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Technique for Concept Selection Using Interactive Probabilistic Multiple Attribute Decision Making

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Design is a decision-making process that depends on multiple attributes. Analysis of alternatives with respect to a single metric representing the "goodness" of the concept is difficult without resorting to subjective weightings on an overall evaluation criterion. The use of subjective factors in a decision-making process is often met with criticism, as the selection of a design may be traced to preferential decisions made on a certain day by a single individual. A methodology is needed that reduces the impact of uncertainty in the subjective weighting factors while retaining the traceability, defensibility, and rigor provided by traditional multiple attribute decision-making techniques. In this work, a standard process for systems engineering using the quality function deployment approach with a multiple attribute decision-making technique for concept selection is supplemented through the use of parametric slide bars to play "what-if" games and a probabilistic environment that plays all possible "what-if" games and summarizes the results. Using the modified process, families of concepts can be rapidly examined based on varying levels of subjective preferences. Decision makers, armed with a rapid parametric sensitivity analysis tool, can make more informed decisions about future concepts, policies, and acquisition decisions. An interactive graphical environment can be used to visualize the diverse sets of trades and understand non-intuitive answers by tracing customer needs to proposed solutions in real-time. In practice, the proposed process facilitates iteration between needs and concepts and fosters and increased understanding of the concept space between designer and decision maker.

Nomenclature

C	Overall concept goodness
Cd_o	Zero-lift drag coefficient
K_i	Kill switch value [0, 1]

I. Introduction

"*Design is a decision making process, and the selection of design parameters represent decisions.*"

– *G. A. Hazelrigg* [1]

DESIGN is an artful, scientific, and practical process for decision making in the presence of constraints. While the laws of physics govern many trades in engineering design, subjective requirements that take the form of

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customer or designer preference constrain additional degrees of freedom and may contribute to increased risk or cost. In the early stages of design, many of these degrees of freedom are constrained by the selection of an architecture, concept, or platform which is essentially a "bundle" of decisions that defines the basis of further design efforts. The selection of the "best" concept depends not only on the requirements levied on the design, but also the subjective weighting of these requirements, defining the customer's notion of "best." A popular approach to evaluating design alternatives is the establishment of an overall evaluation criterion (OEC) of the form:

$$OEC = W_1 \frac{P}{P_{\text{Max}}} + W_2 \frac{P}{P_{\text{Max}}} + W_3 \frac{C_{\text{Max}}}{C} \tag{1}$$

where P represent performance factors, C represent cost factors and W represent the subjective weighting factors that define the customer's preference of the "best" design[‡]. In practice, the selection of a concept is highly dependant on the identification of these subjective weighting factors that are difficult to define a priori. While subjective estimates from the right experts are often on par with the quantitative estimates of the best physics-based models, the consequence of selecting a suboptimal concept in the early stages of design can be disastrous to a project. A methodology for concept selection that accounts for the subjectivity of the concept identification process and provides decision makers with insight into the variability of identified concepts with respect to the subjective inputs is needed. This issue can be addressed primarily through the use of *parametric slide bars* to enable rapid "what-if" trade studies and the use of *probabilistic techniques* to examine distributions of input parameters. With these two modifications, the customer can better understand the sensitivity to changing the subjective weighting factors, which not only characterize the customer's perception of value (which may be negotiable), but also represent the non-physical constraints levied on the conceptual phase of design.

II. Tools and Methods for Concept Selection in Systems Engineering

The methods in this work originate from the intersection between systems engineering and conceptual design. Systems engineering (SE) is "an interdisciplinary approach and means to enable the realization of successful systems" [2]. Major functions of SE include defining customer needs, documenting requirements, and performing design synthesis and system validation. Conceptual design is an early step in the design of new systems and products where required functionality, derived from customer needs, is correlated to potential alternatives that can provide such functionality. Numerous handbooks exist that define similar processes for concept selection in systems engineering [3–6]. Several of the best practices in these guides are synthesized to demonstrate a dynamic, interactive process for concept selection using an example of a liquid propellant missile target for the 2004 AIAA Graduate Strategic Missile Design Competition. Subsequent sections introduce two key methods, quality function deployment (QFD) for needs identification and multi-attribute decision making (MADM) for concept selection.

A. Quality Function Deployment (QFD)

The QFD technique is a systematic mathematical and social process used to translate the "Voice of the Customer" into the "Voice of the Engineer." Developed by Dr Yoji Akao and Dr. Shigeru Mizuno in the 1960s, QFD has found widespread application in the development of products for the aerospace, automotive, electronics, and other industries [7]. A primer on the QFD methodology can be found in the INCOSE Systems Engineering Handbook [8]. According to the USAF Space and Missile Systems Center, "QFD is an excellent tool for both planning and requirements flowdown" [4]. The primary matrix-based approach of the QFD technique, called the House of Quality (HoQ) for its trademark appearance, uses a series of "rooms" to represent relationships. The data in each room are populated through interaction with the customer. The interrelationship matrix, the center of the QFD, describes how customer requirements in the left room impact engineering characteristics in the top room. Typically, symbols are used to represent the numerical values of these interactions: 1 = weak, 3 = medium, and 9 = strong. The "roof" of the QFD uses symbology to represent weak and strong positive correlations and weak and strong negative correlations

[‡] While these weighting factors are occasionally formulated from empirical estimates of historical data, in practice the uncertainty associated with the concept identification phase relies on subjective judgment for the determination of the weighting coefficient values.

respectively. Estimates of these relationships are traditionally achieved through a consensus-building elicitation exercise between customers and engineers. In practice, the elicitation of these estimates from a group of experts is not a trivial prospect. "Project Delphi" was the name given to an Air Force sponsored study by the RAND Corporation on the use of expert opinion in decision making and long-range forecasting [9,10]. Today, many techniques including chip voting [11], the Kano method [12], web-based elicitation methods, and electronic voting schemes are used to gather data and reach consensus opinions for the purpose of executing mathematical decision support algorithms [13].

The left room of the QFD lists customer requirements as either directly specified or derived from a Request for Proposal (RFP) or other means. Engineering characteristic headings are defined by an Integrated Product Team. The objective of the technique is to calculate the relative importance of each engineering characteristic with respect to the subjective weightings for the importance of each customer requirement and the relationship mapping between the two as defined by the interrelationship matrix. For example, the relative importance of an engineering characteristic, j, is given as

$$(\text{Engineering Characteristic})_j = \sum_{i=1}^{n} (\text{Customer Requirement})_i (\text{Interrelationship})_{ij} \tag{2}$$

Using Eq. (2), the importance of the engineering characteristics can be calculated and prioritized [14]. By calculating the importance of the engineering characteristics, the QFD acts *as a transfer function between customer requirements and measurable engineering quantities that can be designed to*. In a sense, QFD is a method for requirements decomposition to subsequent tiers or levels through a traceable and well-defined mathematical process based on the quantification of these subjective relationships. An example QFD matrix for a Tunable Infrared Signature Missile Target is shown in Fig. 1.

