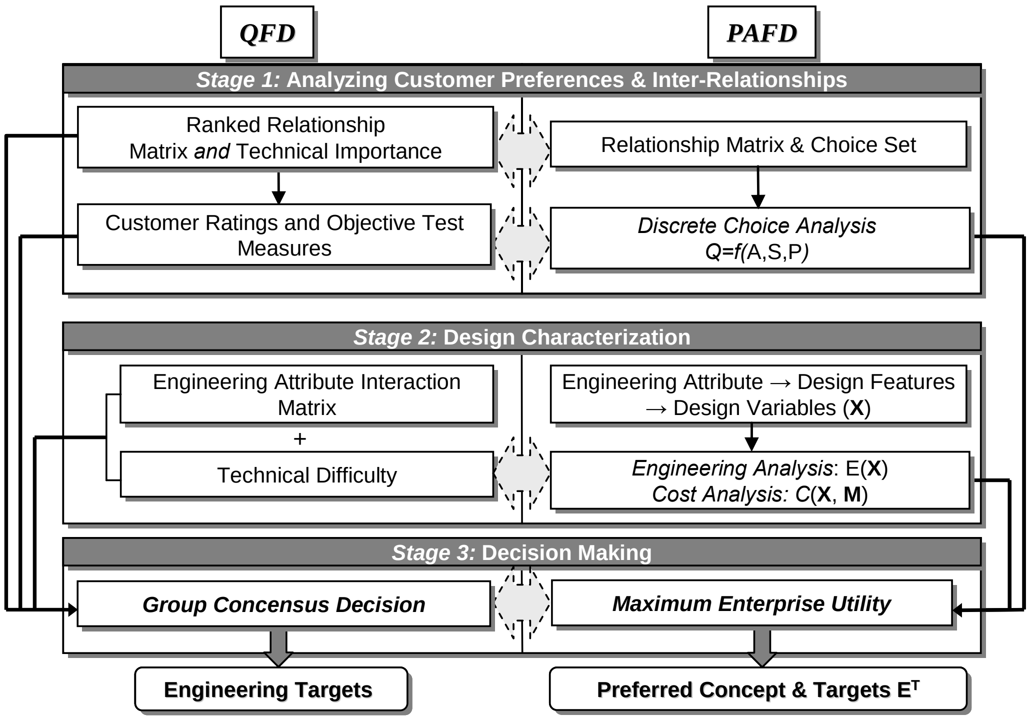


Figure 1. 3 Stages of PAFD and QFD

In the first stage of both methods, customer preference is quantified: PAFD uses a DCA model to express consumer demand for an entire product in competing with other existing products, whereas QFD uses a ranking of consumer preferences for specific product attributes to assess consumer acceptance of a product. In the second stage, the engineering design is characterized: PAFD utilizes preliminary analysis models to capture the costs and technical trade-offs among **E** (details provided later), versus the technical difficulty rating and correlation matrix mapping used in QFD. PAFD explicitly considers engineering attributes resulting from customer ($\mathbf{E_A}$), corporate ($\mathbf{E_C}$), regulatory ($\mathbf{E_R}$), and physical ($\mathbf{E_P}$) sources [15], whereas QFD is primarily focused upon those engineering attributes **E** resulting from customer desires.

The conceptual design of an automotive pressure sensor is used as a case study to demonstrate the PAFD methodology, and the differences between PAFD and QFD. The specific example considered is to design a standard next-generation 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. 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 concept must be made and target levels of product performance must be established.* A *risk adverse* attitude is assumed for the enterprise, and the market size is assumed to grow by 10%/yr. over the time interval, *t*, of 4 years considered in the forecast.

3.1 PAFD Analysis of MAP Sensor

Stage 1: Understanding MAP Sensor Requirements and Inter-relationships

A “house” structure is used to accomplish the Stage 1 processes of the PAFD method as shown in Figure 2. Similar to the conventional QFD analysis is the deployment of mapping between **E** and **A**, as well as the collection of engineering attribute levels from competitors’ products (competitive analysis). The Engineering Attributes determined in this matrix are the **E** related to customer desired attributes **A**, identified as $\mathbf{E_A}$. Also unique to PAFD, customer demographic attributes **S** are considered and interactions (**A**×**S**), later transformed to ($\mathbf{E_A}$×**S**) in demand modeling, 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 through estimation of product demand.

