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Architecture value mapping: using fuzzy cognitive maps as a reasoning mechanism for multi-criteria conceptual design evaluation

Atmika Singh

ARCHITECTURE VALUE MAPPING: USING FUZZY COGNITIVE MAPS AS A

REASONING MECHANISM FOR MULTI-CRITERIA CONCEPTUAL DESIGN

EVALUATION

by

ATMIKA SINGH

A DISSERTATION

Presented to the Faculty of the Graduate School of the

MISSOURI UNIVERSITY OF SCIENCE AND TECHNOLOGY

In Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

in

SYSTEMS ENGINEERING

2011

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ABSTRACT

The conceptual design phase is the most critical phase in the systems engineering life cycle. The design concept chosen during this phase determines the structure and behavior of the system, and consequently, its ability to fulfill its intended function. A good conceptual design is the first step in the development of a successful artifact. However, decision-making during conceptual design is inherently challenging and often unreliable. The conceptual design phase is marked by an ambiguous and imprecise set of requirements, and ill-defined system boundaries. A lack of usable data for design evaluation makes the problem worse. In order to assess a system accurately, it is necessary to capture the relationships between its physical attributes and the stakeholders' value objectives. This research presents a novel conceptual architecture evaluation approach that utilizes attribute-value networks, designated as 'Architecture Value Maps', to replicate the decision makers' cogitative processes. Ambiguity in the system's overall objectives is reduced hierarchically to reveal a network of criteria that range from the abstract value measures to the design-specific performance measures. A symbolic representation scheme, the 2-Tuple Linguistic Representation is used to integrate different types of information into a common computational format, and Fuzzy Cognitive Maps are utilized as the reasoning engine to quantitatively evaluate potential design concepts. A Linguistic Ordered Weighted Average aggregation operator is used to rank the final alternatives based on the decision makers' risk preferences. The proposed methodology provides systems architects with the capability to exploit the interrelationships between a system's design attributes and the value that stakeholders associate with these attributes, in order to design robust, flexible, and affordable systems.

ACKNOWLEDGMENTS

It is my pleasure to thank the individuals whose help and support made this dissertation possible. At the very outset, I want to express my gratitude to my advisor, Dr. Cihan H. Dagli, for his guidance and encouragement. His sagacious direction and cogent advice were the driving forces behind this research.

I thank my committee, Dr. V. Allada, Dr. S. Corns, Dr. I. Guardiola and Dr. V. Samaranayake, for their perceptive comments and insightful criticisms that helped me question and refine the assumptions on which this research is based. Special thanks are owed to all my colleagues from the Smart Engineering Systems Laboratory. I will cherish our numerous intellectually stimulating and entertaining discussions.

I am deeply grateful to my family whose sacrifices have made this endeavor successful. I thank my parents for their unflinching support, and faith in me. Without the opportunities they provided, I would not have been where I am today. To my son, thank you for always understanding that mommy needed to work. Finally, and most importantly, I thank my husband for always standing by my side and for having absolute confidence in me. His endless patience, love and motivation have sustained me through this process.

TABLE OF CONTENTS

LIST OF ILLUSTRATIONS

LIST OF TABLES

1. INTRODUCTION

The discipline of systems engineering emerged in response to the need for a structured approach for designing and developing unprecedented systems, primarily in the areas of defense and space research [1]. It has since emerged as an interdisciplinary field of engineering focused on the creation and building of systems too complex to be treated by engineering analysis alone [2]. Its primary pursuit is to bring into being systems that meet customer expectations.

Figure 1.1 shows the processes that constitute the acquisition phase of the systems engineering life cycle. Very generally, these activities consist of scoping, aggregating, partitioning, integrating and finally validating. The design process starts with an abstract definition of needs, and ends with the production of a tangible artifact. During the earliest stages of the design lifecycle, the problem is that of defining a technically feasible system concept from vague and ill-defined needs. Design activities during this stage are largely guided by heuristic design principles. The design becomes progressively more refined with every phase, and the heuristic design principles are replaced by more rational and mathematically rigorous methodologies [2].