B. Multiple Attribute Decision-making (MADM) Techniques

Multiple Criteria Decision Making (MCDM) "refers to making decisions in the presence of multiple, usually conflicting, criteria" [15]. MADM is a subset of this discipline focused on product selection. In the 1960s and 1970s, the Department of Defense developed a variety of mathematical techniques for MADM that are summarized in [16]. These techniques can largely be considered more sophisticated approaches to developing an OEC like the one shown in Eq. (1). The most widely used MADM technique used in the literature is the Analytical Hierarchy Process (AHP) developed by Thomas L. Saaty in the 1970s [16]. Recognizing that decision making is a process based on applied mathematics and human psychology, Saaty's AHP decomposes a complex problem into a hierarchy of manageable subproblems and distinguishes between alternatives through a series of pairwise comparisons that represent the decision maker's subjective preference across the criteria/solution space. While it has gained widespread popularity through the use on multiple problems (many of which are summarized by Zahedi [17]), the arbitrary nature of the user-defined hierarchy, the lack of underlying statistical theory, and mathematical anomalies in the technique (such as "rank reversal") have been the subject of much controversy in the management science community [18–22]. A primary drawback in the use of the method for conceptual design is that consideration of a large number of factors with a simultaneously large number of alternatives requires a cumbersome number of pairwise comparisons to evaluate solutions. A related technique that addresses this concern is the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) proposed by Hwang and Yoon in 1981 [15]. Of the suitable MADM techniques for concept selection, TOPSIS balances the information required with the customer against algorithmic complexity. TOPSIS technique examines proposed alternatives in multiple dimensions and formulates a theoretical "best-in-class" solution across the multidimensional trade space. Mathematically, TOPSIS uses the concept of Euclidean distance to calculate the distance from an "ideal positive" and "ideal negative" solution in multiple dimensions. These distances from these ideals are defined as S^+ and S^- respectively and the overall goodness of a concept, j, is given by the variable, C, where

$$C_j = \frac{S_j^-}{S_j^+ + S_j^-} \tag{3}$$

Based on Eq. (3), maximum goodness is defined by a solution which is farthest from the negative ideal and closest to the positive ideal. Though its use is not as widespread as AHP, TOPSIS has found a variety of applications in many fields. TOPSIS has been used by Benitez et al. to assess quality of service in the hotel industry [23]. Chu and Lin used the technique for robot selection and implemented fuzzy logic to account for linguistic factors [25]. Braglia et al. applied TOPSIS to failure mode, effects, and criticality analysis (FMECA) to prioritize failure modes associated with commercial appliances [26]. Méndez et al. implemented TOPSIS as a means to identify preferred solutions in a Multi-Objective Evolutionary Algorithm. The algorithm is used to develop a frontier of non-dominated solutions for a nuclear power plant safety system [27].

The process outlined in this paper is generally independent of the MADM technique selected; however, TOPSIS is used in the example application owing to its simplicity and traceability.

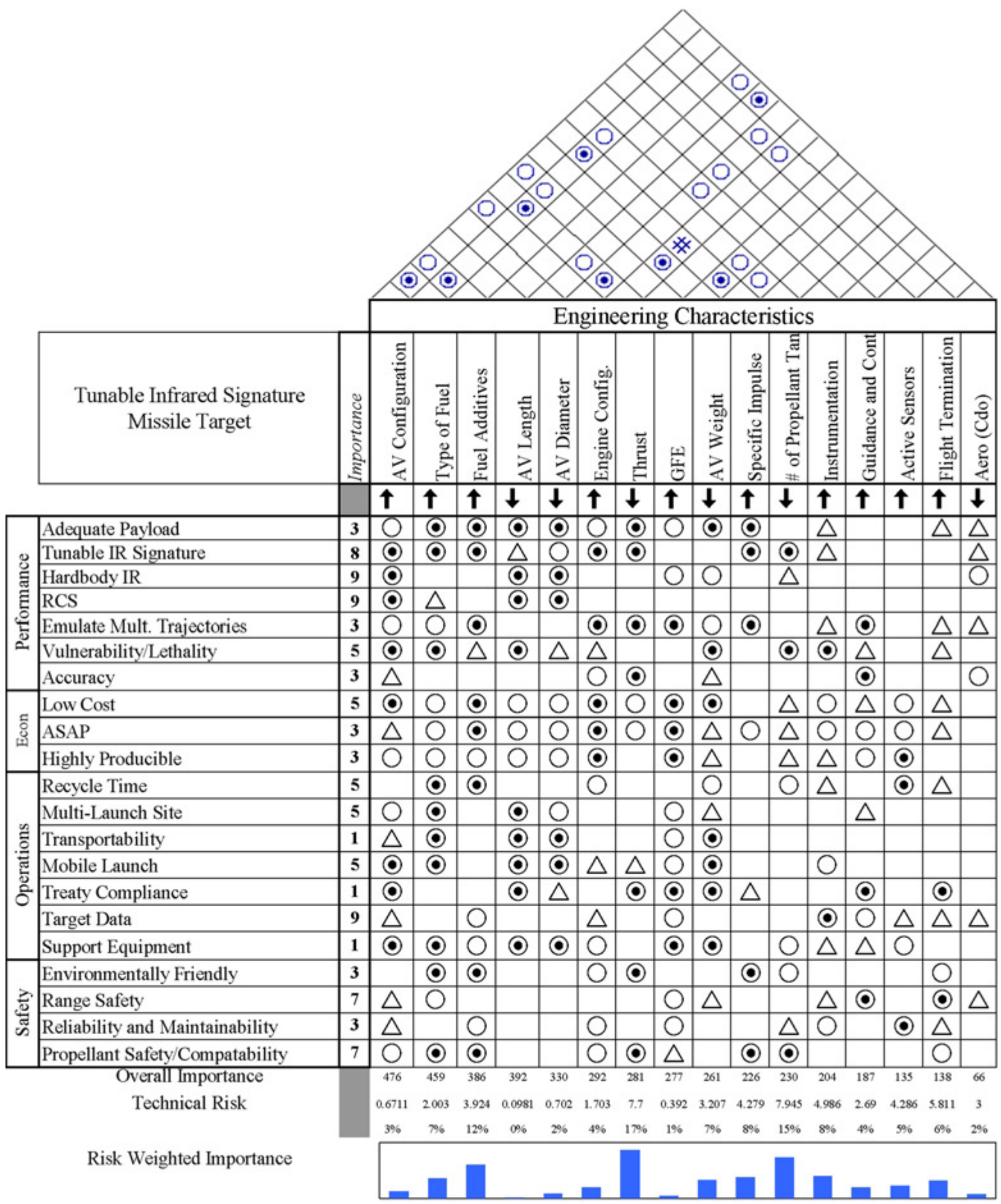

Fig. 1 House of Quality (HoQ) matrix for a tunable infrared signature missile target for the AIAA 2004 Graduate Strategic Missile Design Competition [24].

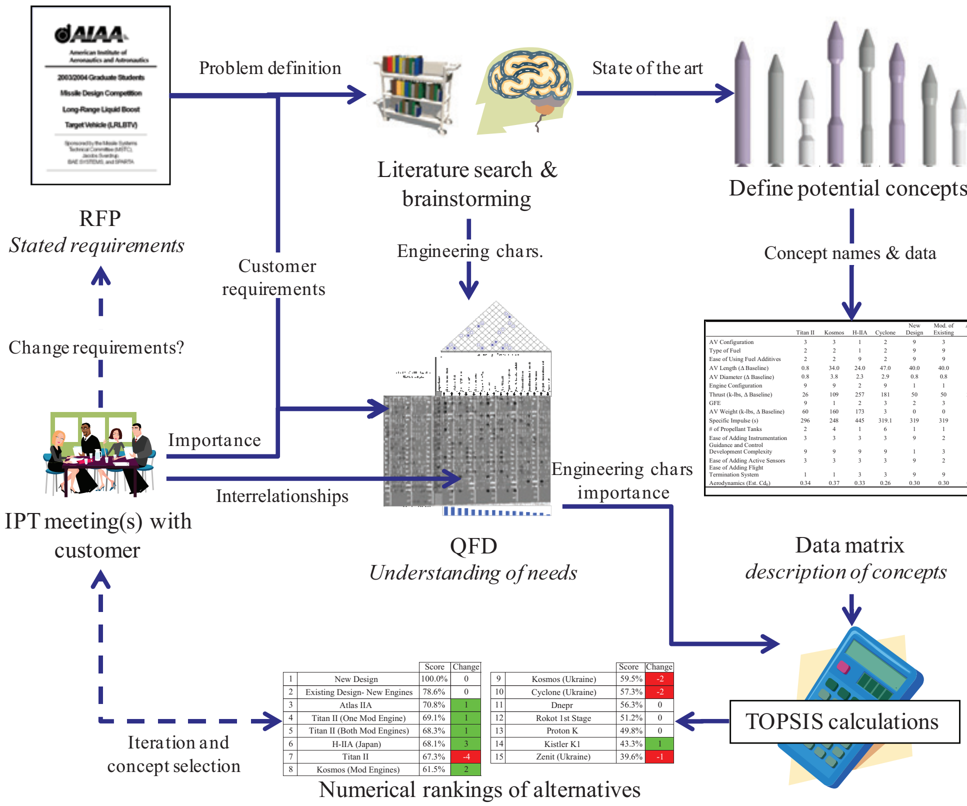

Fig. 2 A process for concept selection using systems engineering tools.