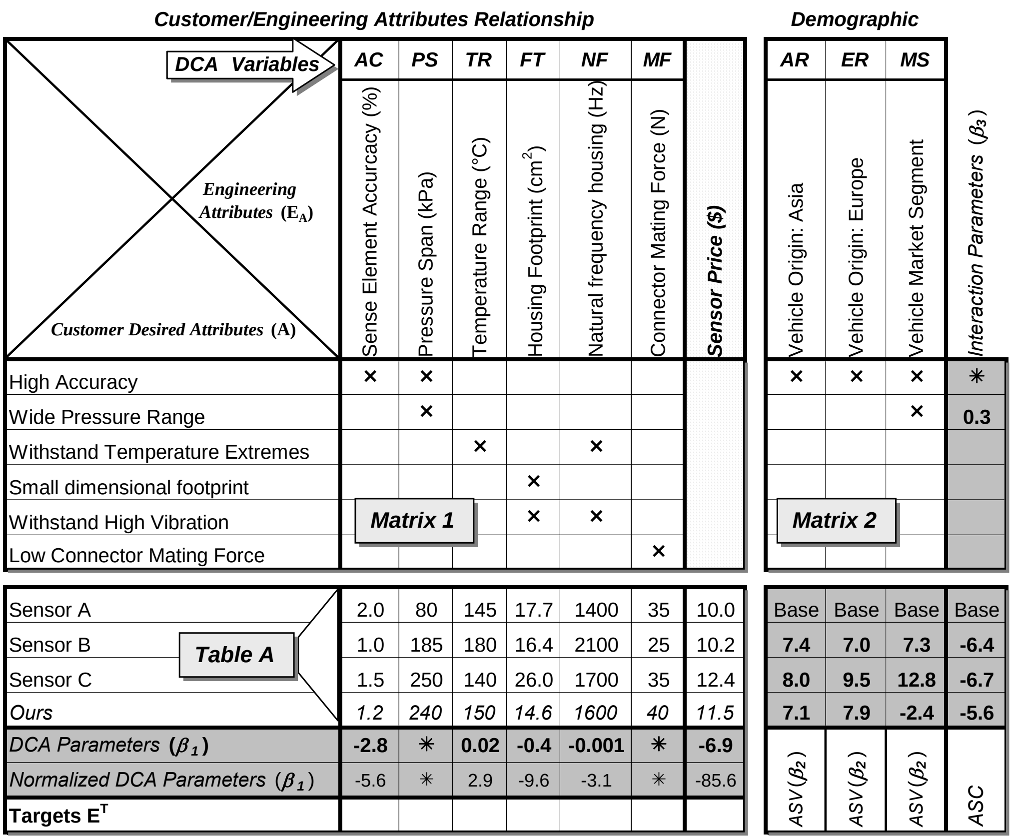


Figure 2. PAFD House 1 for MAP Sensor

To begin the analysis, key customer desired attributes **A** and engineering attributes $\mathbf{E}_A$ are placed in the appropriate rows and columns in the same manner as QFD analysis. Different than QFD analysis, demographic attributes **S** (e.g. *Vehicle Market Segment*) are also identified and tabulated. Note that the **S** for the industrial customers are company-specific attributes, such as the corporate location or the specific market niche in which the company competes. As described in Section 2, the **S** account for the heterogeneity of customer choice, *i.e.* they explain why different customers choose different MAP sensors for similar applications. With **A**, $\mathbf{E}_A$, and **S** identified, hypothesized relationships are marked by an "×" in matrix 1 (unlike QFD, PAFD does not use rating scales) identifying the linking of the $\mathbf{E}_A$ to **A**, and in matrix 2 identifying the potential interactions among the **S** and **A** which influence choice behavior, such as the interaction of *High Accuracy* and *Vehicle Market Segment*.

To acquire the choice data necessary to estimate the DCA model, a market study (Stated Preference) is conducted in which 40 potential customers are surveyed simply for *choice* behavior among four competitive sensors (A, B, C, *Ours*), unlike the QFD analysis in which respondents are asked to rank-order the performance of each sensor for each **A**. Also different from the QFD analysis, in which customers are treated as a group, the demographic data **S** for each customer surveyed is recorded in the PAFD method. The $\mathbf{E_A}$ and *P* of each of the alternatives is tabulated in Table A (Figure 2), enabling a MNL DCA model to be formulated as a function of the values of $\mathbf{E}_A$, *P*, and **S** using the choice data collected for the four sensors.