At its core, systems engineering is a decision-making activity. It is an iterative process of evaluating a set of alternatives and selecting the most appropriate ones. In the early stages, the design evaluation methodologies are mostly heuristic in nature. As the design lifecycle progresses, the design alternatives become increasingly detailed and the design evaluation methodologies more and more domain specific. Thus system design is, essentially, the 'hierarchical reduction of ambiguity' in search of a physical embodiment of the stakeholders' needs, both stated and implicit.
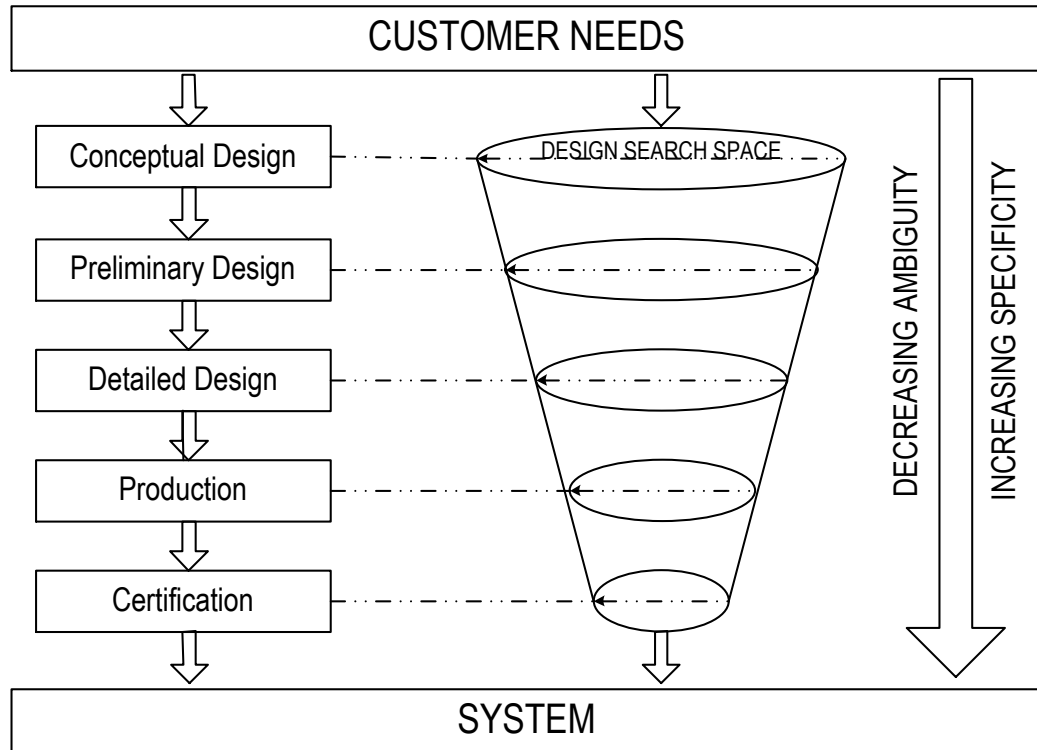
Figure 1.1. Systems Engineering Lifecycle as the 'Hierarchical Reduction of Ambiguity'

1.1. CONCEPTUAL ARCHITECTURE

System architecture is defined by Dori [3] as the combination of a system's structure and behavior that enables it to achieve its functions. Based on this definition, he further defines the conceptual architecture as the system engineer's strategy for a system's architecture [3]. It is important to state what the conceptual architecture is, and more importantly, what it is not. The conceptual architecture does not specify a detailed design of the system; it only stipulates a category of technically feasible high-level system concepts that become the framework for downstream systems engineering activities, including, functional allocation, packaging and design synthesis. The selection of a system concept is one of the first decisions the systems engineer makes during the

design lifecycle. The conceptual architecture is the first embodiment of these early design decisions.

1.1.1. The Significance of Conceptual Design.

During the conceptual design phase, the systems engineer generates various strategies for the system's concept, evaluates them, and selects the best one for further refinement. These early decisions guide the system design process and have far-reaching consequences on the final form and function of a system [4]. The selection of the most appropriate system concept is critical because, not only does the conceptual architecture establish a system's structure and behavior, it also determines how effectively the system will perform those functions. In fact, a key observation of retrospective studies of large-scale systems has been that the ultimate success or failure of such systems is often traceable to their very beginnings [2] . There is considerable design freedom while making the selection of the most appropriate conceptual architecture alternative. However, once a design concept has been finalized the design search space becomes significantly narrower, and many potentially suitable system concepts may remain overlooked. At this point the systems engineer's design freedom is significantly reduced and any changes to the design can negatively impact the final system [4].