C. A Process for Concept Selection

Though systems engineering handbooks and texts review a number of methods for concept selection in a systems engineering process, the Integrated Product and Process Development (IPPD) approach advocated by Schrage is used as the baseline process in this work [28]. This process, which links QFD and MADM to promote requirements-focused concept selection, is depicted in Fig. 2. First, the need for a new product is often explicitly stated through the release of a RFP. The first step in the process shown in Fig. 2 is to mine the RFP and determine the customer requirements in terms of short declarative sentences or phrases. The discipline of requirements analysis describes many processes for such decomposition [29,30]. Simultaneously, to further define the problem, a literature search is conducted to determine the engineering characteristics that are likely to be used to describe a product of the intended type and to survey the state-of-the-art to identify potential concepts that will meet the customer need. When existing concepts are lacking, the concept of the Interactive Reconfigurable Matrix of Alternatives (IRMA) proposed by Engler et al. may be implemented to synthesize new concepts from their basic constituent elements [31]. In practice, the conceptual synthesis and literature search phases must go hand-in-hand to identify the full range of potential engineering characteristics that may be related to the customer requirements. It is also important to note that measurable comparisons between concepts are best performed when these concepts can be measured against similar engineering characteristics. For instance, in the example problem, the concepts are all types of missiles and can be measured by the same physical parameters. Assessing aircraft, tanks, and missiles against each other requires definition of measurable engineering metrics on reasonably consistent scales to avoid an ill-posed problem for the MADM algorithm. Practical applications of this technique address this issue by comparing concepts on the basis of higher-level parameters based on fundamental engineering quantities or the intended functions of the product.

Table 1 Example data matrix for the AIAA Graduate Missile Design competition (values [32][†])

	Titan II (USA)	Kosmos (Ukraine)	H-IIA (Japan)	Cyclone (Ukraine)	New Design	Mod. of Existing	Atlas IIA (USA)
AV configuration (Rating)	3	3	1	2	9	3	2
Type of fuel (Rating)	2	2	1	2	9	9	3
Ease of using fuel additives (Rating)	2	2	9	2	9	9	3
AV length (Δ Baseline, m)	0.8	34.0	24.0	47.0	40.0	40.0	14.4
AV diameter (Δ Baseline, m)	0.8	3.8	2.3	2.9	0.8	0.8	0.9
Engine configuration (Rating)	9	9	2	9	1	1	2
Thrust (k-lbs, Δ Baseline)	26	109	257	181	50	50	25.5
Use of GFE (Rating)	9	1	2	3	2	3	9
AV weight (k-lbs, Δ Baseline)	60	160	173	3	0	0	13.5
Specific impulse (s)	296	248	445	319.1	319	319	261
No. of propellant tanks	2	4	1	6	1	1	1
Ease of adding instrumentation (Rating)	3	3	3	3	9	2	3
Control system complexity (Rating)	9	9	9	9	1	3	1
Ease of adding active sensors (Rating)	3	3	3	3	9	2	3
Aerodynamics (estimated Cd_0)	0.34	0.37	0.33	0.26	0.30	0.30	0.30

[†]The example problem used for this demonstration contains only information available in the public domain.

From the RFP review and the literature search, the basic shell of the QFD's HoQ matrix can be constructed. IPT meetings with the customer and interactive voting sessions are used to identify the importance of the RFP-derived requirements and the interrelationships between the customer requirements and engineering characteristics. In practice, the latter can be extremely time consuming and is aided by efforts to consolidate the dimensionality of the HoQ matrix. The QFD exercise produces a prioritized list of important engineering factors. These subjective values are combined with descriptive data on the potential concepts in the data matrix. In practice, the rows of this matrix represent the engineering factors, the columns represent concepts, and the body contains information relating concepts to the engineering factors. This matrix may contain a mix of qualitative and quantitative data. An example data matrix is shown in Table 1. In the absence of quantitative data, a subjective scale can be used to represent relative contributions in a given dimension, labeled as "rating" in Table 1. The TOPSIS algorithm takes the subjective weightings from the QFD output and the data matrix to produce a set of numerical rankings for each alternative.

The process for linking QFD and MADM techniques has been implemented across the engineering community, though it is often performed in two serialized steps as opposed to a single integrated process. For example, Liao et al. linked QFD and MADM to identify packaging issues for notebook computers and provide feedback to engineers in an effort to increase logistics efficiency [33,34]. Crowley et al. used this method to propose a low-cost solution to small satellite space access and evaluated 11 concepts across 19 decision criteria [35]. Other applications include the design of an Apollo-like spacecraft [36], subsonic transport aircraft [37], a civil tiltrotor [38], an ICBM-derived space launch vehicle [39], and hypersonic air vehicles to name a few [40]. Ho provides a survey of AHP and its applications and highlights 16 references where QFD and AHP are combined to produce an integrated decision-making environment across the fields of higher education, manufacturing, logistics, and military force selection [41].

While the solid lines in Fig. 2 summarize the process in use today, the dashed lines in Fig. 2 represent a more idealized *iterative process* where the customer is involved in an assessment of the alternatives and may choose to revise requirements or alter their perception of important factors based on the result. Subsequent sections identify a rapid, dynamic, and traceable way for not only mechanizing the process shown in Fig. 2 with a graphical analysis tool, but also for accounting for the uncertainty in subjective requirements through the use of probabilistic methods.

D. Drawbacks to the Current Process

While the process shown in Fig. 2 can be used to identify concepts that satisfy the customer need, it has several major drawbacks:

1. Although the tools provide a traceable process for concept identification, the setup time for the process is considerable to perform a *single* design study.

2. The selection of a concept is dependent on the *subjective* importance placed on the customer requirements and the subjective relationships identified by the engineering IPT in the interrelationship matrix.
3. A committee approach is often used to specify the subjective weightings of the customer importance. Lengthy discussions tend to result and the final values are often dominated by the most outspoken member of the customer team.

Each of these challenges has the potential to cause dismissal of the study by the customer. For example, if non-intuitive answers result or if the customer (or contractor) is unhappy with the final answer, any participant can question the assumptions of the study. The second and third issues are closely related: as the answer depends on subjective preference, participants dominated by the loudest member in the group tend to become disillusioned. The effort expended for the lengthy discussion to arrive at the "unacceptable" answer tends to leave some members of the IPT and customer team with a negative view of the process.

When a non-intuitive answer results, there are several possibilities: (1) the QFD or TOPSIS algorithms were incorrectly calculated, (2) there is an error in the data matrix, (3) there is an error in the interrelationship matrix, (4) the subjective weightings on the customer requirements are not correct, or (5) the non-intuitive answer is the correct answer. The subsequent section proposes a modification to the methodology in Fig. 2 that addresses the three drawbacks and postulates solutions to each of the five possibilities above.

III. Proposed Approach

To address the aforementioned shortcomings of the existing process, two key advances, *parametrics* and *probabilistics* are proposed and discussed in the subsequent sections.