The model parameters β determined to create a demand model with good fit statistics are composed of linear (e.g. *Accuracy*, *Temperature Range*), interaction (e.g. *Accuracy* × *Vehicle Market Segment*) and alternative specific variables (ASV) (e.g. *Alternative*$_j$ × *Vehicle Market Segment*), with alternative specific constants (ASC) to capture inherent preference for each alternative. The results are shown in Figure 2, which includes a summary of the β parameters in the grey region (note that not all E_A enter W as indicated by a ✳, as some parameters are not statistically significant, or are highly correlated with other E_A). Referring to Eq. (4), the β parameters establish the customer choice utility function, W, of each alternative. In particular, each alternative shares a common set of product selection attribute parameters, which form the *common* customer choice utility function:

$$W_{Common} = -2.8(AC_i) + 0.02(TR_i) - 0.4(FT_i) - 0.001(NF_i) - 6.9(PRICE_i) + 0.3(PS_i \times MS) \qquad (6)$$

The specific customer choice utility functions for each of the competitive alternatives can then be determined for use in Stage 3, using the common utility formulation and adding the appropriate alternative specific constants (ASC) and variables (ASV):

$$\begin{aligned} W_{\mathbf{A}n} &= (W_{common})|_{i=1} \\ W_{\mathbf{B}n} &= -6.4 + (W_{common})|_{i=2} + 7.4(AR) + 7.0(ER) + 7.3(MS) \\ W_{\mathbf{C}n} &= -6.7 + (W_{common})|_{i=3} + 8.0(AR) + 9.5(ER) + 12.8(MS) \end{aligned} \qquad (7)$$

A customer choice utility function can also be developed for *Our* sensor design:

$$W_{\mathbf{OURS}n} = -5.6 + (W_{common})|_{i=4} + 7.1(AR) + 7.9(ER) - 2.4(MS) \qquad (8)$$

Examination of the utility function provides insight into customer choice behavior. The sign of the parameter indicates the effect of an attribute upon customer choice utility W, for example increasing *Price* (β = -6.9) of a sensor decreases W, and hence the probability of choice, *ceteris paribus*. Additionally, the effect of **S** upon utility can also be examined. For example, W and hence the probability of choice, of Sensors B, C and *Our* sensor increases relative to the reference (Sensor A) if the customer is located in Asia (*AR*) or Europe (*ER*); the greatest increase in W is for Sensor C as indicated by the magnitude of the β_2 parameters for *AR* (β = 8.0) and *ER* (β = 9.5) in the $W_{\mathbf{C}n}$ expression. To understand the engineering priority of each $\mathbf{E_A}$ and $\mathbf{E_A}\times\mathbf{S}$ in terms of their impact on demand, the β coefficients can be normalized as shown in Figure 2 to allow the importance of each attribute to be estimated based upon their magnitude. For example, *Price* is the most important attribute (β_{NORM} = -85.6) while *Temperature Range* is the least important (β_{NORM} = 2.9).

With a customer choice utility function available for each alternative, Eq. (5) can be utilized to determine the demand for the new design concepts based upon the values of $\mathbf{E_A}$ and *P* substituted into Eq. (8) during the decision-making phase in Stage 3.

Stage 2: MAP Sensor Design Concepts Identification and Characterization

Stage 2 of PAFD utilizes a "house" structure (House 2) as shown in Figure 3. This stage results in *preliminary* engineering and cost analysis models which are intended to capture the high-level relationship between design concepts and both engineering performance and cost, as opposed to use in creating detailed product designs. In contrast to QFD, the PAFD analysis explicitly considers specific design concepts, while the QFD analysis requires the design characterization to be carried out at the engineering attribute level, with rankings of technical difficulty and attribute interactions used in place of established engineering and cost analysis methods.