A majority of the final cost and scheduling commitments are made during the conceptual design phase [5]. Figure 1.2 shows the percentage of cost commitments made and costs incurred during the various phases of the systems engineering lifecycle. While less than 20% of a project's overall costs are incurred during the early design phases, nearly 60-80% of the overall costs are usually committed by the end of the detailed design phase. Decisions made at this level in the systems engineering process are easy to

modify at a minimal cost as compared to design changes made in the later design phases. Beyond this phase, the reduced design freedom makes design alterations very expensive, both, in terms of time and money.
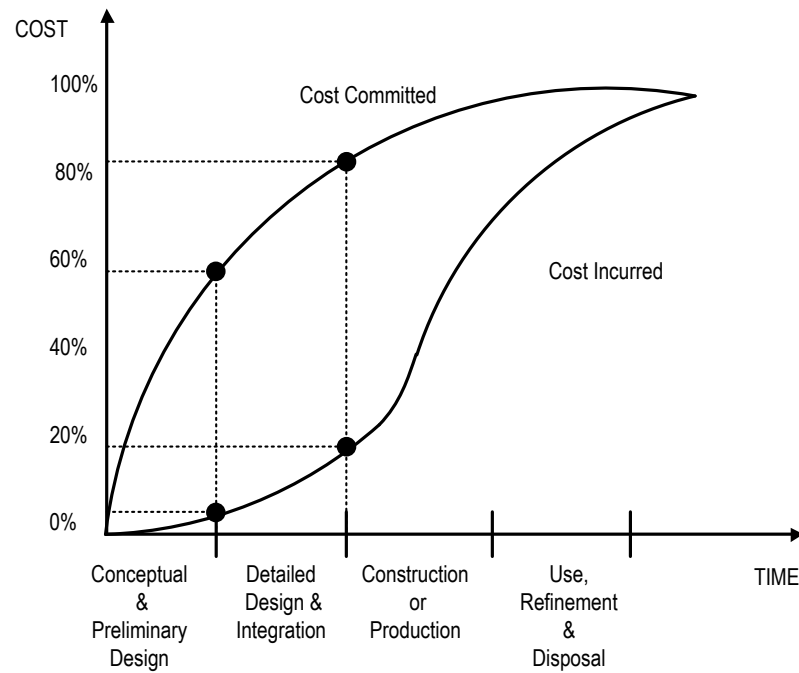
Figure 1.2. Cost Commitments and Costs Incurred during Various Phases of the System Design Lifecycle [5]

As important as conceptual design evaluation decisions are, they are also difficult to formalize due to the limited availability of design specific information, and the subjective nature of the design information that is available at this stage. This has led some authors to describe conceptual design as more of an art than a science [2] .

1.1.2. Conceptual Architecture Evaluation Criteria.

Decision making activities are integral to every phase of systems engineering. The evaluation of acceptable conceptual design strategies is the activity of determining the merit or worth of an architecture alternative, and selecting the one with the highest value. Successful evaluation of a system concept requires the specification of two inputs: a decision maker whose judgment of a system's value will determine its success or failure, and the criteria on which the alternatives will be evaluated [6]. The stakeholders are the final adjudicators of a system's worth, as evidenced by two popularly used design evaluation heuristics:

Success is defined by the beholder, not by the architect. [2]

The most important single element of success is to listen closely to what the customer perceives as his requirements and to have the will and ability to be responsive. (Steiner, J. E., 1978) [2]

The means to evaluate potential system concepts are provided by a set of criteria that emerge from the definition of need and the requirements analysis process. Criteria are measures, standards or rules that guide decision-making [7]. The term criterion is an overarching designation for four system traits, which are relevant to the formulation of the design evaluation problem at hand. These are the Design Attributes (DA), Measures of Performance (MOP), Measures of Effectiveness (MOE), and Stakeholder Value Objectives (SVO). The primary distinguishing characteristic of these criteria is the level of abstraction or specificity with which they describe a design concept. The stakeholders

ascribe value to each potential system concept based on how well it is perceived to perform on these criteria and the relative importance of the criteria themselves.

Stakeholder value objectives are a stakeholder's perception of what he expects to derive from the system and are key indicators of the system's success or failure. These values are stakeholder specific, in the sense that, they are subjectively dependent on the needs of each individual stakeholder. The utility of the system for a stakeholder depends on the satisfaction of these values. Depending on their value expectations, a system may mean different things to different stakeholders. Design attributes are solution-specific characteristics of a system that describe a potential concept variant. Each complete set of design attributes represents a unique strategy for a system's conceptual architecture. These attributes are the features of a design concept that the decision maker judges in order to make a selection.