A. Enabling "What-if?" Trade Studies Using Parametric Slide Bars

The process defined in Fig. 2 is a serial mathematical process that is traditionally performed in distinct phases with physical handoff of the data between steps. The first recommended modification to this process is the direct integration of the TOPSIS MADM technique to the output results of the QFD. Incorporating both algorithms in a single spreadsheet allows the overall goodness of a series of concepts to be evaluated *in real time* as customer requirements are changed. To facilitate rapid trade studies, an interface called the Interactive Concept Evaluation Environment (ICEE) was created in Microsoft Excel® to perform the calculations (Fig. 3) [24]. The QFD matrix is imported as shown in Area 1 in Fig. 3. Using the *Forms* toolbar in Microsoft Excel®, graphical slide bars were added to the interface and linked to the input cells to the customer importance rankings in the QFD (Area 2 in Fig. 3). Moving the slide bars instantly updates the relative importance of the engineering characteristics (Area 3) as well as the overall ranking of concepts from the TOPSIS calculations (Area 7). Several additional areas of the ICEE are used to perform dynamic trades and assess the sensitivity of the overall ranking. Area 4 contains the data matrix for 15 concepts of interest. If there is an error in the data matrix, it can be corrected in real-time by changing the values in the Excel® spreadsheet. Area 5 adds parametric slide bars for the risk-weighted customer importance. Using these slide bars, a designer can scale the QFD rankings to perform trade studies directly on the engineering characteristics. While this final approach overrides the QFD and tends to discount the voice of the customer, it is useful for performing "what-if" studies to assess the sensitivity of concepts and identify the conditions under which certain alternatives are more viable. This area of the tool is most useful to explain the rankings of individual alternatives by demonstrating the mathematical traceability to customer requirements and is often helpful in explaining non-intuitive results.

The TOPSIS technique allows the relative importance of different factors to be taken into account; however, what if a certain requirement is not just important, but is absolutely required? To address this issue, a series of "kill switches," K_i are used (Area 6 in Fig. 3). If an attribute value for a concept is within the minimum and maximum ranges defined by the designer, K_i is equal to unity. Otherwise, the kill switch is set to zero. The overall goodness criterion, C_j, is modified such that

$$C'_j = C_j \sum_{i=1}^{n} K_i \tag{4}$$

For n kill switches. In this manner, customer requirements can be set as *important* or *absolutely required*. Concepts which do not meet the requirement thresholds will have an overall goodness of zero when the kill switches are

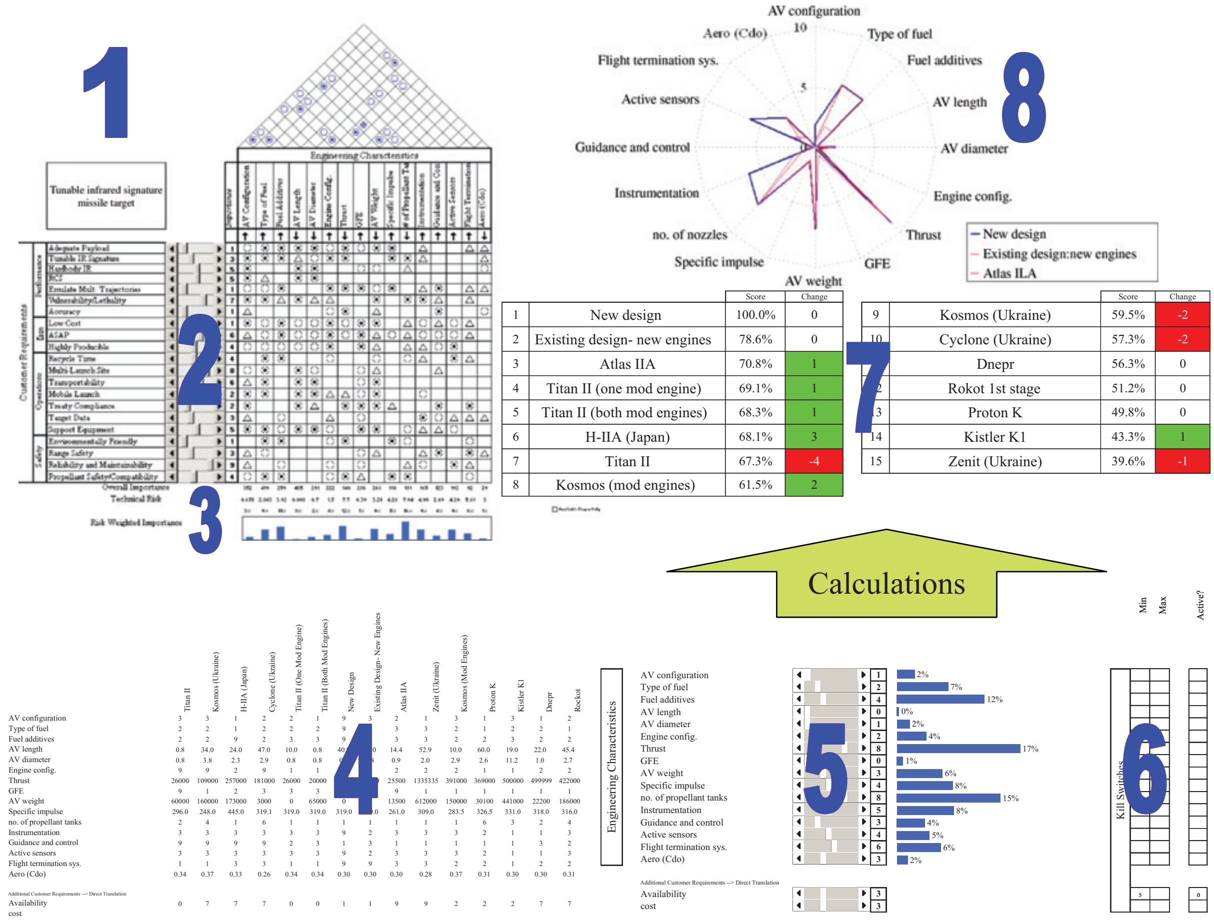

Fig. 3 Interactive concept evaluation environment (ICEE) for a tunable infrared signature missile target for the 2004 AIAA Graduate Strategic Missile Design Competition [24].

activated and satisfactory concepts will be ranked according to the original algorithm. For example, the baseline output ranking using the interactive TOPSIS (Area 7 in Fig. 3) is shown in Fig. 4.

When a threshold is placed on the dimension of *availability* by setting an upper bound and activating the associated kill switch, the rankings change significantly as shown in Fig. 5. The "change" column indicates how the concepts have been rearranged from the baseline case. Note that all concepts after position 7 have a score of 0 indicating that the kill switch is active.

Finally, it is important to note that the traditional C value of the TOPSIS method has no physical meaning and is merely relative to the C value for the other ranked concepts. To improve the readability of the results, it is recommended that all C values be normalized by the C value for the top-ranked concept, yielding a relative percentage where the best concept represents a perfect score of 100%. The final modified goodness equation, C''_j is shown below where j is the index for each concept considered. C'_j is given by Eq. (4).

$$C''_j \frac{C'_j}{\max_j (C')} \tag{5}$$

In addition to the overall ranking, a designer may wish to identify *why* a given concept tends to win. The radargram or spider chart is a useful graphical depiction of requirements satisfaction in multiple dimensions. The radargram depicts the value of an attribute along weighted radial axes from the center of the chart: a better overall score

		Score	Change
1	New design	100.0%	0
2	Existing design: new engines	81.2%	0
3	Atlas IIA	74.1%	0
4	Titan II (one mod engine)	72.5%	0
5	Titan II (both mod engines)	72.0%	0
6	Titan II	71.6%	0
7	H-IIA (Japan)	71.0%	0
8	Kosmos (Ukraine)	64.6%	0
9	Kosmos (mod engines)	63.8%	0
10	Cyclone (Ukraine)	61.8%	0
11	Dnepr	58.3%	0
12	Rokot 1st stage	54.8%	0
13	Proton K	53.4%	0
14	Kistler K1	46.9%	0
15	Zenit (Ukraine)	37.0%	0

Fig. 4 Ranking of the top15 missile concepts using TOPSIS.

		Score	Change
1	Atlas IIA	100.0%	2
2	H-IIA (Japan)	95.8%	5
3	Kosmos (Ukraine)	87.1%	5
4	Cyclone (Ukraine)	83.3%	6
5	Dnepr	78.6%	6
6	Rokot 1st stage	73.9%	6
7	Zenit (Ukraine)	49.9%	8
8	Kistler K1	0.0%	6
9	Proton K	0.0%	4
10	Kosmos (mod engines)	0.0%	-1
11	Existing design : new engines	0.0%	-9
12	New design	0.0%	-11
13	Titan II (both mod engines)	0.0%	-8
14	Titan II (one mod engine)	0.0%	-10
15	Titan II	0.0%	-9

Fig. 5 Ranking of the top 15 missile concepts using the modified algorithm to include kill switches.

is analogous to a larger area on the graph. The ICEE in Fig. 3 shows a radargram with respect to *engineering characteristics*; however, using the QFD technique in conjunction with the TOPSIS algorithm, it is also possible to depict the overall goodness in terms of top-level customer requirements as shown in Fig. 6. This depiction is called the "requirements radar."