		DESIGN CONCEPT 1					DESIGN CONCEPT 2					
	Design Variables (X)	Length, Thickness	Resolution, Error(T)	Width, Length, Polymer Mating Force	Thickness, Material	Thickness, Material	Area, Separation	Resolution, Error(T)	Width, Length, Polymer	Thickness, Material	Mating Force	Thickness, Material
	Component Design Features (F) / **System Engineering Attributes (E)**	Piezoresistive Sense Element	Digital Signal conditioning IC	Integral housing/USCAR connector	Steel Housing Reinforcement	Rubber Pressure Seals	Capacitive Sense Element	Digital Signal conditioning IC	Polymer Housing	Steel Housing Reinforcement	USCAR Connector	Rubber Pressure Seals
E_A	Sense Element Accurcacy (%)	×	×				×	×				
E_A	Pressure Span (kPa)	×	×			×	×	×				×
E_A	Temperature Range (°C)	×		×			×		×			
E_A	Housing Footprint (cm^2)			×					×			
E_A	Natural frequency housing (Hz)				×					×		
E_A	Connector Mating Force (N)			×							×	
E_C	Common Platform	×	×				×	×			×	
E_R	UL Flamability Resistance			×					×		×	
E_T	Housing Stress (kPa)				×					×		
	Estimated Manufacturing Cost	$0.25	*	$1.00	$0.10	$0.20	$0.40	*	$0.40	$0.10	$0.55	$0.20
	Manufacturing Attributes (M)	*Micromachining*	** Catalog*	*Insert Molding*	*Stamping*	*Transfer Molding*	*Micromachining*	** Catalog*	*Injection Molding*	*Stamping*	*Insert Molding*	*Transfer Molding*

Figure 3. PAFD House 2 for the MAP Sensor

To begin Stage 2, the $\mathbf{E}_A$ identified in House 1 are transferred to the **E** Column in House 2 (Figure 3) and additional engineering design attributes derived from cooperate, regulatory, and physical requirements, such as *Common Platform* as $\mathbf{E}_C$, *UL Flammability Resistance* as $\mathbf{E}_R$, and *Housing Stress* as $\mathbf{E}_P$ are established to form the complete set of **E**. With **E** identified, design concepts and their corresponding design features **F** can be formulated. A *design concept* is defined as a high–level system configuration, composed of multiple subsystems and corresponding key *design features* **F**. For this problem, two design concepts were identified: *Concept 1* utilizes a piezoresistive (PRT) sensing element with a micro–machined sensing diaphragm, which senses pressure due to bending of the diaphragm, and *Concept 2* utilizes a two–plate capacitive sense element, which senses pressure due to change in the capacitor plate separation distance. Due to differences in the design of the sensing element, the piezoresistive concept is inherently less expensive and results in a smaller package, whereas the capacitive concept is more robust to temperature and pressure extremes.

To facilitate preliminary cost and engineering analysis of the concepts, each design feature F_i is represented by integer, discrete, or continuous *design variables* **X**, such as material type, dimension, etc. The **X** selected *are the minimum, high–level* set necessary to estimate the cost C_i of each feature and to represent the coupling of the design features in the decision-making process to select a preferred concept and set targets $\mathbf{E}^T$; the specific form and complete set of the X_i will be established in the detailed design process. For each design concept, the attribute mapping shown in Figure 3 provides the qualitative relationship between the **E** and **X** through a mapping of **E** to **F**. From the qualitative relationship, the quantitative functional relationships $E_i=f(\mathbf{X})_i$ are established using preliminary engineering analysis. These relationships differ for each concept: for example, concept 1 utilizes the piezoresistive sensing element with a resistance output given by the relation [20]:

$$Pressure\ Span = k(\Delta L_E / L_E) \tag{9}$$

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

$$Pressure\ Span = \varepsilon_0 \varepsilon_r \left(A_E / \Delta D_E \right) \tag{10}$$

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

After establishing the set of design concepts and specific high-level design features, preliminary *manufacturing process attributes* **M** are identified for each concept, and mapped to **F**. For the MAP sensor, **M** such as micro-machining, injection molding, etc., are identified for each design concept, and placed in the columns corresponding to the associated design feature **F**, shown in Figure 3. The **M** are used to estimate processing costs and to identify constraints on **X** resulting from manufacturing process limitations to be considered in the decision-making stage of PAFD (Stage 3), as well as ensuring appropriate manufacturing processes are identified for each design feature. Using the identified **X** and **M**, estimation of the total cost, C^k, for each design concept, k, is estimated by:

$$C^k(\mathbf{X}^k, \mathbf{Y}, Q, t) = \sum_N C_D^k\left(\mathbf{X}^k, \mathbf{Y}, Q, t\right) + C_C^k(t) + C_F^k(t) \tag{11}$$

where $C_D^k\left(\mathbf{X}^k, \mathbf{Y}, Q, t\right)$ is the material and processing cost for each design option, N is the number of design variables, $C_C^k(t)$ is the cost of capital, and $C_F^k(t)$ is fixed corporate overhead cost for each design concept. The reason for establishing both preliminary engineering and cost analysis in PAFD is to capture the real trade-off behavior of engineering attributes, to ensure design selections resulting from the tool are optimal, and target performances are actually achievable. Each concept requires a specific manufacturing process, and the different sets of **M** result in a differing cost structure and place different constraints upon the **X**.

Examination of the completed House 2 provides insight into the motivations for the PAFD processes. As seen, the technology selection drives specific design features and the corresponding set of design variables 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 because of the large size and electrical interconnect of the capacitive element. The mapping process identifies the trade-offs which must be considered in the design selection process. For example piezoresistive sense element *thickness* is a continuous variable to be determined based on the trade-off among element length, manufacturing limitations, and cost; integrated circuit A/D discretization *resolution* is a discrete variable to be determined based on the trade-off between sensor accuracy and cost.

Stage 3: Design Concept Selection and Target Setting

Stage 3 of PAFD is conducted by formulating the decision-making problem as shown in Table 1. As described in Section 2, PAFD evaluates designs through the maximization of expected enterprise utility $E(U)$, using the single selection criterion, V, constructed from the DCA demand modeling (stage 1), engineering, and cost models (stage 2). Uncertainty is also considered in this problem: the Piezoresistive 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. In addition to selecting a preferred design concept and setting performance targets, PAFD like QFD can also aid in setting engineering priority, through a global sensitivity analysis of the $E(U)$ function to determine which product attributes should receive the greatest resource allocation during the detailed design phase. In contrast and demonstrated in Section 3.2, the evaluation process used by QFD is a (human) group consensus decision, in which the multi-attribute decision criterion requires synthesis of technical importance, technical test measures, technical difficulty, and attribute correlations by the decision maker(s). Additionally, engineering targets are set individually for each engineering attribute based upon the best measured performances from the competing products, a methodology shown to be potentially faulty in Section 1.

Table 1. Pressure Sensor Decision-Making Formulation

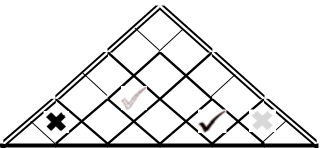
Given
Mid-Size Sedan Market Size: 1,000,000 [sensors/year] growing at 10% per year
Demographic data of targeted industrial customers **S**
Engineering Attributes $\mathbf{E_A}$ (PAFD: House 1)
$\mathbf{E_A}$ determined as a function of the high-level design options **X** (E(X))
Design Concept (PAFD: House 2)
Two (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 Eq. (11).
Demand Model *Q* (PAFD: House 1)
Obtained from the MNL model of the competitive alternative attribute data.
Single criterion $V = QP$-C (Eq. (1))
Find:
Design Variables **X**, Target Engineering Levels $\mathbf{E^T}$ (PAFD: House 1) and Price *P*
Maximize:
$E(U)$, assuming an enterprise risk adverse attitude (Eq. (2))
Subject To (PAFD: House 2):
$g(\mathbf{X}, \mathbf{E}) \leq 0$ $T_E - 14.0 \leq 0$; $D_E - 12.0 \leq 0$: **Constraints from M**
$g(\mathbf{X}, \mathbf{E}) \leq 0$ $PS - 80.0 \leq 0$; $NF - 1400.0 \leq 0$: **Constraints from $\mathbf{E_C}$ and $\mathbf{E_P}$**

3.2 Comparison of PAFD and QFD Results

A QFD analysis is completed for comparison to the results of the PAFD method. Similar to beginning the PAFD analysis, the **A** and the key $\mathbf{E_A}$ are placed in the appropriate rows and columns of the HoQ as shown in Figure 4. The engineering team must rank order the importance of each **A**, fundamentally establishing a "group utility" for each attribute as described previously, and determine a "direction for improvement" for each of the $\mathbf{E_A}$ based on engineering judgment, as shown by the "+" and "–" signs preceding each $\mathbf{E_A}$. The relationship matrix is then be completed, with the engineering team determining the strength of relationship between the $\mathbf{E_A}$ and **A**, using a largely subjective evaluation based on the experience level of the team members. With the relationship matrix complete, the *Technical Importance* can be calculated for each E_A to determine engineering priority for each attribute, a higher importance rating indicating higher engineering priority. The "roof" *Correlation Matrix* is completed, with ✓ indicating positive correlation and ✖ negative correlation between attributes, and the *Technical Difficulty* rating is estimated (higher number indicates greater difficulty). These analyses can be viewed as highly simplified, empirical forms of the engineering and cost analyses explicitly formulated in the PAFD method.