In the above figure, the shaded area represents the value of each customer requirement as defined by the parametric inputs to the interactive interface in Fig. 3. The outer solid line shows how well the concept **New Design** meets the customer requirements. For comparison, the inner solid line shows how an underperforming concept differs from the top choice. The numerical values of importance are scaled by the relative importance of each requirement so that no concept can score outside the shaded region. Maximum satisfaction of customer requirements therefore occurs when any solid line (representing a concept) entirely overlaps the shaded area (representing customer requirements). The difference between the shaded area and solid line in any one dimension is the requirements gap in that dimension, which provides information to designers on how individual concepts may be modified to better meet customer requirements.

B. Accounting for Subjectivity from the Selection Processing Using Probabilistic Techniques

The parametric technique is a powerful tool for assessing the sensitivity of concepts to changing customer preference; however, what is ultimately desired is a technique that reduces the impact of uncertainty in the subjective criteria. As previously mentioned, subjective estimates of customer preference gathered through consensus-building elicitation methods are a useful and effective way of understanding customer needs; however, uncertainty and disagreement in these values guides designers to suboptimal concepts and may lead to the development of a product

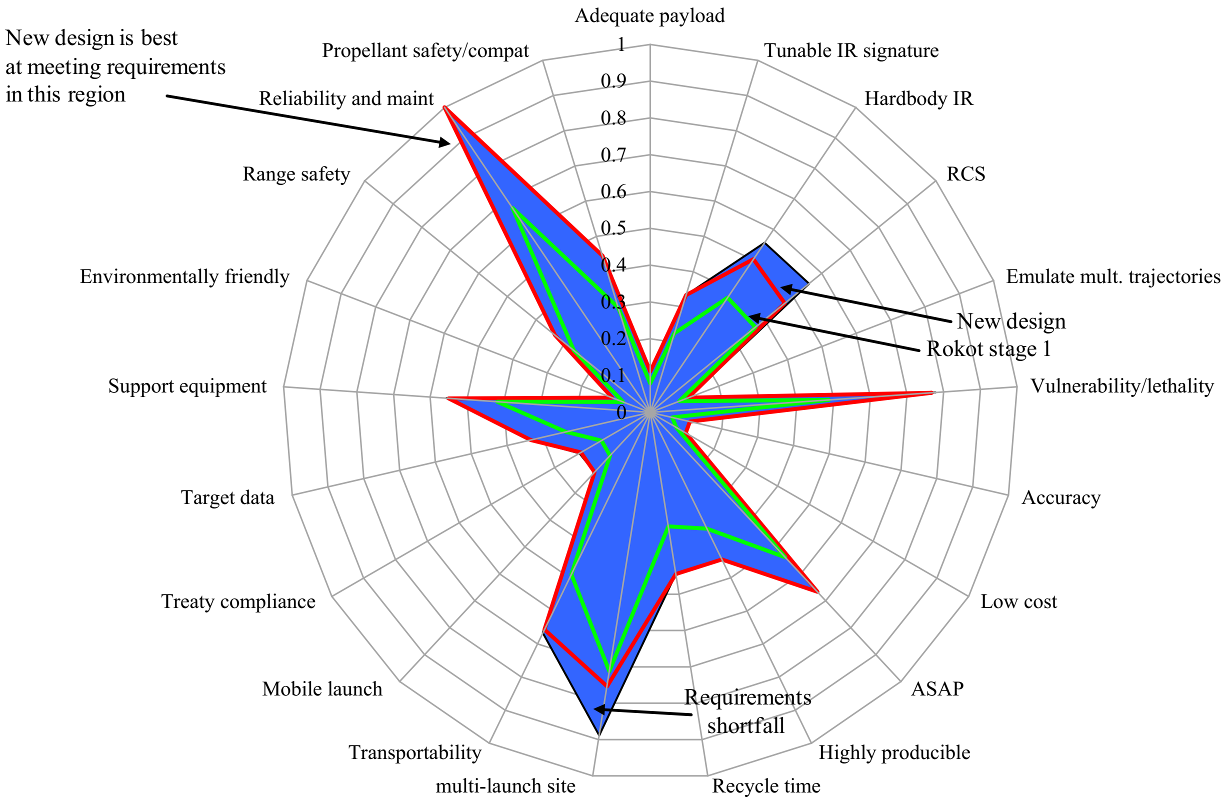

Fig. 6 Requirements radar showing two alternative concepts against top-level customer requirements.

that does not meet customer needs. While a designer can use the parametric slide bars to play a number of "what-if" games, a key question arises: "Can we play *all* the games and track the results?"

Once the parametric environment has been created, a probabilistic wrapping utility can be used to execute a Monte Carlo Simulation (MCS) on the customer importance values [42]. In place of the single data value driven by a parametric slide bar, a distribution of importance from zero to nine can be defined. A uniform distribution, shown in Fig. 7, acts as a random number generator and will select importance values uniformly between the specified minimum and maximum. This distribution is most effective when there is no preference for a customer requirement

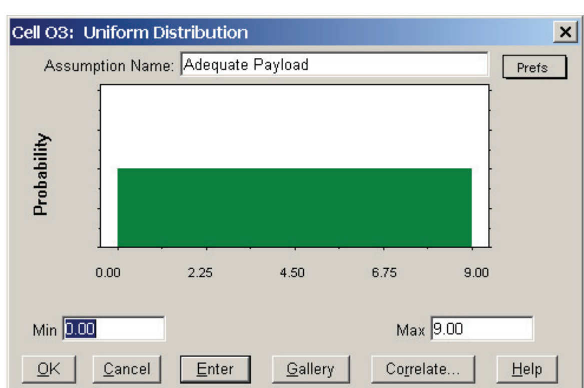

Fig. 7 Definition of a uniform distribution.

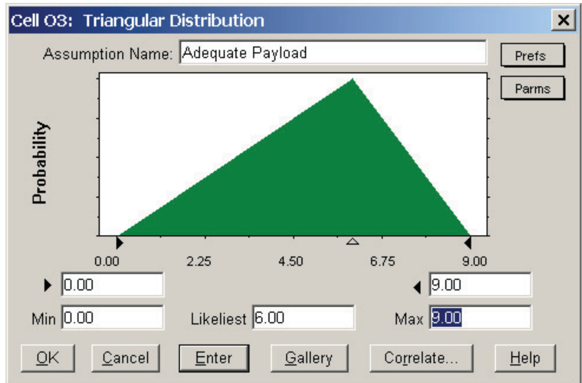

Fig. 8 Definition of a triangular distribution.

or when no decision can be reached by consensus. The triangular distribution shown in Fig. 8 is most appropriate when a likely value is generally agreed upon but there is some disagreement around a preferred point.

The triangular distribution will preferentially select random numbers closer to the likeliest value while including values up to the extremes and is most appropriate for design activities where there is some group disagreement around a median value. It is important to note that only anchored distributions are appropriate for this technique to avoid calculation errors in ICEE framework. Due to the relatively simple nature of the calculations in the TOPSIS algorithm, the MCS runs very quickly. Experiments were conducted using commercially available MCS tools including Crystal Ball by Decisioneering, Inc. [43] and ProbWorks by Pi Blue Software, Inc. [44].