To complete the *Customer Ratings*, a market study is conducted in which several customers are surveyed to determine consumer perception of current competitive MAP sensors on the market. The respondents are asked to rank order the performance of three competitive sensors (A, B, C), plus our current generation sensor (*Ours*), with respect to each **A** they have identified, with ranking results shown in Figure 4. For example, the customer group evaluation for *High Accuracy* indicates that Sensor B is perceived as having the best accuracy and Sensor A the lowest accuracy. Note that with QFD, the customer ranking must be aggregated in order to achieve a single rank order for each **A**, a process shown to be potentially problematic [10]. To complete the QFD analysis, the actual measured performance levels of each engineering attribute are determined for each of the four sensors and documented in the *Technical Test Measures* portion of the HoQ.

With the HoQ completed, performance targets for the sensor are determined through a multi-attribute consideration of the *Technical Test Measures*, *Customer Ratings*, *Technical Difficulty*, and *Correlation Matrix*. The performance target decision is made relative to the current levels of performance of *Our* sensor, in which the values identified in the *Technical Test Measures* represent the best known levels of performance for each **E** which should be targeted by the new sensor**,** while the *Technical Difficulty* and *Correlation Matrix* provide subjective constraints upon performance. Using the QFD methodology, the targets are shown at the bottom of the HoQ in Figure 4. It was decided that the new sensor should have improved target performances for *Accuracy*, *Pressure Span*, and *Temperature Range*, since these have high technical importance, and our current sensor is not perceived as the market leader in these areas. Also, it was decided to improve the target for *Connector Mating Force* since it has a low technical difficulty. It was decided not to improve the target for *Housing Footprint*, since we are the market leader, or *Natural Frequency* due to high technical difficulty and low technical importance.



Engineering Attribute (E) / Customer Attribute (A)	Importance	– Sense Element Accurcacy	+ Pressure Span	+ Temperature Range	– Housing Footprint	+ Natural frequency housing	– Connector Mating Force	Customer Ratings 1 ⟷ 5 (L) (H)			
High Accuracy	8	9	3					*A*	*C*	*Ours*	*B*
Wide Pressure Range	6		9					*A*	*B*	*Ours*	*C*
Withstand Temperature Extremes	6			9				*C*	*Ours*	*A*	*B*
Small dimensional footprint	4		1		9		1	*C*	*A*	*B*	*Ours*
Withstand High Vibration	4			1	3	9	1	*A*	*Ours*	*C*	*B*
Low Connector Mating Force	2						9	*Ours*	*C*	*A*	*B*
Technical Test Measures: Sensor A		2.0	80	145	17.7	1400	35				
Technical Test Measures: Sensor B		1.0	185	180	16.4	2100	25				
Technical Test Measures: Sensor C		1.5	250	140	26.0	1700	35				
Technical Test Measures: *Ours*		1.2	240	150	14.6	1600	40				
Technical Difficulty		8	4	3	5	7	2				
Technical Importance		*72*	*82*	*58*	*48*	*36*	*26*				
Targets		**1.0**	**250**	**180**	**14.6**	**1600**	**35**				

Figure 4. Comparison QFD Analysis of MAP Sensor

The results of both the PAFD and QFD analyses are shown in Table 2. The PAFD decision results in performance targets $\mathbf{E}^T$, and values of demand, price, and cost for both Concepts 1 and 2. The preferred design concept for this problem is *Concept 1*, which results in the highest utility for the enterprise considering uncertainty ($E(U)$ = 2,085,000 *utils*), with a risk-adverse attitude assumed by the enterprise. The QFD analysis results in performance targets only, which are not associated with a design concept, and additionally QFD has no mechanism for determining price P. For the purpose of comparison, the unit price of the QFD design is set at the same price ($10.42) as concept 1, the preferred design from the PAFD method, and profit and utility estimated using this price.

Compared to the PAFD results, the QFD identifies targets based upon the best values of $\mathbf{E_A}$ identified in the competitive analysis, which subsequently leads to a lower value of $E(U)$ of 170,000 *utils*. The reason the QFD resulted in such low enterprise utility is that although the estimated demand, Q, for a sensor meeting the targets set by QFD is somewhat higher than estimated demand for those identified by PAFD, the cost to make such a sensor is significantly higher ($10.34). As described in

Section 1, QFD is biased toward meeting customer product desires and does not explicitly consider cost, leading to a sensor design with good customer acceptance potential but low expected enterprise utility. Additionally, because parameter relationships identified through engineering analysis and constraints determined in the PAFD Stage 2 process are not utilized, it is not known with confidence if these QFD targets can actually be achieved by either Concept 1 or 2. For the PAFD analysis, the target levels identified for the preferred concept reflect the actual achievable levels of $\mathbf{E}_A$ which maximize enterprise utility for this design concept, based upon the constraints imposed in the decision-making problem. This is further illustrated by noting that concept 2 has a different set of $\mathbf{E}^T$ corresponding to the maximum enterprise utility for that particular concept.

Table 2. Comparison of Decision Results–Preferred Concept (shaded)

Engineering Attribute E	***PAFD* ($\mathbf{E}^T$)**		***QFD* ($\mathbf{E}^T$)**
	Concept 1	**Concept 2**	
Sense Element Accuracy (%)	1.32	1.40	1.0
Full Scale Span (kPa)	176.0	201.0	250.0
Temperature Range (°C)	140.0	140.0	180.0
Housing Footprint (cm^2)	15.3	18.0	14.6
Natural frequency (Hz)	1400.0	1300.0	1600.0
Connector Mating Force (N)	40.0	40.0	35.0
Q: Demand / year (*# sensors*)	465,000	515,000	541,000
P: Unit Price (*USD*)	$10.42	$10.63	$10.42
C: *Unit Cost* (*USD*)	$8.97	$9.64	$10.34
Expected (*U*) (*utils*)	***2,085,000***	***1,671,000***	***170,000***

To set engineering priority using the PAFD analysis, a global sensitivity analysis is conducted as recommended previously to study the total effect of individual engineering attributes on the *E(U)*. The results of this analysis indicate that the greatest resource allocation should be made to achieving the targets for *Housing Footprint* and *Pressure Span*, due to the sensitivity of enterprise utility to these parameters. For QFD, the *Technical Importance* measure is used to establish engineering priority, resulting in selection of *High Accuracy* and *Pressure Span* as highest priority. The difference in priority results from the different focuses of the two tools, with PAFD focused upon maximizing enterprise utility and QFD focused primarily upon customer product acceptance. In summary, the PAFD method has provided a clear conceptual direction and engineering targets necessary to begin the detailed design of the MAP sensor; detailed engineering analysis can be utilized to create the specific feature designs which meet these targets.

5. CONCLUSION

In this work, the Product Attribute Function Deployment (PAFD) method is presented to offer a mathematically rigorous, decision-theoretic process tool for use during the product planning phase of a product development program. The need for developing such a method results from a close examination of the needs during the conceptual design phase, and the limitations of current methods, such as QFD, currently used for this purpose. 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 decisions.

In addition to presenting the PAFD method, a comprehensive comparison of QFD and PAFD was conducted in this work, demonstrating the parallels between the two methods and the improvements achieved by utilizing DBD principles in the new tool. The use of single-objective utility optimization provides a rigorous mathematical framework for decision making under uncertainty, alleviating the difficulties associated with weighting factors and multi-objective decision-making in QFD. 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 setting engineering targets consistent with enterprise objectives. Heterogeneity of customers is addressed through the inclusion of demographic attributes **S** in the DCA model, addressing the aggregation issues present in QFD. The subjective ratings and rankings present in QFD are replaced with established methodologies in engineering, cost, and decision analysis to set targets for performance which can be achieved in practice. Uncertainty is explicitly addressed through the use of expected enterprise utility as the decision criterion.

Future research includes expanding the design definition to include enterprise-financial planning decisions that have a direct impact on those non-engineering related customer attributes. Further, the extension of this method to a complex system, such as an automobile, will be investigated. In such designs, qualitative customer-desired attributes may be expressed as a rating or ranking, requiring a more complex mapping process to quantitative engineering attributes than currently considered.

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