IV. Interpreting the Results

As the input values have transitioned from deterministic numbers to probability distributions, the output results are also displayed in probabilistic terms. One method for viewing the output is in the form of a probability density function (PDF) or histogram, as shown in Fig. 9. As opposed to the single numerical values representing each concept's ranking with respect to its peers as shown in Figs. 4 and 5, the histogram view shown in Fig. 9 visually depicts the variability of the concept owing to uncertainties in subjective factors when probability distributions are used. The median value of the histogram corresponds with the absolute numerical scales of Figs. 4 and 5. The extreme values for a given concept indicate the best and worst possible scores for C'' across the range of customer requirement preferences as defined by the probabilistic inputs. When the histograms overlap, it is possible for the two concepts to change order in the rankings (shaded areas in Fig. 9). For the example shown in Fig. 9, a uniform distribution was run over all values of the customer requirements[§] . The histogram shows the distribution of the resulting overall goodness as the customer requirements are varied over all possible scenarios. The example in Fig. 9 shows that the **New Design** tends to win under most circumstances, although **Existing Design-New Engines** and **Titan II** tend to score well for a large range of scenarios. One of the shaded areas highlights the range of cases where the customer requirements may be set such that the **Titan II** outperforms the **New Design**. It is also interesting to note that the **Kistler K1** concept is generally outperformed by all peer concepts except for a very small range of scenarios where it can perform better than one or more alternatives. It is important to note that just because the **Kistler K1** beats the **New Design** for a vanishingly small number of situations, this does not necessarily mean that the **Kistler K1** is the "best" solution because the same scenarios that penalized the performance of the **New Design** may also have benefited other concepts.

Another way of interpreting the results to gain a measure of overall goodness using the probabilistic technique is to track the highest rank attained by a concept and how many times this rank is attained. For each setting of the importance on the customer requirements, the candidate concepts will be ranked according to the flowdown of

[§] Only four of the candidate concepts are shown on the histogram for clarity. The remaining concepts feature median values that fall between the **Kistler K1** and the **Titan II**.

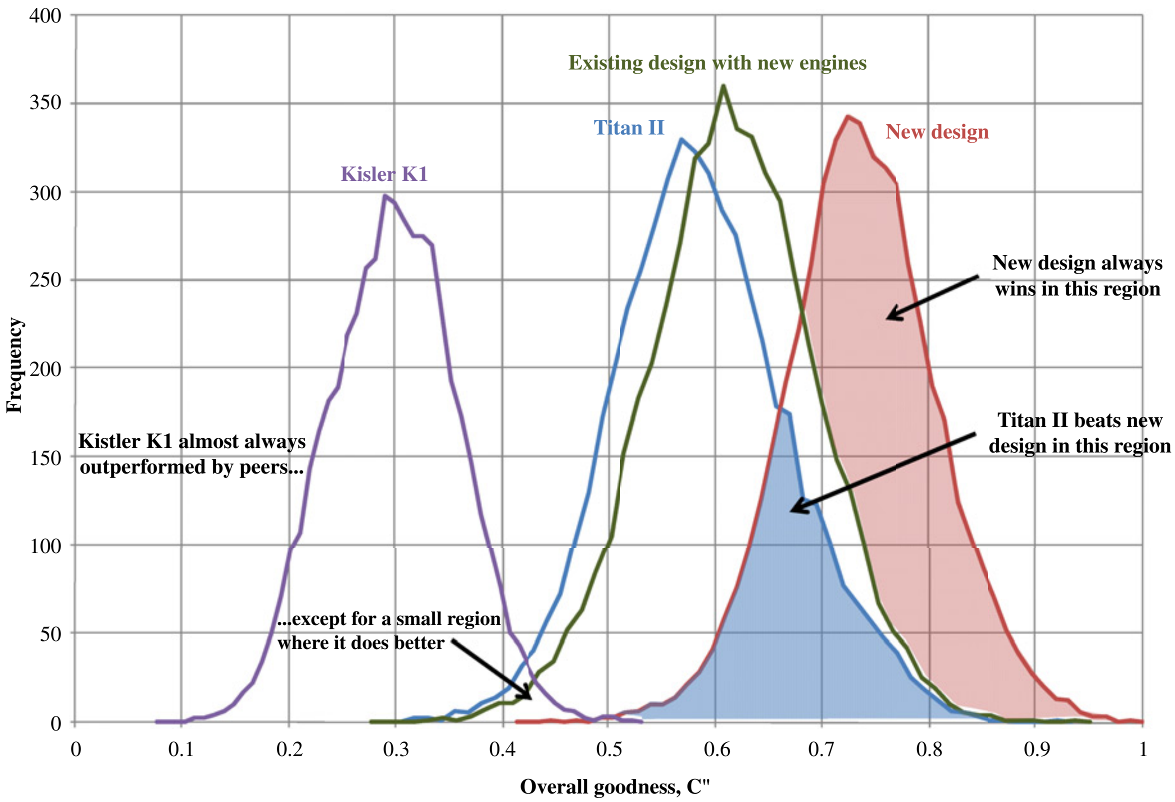

Fig. 9 Histogram for 15 missile concepts using a uniform distribution on the customer requirements.

mappings through the QFD. By tracking how many times each concept attains each rank, a designer can gain an appreciation for the overall goodness of a concept with respect to its peers. For example, if a given concept is ranked first regardless of customer preference then the concept may be considered robust to changing customer preference in the presence of the identified peer concepts. This depiction of the overall results tends to follow the same trend as the histograms shown in Fig. 9; however, the results are easier to interpret. It is important to note that the same MCS that generates the histogram can be data mined in a different manner to obtain this information. The simplified summary is shown in Table 2. When uniform distributions across all requirements are used, ten of the proposed concepts can attain the first place rank, although many only do this a handful of times. From Table 2 and Fig. 9, it can be determined that the New Design is the "ideal concept" with respect to overall score and varied requirements. Using different distributions or activating kill switches would change this result.

Further examination of Table 2 shows that there are only five concepts worth considering when uniform distributions are used on the customer preference: the sixth place concept, **Titan II (Both Mod Engines)** attains a first place rank less than 1% of the time. These results represent a case where the customer has *no* preference to any of the requirements, which is very unlikely. In practice, using different distributions or eliminating concepts from consideration will change the results of Table 2 dramatically. Concepts are not considered in absolute terms, they are considered relative to the other choices offered. Removing concepts from the selection pool or focusing the probability distributions to a certain area of the requirements spectrum has a significant impact on the rankings of each candidate concept.

Although uniform distributions were used to demonstrate the concept of probabilistic assessments, these distributions imply that the customer has *no* preference toward any of the requirements. In practice, triangular distributions are more appropriate for showing the variation of customer preference around a median value. When triangular distributions are used, the spread of the histograms in Fig. 9 decreases dramatically and the histograms tend to cross

Table 2 High scores and frequency of occurrence for 15 missile concepts

Alternative	Best rank	Number of times	% of best
New design	**1**	**1929**	**38.5%**
Existing design: new engines	**1**	**1155**	**23.1%**
Titan II	**1**	**933**	**18.6%**
Titan II (one stage with modified engine)	**1**	**445**	**8.9%**
Atlas IIA	**1**	**476**	**9.5%**
Titan II (both stages with modified engines)	1	27	0.5%
H-IIA (Japan)	1	23	0.5%
Kosmos (Ukraine)	1	5	0.1%
Cyclone (Ukraine)	1	4	0.1%
Kosmos (modified engines)	1	2	0.0%
Rokot 1st Stage	2	1	0.0%
Dnepr	2	3	0.0%
Proton K	4	2	0.0%
Zenit (Ukraine)	5	1	0.0%
Kistler K1	5	1	0.0%

far less often. Similarly, the values in Table 2 tend to be more discriminated, with fewer alternatives attaining a rank of 1.

The most general application of this technique is to apply probability distributions to the customer importance values; however, it is also possible to assign a distribution to values in the data matrix to represent design uncertainty or to any cell in the QFD interrelationship matrix to represent disagreements in the mapping of customer requirements to engineering characteristics. A similar technique was demonstrated by Otto and Wood using probability distributions on the values in a Pugh selection matrix [45]. On one hand, as more probability distributions are added the variance of the overall rankings will increase making it more difficult to definitively select a single answer; however, if the same concept wins regardless of how many distributions are used this concept is *robust* with respect to changing requirements. A compromise process is to run two MCS: one with uniform distributions to see how concepts behave across all possible "what-if" games and a second MCS with triangular distributions representing likely scenarios. The outputs of this process are shown in Fig. 10 for the case of pure uniform distributions and in Fig. 11 with triangular distributions on some input parameters.

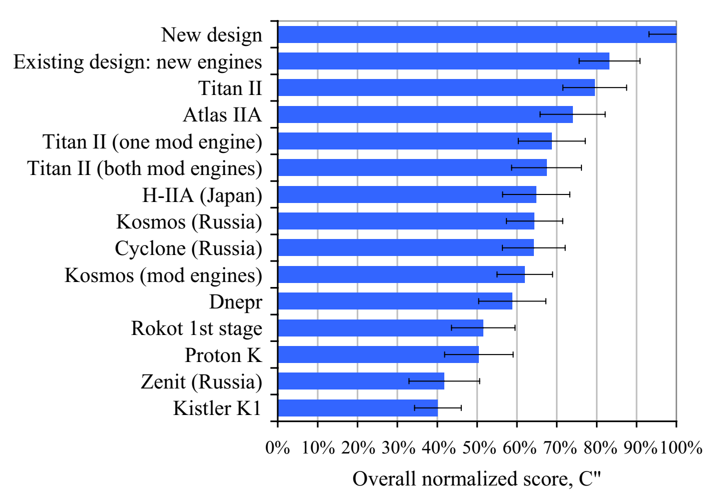

Fig. 10 Probabilistic rankings with uniform distributions on all inputs.

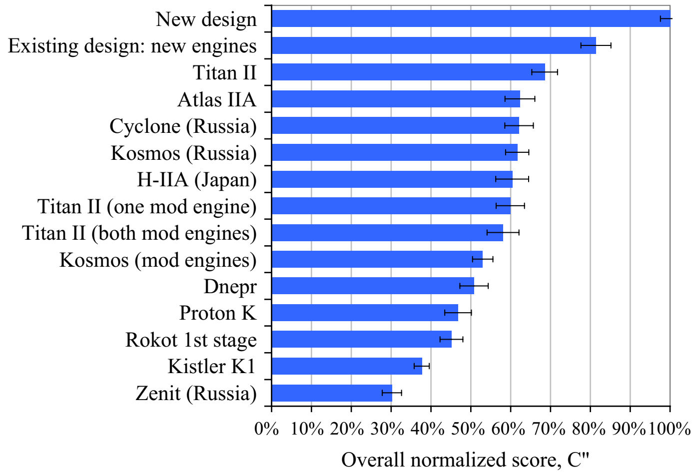

Fig. 11 Probabilistic rankings with some triangular distributions.

The figures show the overall score of each concept with the error bars representing the relative amount of change present when the probability distributions are used. The error bars are smaller in Fig. 11 owing to the more restrictive triangular distributions. Also, some concepts have changed positions between the two cases. This is indicative of the shift in the mean caused by the settings of the three parameters (minimum, most likely, and maximum) of the triangular distributions that impact the type of "what-if" games played in the second case.

Occasionally, a non-intuitive answer results from applying a mathematical algorithm to the decision support process. The rankings are often traceable back to the customer's subjective preference on the requirements and can thus be understood and the inconsistencies mitigated with the approach proposed in this paper. Sometimes, the discrepancies are attributable to misrepresentation of the concept in the data matrix. For example, the **New Design** scores well in all of the examples shown. This concept, designed specifically to meet the needs of this RFP, would have performance precisely tuned to address customer needs; however, the data matrix used for this example does not give an estimate of the technical risk associated with new product development, the long development times or cost associated with such endeavors. Notional concepts or "paper airplanes" always tend to outperform known systems when compared using qualitative methods because performance estimates tend to be overestimated and cost estimates tend to be underestimated. Another common problem that results in non-intuitive solutions is the use of two similar and reinforcing customer requirements. When scoring the interrelationship matrix, two similar requirements may result in similarly scored rows, artificially inflating the score for one or more engineering characteristics. The same phenomena can be observed in the relationship between engineering factors and the concept descriptions in the data matrix. To support decision makers and avoid the overinflation phenomenon, engineers must be judicious in their definition of requirements and responsible in the estimation of values for the data matrix. As with any decision support process, users should verify the algorithm's conclusions using sound judgment supported by modeling and simulation to confirm performance estimates where possible. Finally, it is important to note that when non-intuitive results are revealed as the "right" answer in the proposed tool, designers must use both the tool and underlying data to build a case to present the solution to decision makers. The purpose of the proposed process is not necessarily to dictate an answer, but to provide additional insight to decision makers by providing a traceable process that is interactive and provides a measure of uncertainty quantification in regards to subjective preference factors.

V. Conclusion

Subjectivity plays a significant role in concept selection in the design process, and often customer preference factors can have more influence on design decisions than physics-based or technology-driven attributes; however, subjectivity does not imply "bad" decision making. In the case of revolutionary or unconventional approaches, subjective estimates may be the only avenue for comparison when underlying phenomenological models do not exist. The process outlined in this paper does not seek to eliminate the influence of subjective factors, merely to account for the variations endemic to these estimates with a measure of uncertainty in the final results. The proposed modifications to the process for concept identification shown in Fig. 2 address the shortcomings in traditional systems engineering by implementing a dynamic, parametric approach to concept selection and visualization and a probabilistic approach to uncertainty quantification in customer requirements. Using modern software tools, it is possible to assess the sensitivity of potential concepts to changing customer preference in real time using parametric slide bars and off-the-shelf visualization tools. The agility that arises from automating the flow of information from customer preferences to concept selection through a direct linkage of QFD and MADM techniques enables a more customer-centric solution identification process where the impact of subjective decisions on the concept space can instantly be reviewed and revised. Furthermore, leveraging probabilistic techniques for the establishment of customer preference and the mapping of customer requirements to engineering characteristics can reduce the impact of subjectivity on the design process and address the primary criticisms of qualitative systems engineering methods and forecasting techniques. In cases where non-intuitive answers result, the traceable mathematical mappings from customer needs to solutions and the ability to parametrically alter the inputs and observe a chance in rankings helps increase the confidence in the identified answer. Often, non-intuitive answers may provide the greatest benefit in a competitive situation by developing a new way to meet customer requirements that exceeds the benefits offered by traditional approaches. On the other hand, these non-intuitive answers must also be treated with caution and rigorously verified against the input data. In many cases, adding multiple "important" requirements that measure the same phenomena or overestimating the performance of revolutionary concepts may result in a misjudgment of concept performance with respect to known peers. It is important to note that the aforementioned process is best described as a "decision support environment" rather than a "decision-making environment." Implementation of parametric tradeoff environment in a dynamic, graphical tradeoff environment provides decision makers with an interactive, traceable, and justifiable means to validate concept selection decisions and understand sensitivities. The addition of probability distributions in the same parametric environment help engineers and decision makers understand the impact of uncertainty in their subjective decisions and account for the variability of concept performance in the presence of uncertain customer requirements.

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References

[1] Hazelrigg, G. A., *Systems Engineering: an Approach to Information-Based Design*, Prentice-Hall, Upper Saddle River, NJ, 1996.

[2] International Council on Systems Engineering (INCOSE) Technical Board, *Systems Engineering Handbook*, International Council on Systems Engineering Technical Product, San Diego, CA, INCOSE-TP-2003-002-03, Version 3.0, June 2006.

[3] *NASA Systems Engineering Handbook*, SP-610S, June 1995.

[4] United States Air Force Space and Missile Systems Center, *SMC Systems Engineering Primer and Handbook,* 2nd ed., 2004.

[5] United States Department of Defense, *System of Systems Systems Engineering Guide: Considerations for Systems Engineering in a System of Systems Environment*, Version 0.9, 2006.

[6] *Systems Engineering Fundamentals*, Defense Acquisition University, 2001.

[7] Mizuno, S., and Akao, Y., *Development History of Quality Function Deployment, The Customer Driven Approach to Quality Planning and Deployment*, Asian Productivity Organization, Tokyo, Japan, 1994.

[8] International Council on Systems Engineering (INCOSE) Technical Board, *Systems Engineering Handbook*, International Council on Systems Engineering, San Diego, CA, INCOSE-TP-2003-016-02, Version 2a, 1 June 2004.

[9] Helmer, O., and Rescher, R., "On the Epistemology of the Inexact Sciences," Project RAND Report R-353, February 1960.

[10] Dalkey, N., and Helmer, O., "An Experimental Application of the Delphi Method to the Use of Experts," *Management Science,* Vol. 9, No. 3, 1963, p. 458.

[11] Gavish, B., and Gerdes, J. H., "Voting Mechanisms and their Implications in a GDSS Environment," *Annals of Operations Research*, Vol. 71, 1997, pp. 41–74.
doi: 10.1023/A:1018931801461

[12] Kano, N., "Attractive Quality and Must-Be Quality," *The Journal of the Japanese Society for Quality Control*, Vol. 14, No. 2, April 1984, pp. 39–48.
[13] Dummett, M., *Voting Procedures*, Clarendon Press, Oxford, 1984.
[14] Goldberg, B. E., Everhart, K., Stevens, R., Babbitt III, N., Clemens, P., and Stout, L., *System Engineering "Toolbox" for Design-Oriented Engineers*, NASA Reference Publication 1358, December 1994.
[15] Hwang, C., and Yoon K., *Multiple Attribute Decision Making, Methods and Applications, a State-of-the-Art Survey*, Springer-Verlag, Berlin/New York/Heidelberg, 1981.
[16] Saaty, T. L., The *Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation*, McGraw-Hill, New York, NY, 1980.
doi: 10.2307/2583423
[17] Zahedi, F., "The Analytic Hierarchy Process: A Survey of the Method and its Application," *Interfaces,* Vol. 16, 1986, pp. 96–108.
[18] de Steiguer, J. E., *The Analytic Hierarchy Process as a Means for Integrated Watershed Management*, edited by K. G. Renard, First Interagency Conference on Research on the Watersheds, Benson, Arizona: U.S. Department of Agriculture, Agricultural Research Service, October 2003, pp. 736–740.
[19] Hill, S., and Zammet, C., "Identification of Community Values for Regional Land Use Planning and Management," *International Society of Ecological Economists Congress*, 2000.
[20] Dyer, J. S., "Remarks on the Analytic Hierarchy Process," *Management Science*, Vol. 36, No. 3, 1994, pp. 249–258.
[21] Mikhalevic, M. V., "Remarks on the Dyer-Saaty Controversy," *Cybernetics and Systems Analysis*, Vol. 30, No. 1, January 1994, pp. 75–79.
[22] Saaty, T. L., "Response to Holder's Comments on the Analytic Hierarchy Process," *The Journal of the Operational Research Society*, Vol. 42, No. 10, October 1994, pp. 909–914.
[23] Benitez, J. M., Martin, J. C., and Roman, C., "Using Fuzzy Number for Measuring Quality of Service in the Hotel Industry," *Tourism Management*, Vol. 28, No. 2, April 2007, pp. 544–555.
doi: 10.1016/j.tourman.2006.04.018
[24] Biltgen, P., et al., "Proteus: A Long Range Liquid Booster Target Vehicle," AIAA Missile Systems Technical Committee Graduate Strategic Missile Design Competition, Final Report, 2004.
[25] Chu, T.-C., and Lin, Y.-C., "A Fuzzy TOPSIS Method for Robot Selection," *The International Journal of Advanced Manufacturing Technology*, Vol. 21, No. 4, February 2003, pp. 284–290.
doi: 10.1007/s001700300033
[26] Braglia, M., Frosolini, M., and Montanari, R., "Fuzzy TOPSIS Approach for Failure Mode, Effects, and Criticality Analysis," *Quality and Reliability Engineering International*, Vol. 19, No. 5, 2002, pp. 425–443.
doi: 10.1002/qre.528
[27] Méndez, M., Galván, B., Salazar, D., and Greiner, D., "Multiple-Objective Genetic Algorithm Using the Multiple Criteria Decision Making Method TOPSIS," *7th International Conference on Multi-Objective Programming and Goal Programming*, 2006.
[28] Schrage, D. P., "Technology for Rotorcraft Affordability Through Integrated Product/Process Development (IPPD)," *Proceedings of the 55th American Helicopter Society Annual Forum*, 1999.
[29] Grady, J. O., *System Requirements Analysis*, Academic International Press, New York/London/Orlando, FL, 2006.
[30] Hooks, I. F., and Farry, K. A., *Customer-Centered Products: Creating Successful Products Through Smart Requirements Management*, American Management Association, 2001.
[31] Engler, W. O., Biltgen, P. T., and Mavris, D. N., "Concept Selection Using an Interactive Reconfigurable Matrix of Alternatives (IRMA)," *44th AIAA Aerospace Sciences Meeting and Exhibit*, AIAA, Reston, VA, Reno, 2007, AIAA Paper 2007-1194, p. 3.
[32] Isakowitz, S. J., Hopkins, J. B., and Hopkins, J. B., *International Reference Guide to Space Launch Systems,* 4th ed., AIAA, Washington, DC, 2004.
[33] Liao, C.-P., "Packaging Attribute Deployment for New Product Introduction in Notebook Computer Industry," Master's Thesis, Chung Yuan Christian University, Taiwan, Republic of China, 2006.
[34] Rau, H., Liao, C.-P., Shiang, W.-J., and Lin, C.-H., "Using Fuzzy Theory for Packaging Attribute Deployment for New Notebook Computer Introduction," *Lecture Notes in Computer Science*, Vol. 4570, 2007, pp. 250–259.
doi: 10.1007/978-3-540-73325-6_25
[35] Crowley, J., Hutchinson, V. L., Jr., Keisner, A., Young, D., Curry, M., Jackson, J., Maatsch, J., Piletsky, P., and Olds, J. R., "Chimera: A Low Cost Solution to Small Satellite Space Access," *17th Annual AIAA/USU Conference on Small Satellites*, 2003.

[36] Bucher, D., and Reeves, D., "Qualitative Robust Systems Engineering Analysis of Apollo Concepts and Architectures," *1^{st} Space Exploration Conference: Continuing the Voyage of Discovery*, 2005.
[37] Mavris, D. N., and Garcia, E., "Affordability Assessment for a Subsonic Transport," *2^{nd} Joint ISPA/SCEA International Conference*, 1999.
[38] Mavris, D. N., Baker, A. P., and Schrage, D. P., "Implementation of a Technology Impact Forecast Technique on a Civil Tiltrotor," *Proceedings of the 55^{th} American Helicopter Society Annual Forum*, 1999.
[39] Kumpel, A., Barros, P., and Mavris, D. N., "A Quality Engineering Approach to the Determination of the Space Launch Capability of the Peacekeeper ICBM Utilizing Probabilistic Methods," *AIAA Missile Sciences Conference*, AIAA, Reston, VA, 2002.
[40] Hollingsworth, P., and Mavris, D. N., "A Method for Concept Exploration of Hypersonic Vehicles in the Presence of Open and Evolving Requirements," *5^{th} World Aviation Congress and Exposition*, Society of Automotive Engineers, 2000.
[41] Ho, W., "Integrated Analytic Hierarchy Process and its Applications—A Literature Review," *European Journal of Operations Research*, Vol. 186, No. 1, 2007, pp. 211–228.
doi: 10.1016/j.ejor.2007.01.004
[42] Biltgen, P., "Concept Identification and Selection Methods for a Solid-Propellant Target Vehicle to Support the Development of a National Missile Defense (NMD) System," AE 8900 Special Topics Report, Georgia Institute of Technology, July 29, 2004.
[43] "Crystal Ball Version 7.0" Computer Program, Decisioneering, Inc., Denver, CO, 2005
[44] "Probworks" Computer Program, Pi Blue Software, Inc., Atlanta, GA, 2005.
[45] Otto, K., and Wood, K., "Estimating Errors in Concept Selection," *Design Engineering Technical Conferences*, Vol. 2, 1995, pp. 397–411

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