Measures of Effectiveness (MOE) and Measures of Performance (MOP) are descriptors of a system's quality and capability, respectively. MOEs and MOPs, directly or indirectly enable the system to deliver its intended function to the satisfaction of the stakeholders. An MOP indicates what a system is capable of doing, while an MOE is a property that reflects how well a system concept fulfils the stakeholders' value objectives. MOPs are generally tangible and measurable system attributes. On the other hand, MOEs are usually intangible features of a system and are not directly measurable. Stakeholders use the MOEs, such as affordability, flexibility, security, reliability etc., to qualify the value delivered by a system. Sproles [8, 9] distinguishes between MOEs and MOPs using the analogy of effectiveness versus efficiency where Efficiency is an MOP, and effectiveness is an MOP. While a system can be very efficient at performing its

functions, it may not be performing the right functions at all, i.e., have high efficiency with low effectiveness. Value objectives, effectiveness and performance measures, and design attributes are all interlinked. The lower level design attributes are connected to the high-level value objectives via the MOPs and MOEs, forming a means-ends objectives network as defined by Keeney [10]. Since these criteria are used by stakeholders to judge the success of a system, they need to be specified by the stakeholders [11].

1.1.3. Challenges to Design Evaluation during the Conceptual Design Phase.

Design evaluation criteria represent the multiplicity of aspects that must be taken into consideration while making a judgment. These criteria are not always in agreement with one another, and are of varying degrees of importance to the decision maker. Due to the above-mentioned characteristics, the task of judging and selecting one among several system concepts can be termed a Multi-Criteria Decision Making (MCDM) problem. The challenge faced by the decision maker is to identify the best compromise between the multiple and conflicting criteria that characterize an architectural alternative.

The multiplicity of design evaluation criteria is only one of the challenges to conceptual architecture evaluation. As the systems become large and complex, greater numbers of stakeholders emerge; all of whom participate in the decision-making process. The success or failure of a system is determined by the stakeholders' perception of its value to them [2]. Different stakeholders of a project have different sets of evaluation criteria, and rarely do they agree with each other, making conceptual design evaluation a difficult problem to solve. For the purpose of this research, a stakeholder is defined as any individual or entity that contributes resources to the system, and has sufficient power

to influence the system's design. This definition has been condensed from the one provided in [12].

The early design phases are also marked by high levels of ambiguity about the final form and function of the desired artifact. During the nascent phases of design, neither the system's objectives nor the means to attain these objectives are known with much certainty. The unprecedented nature of most systems engineering artifacts precludes the availability of historical data for formulating decision-making problems. The available information is largely qualitative and subjective. Decisions have to be made based on information that is not only imprecise and incomplete, but is also largely qualitative and subjective in nature. The stakeholders' value perceptions are the key to making effective judgments. The fact that these value perceptions may be neither easily measurable, nor meaningfully quantifiable, only adds to the complexity of the design evaluation task [2].

1.2. HYPOTHESIS

The discussion above establishes the importance of design evaluation during the early systems engineering phases and identifies the key factors that make this a challenging task. This research proposes that by applying the notion of 'hierarchical reduction of ambiguity' the stakeholders' value perceptions can be leveraged to formulate design evaluation problems and assess potential system concepts. By performing a stepwise reduction of abstraction, the stakeholders' value objectives can be decomposed into the MOEs, followed by the MOPs. By linking the MOPs with the design attributes, the systems architect can perform trade-offs based on the impact of a design decision on

an associated MOP and the high-level attributes associated with it. Each architectural decision will result in the achievement of a set of SVOs to a particular level. System concepts can be evaluated and selected for further refinement based on the overall impact of a set of design decisions on the SVOs,

1.3. PROBLEM STATEMENT

In the context of conceptual design evaluation, the questions of interest for this research include,

a. How can stakeholder value objectives be leveraged as design drivers to facilitate the development of design solutions that satisfy stakeholders' needs better?

b. How can vague and uncertain design evaluation criteria be modeled in order to compare and contrast concept alternatives?

c. How can subjective and qualitative expert knowledge be incorporated into these design evaluation models?

d. How can the dynamic and inter-related characteristics of design evaluation attributes be modeled?

The specific objective of this research can be stated as follows – To develop and demonstrate a modeling technique by which the stakeholders' value perceptions can be used to formulate the design evaluation problem, and can be used by the systems engineer to assess and select candidate system architectures during the conceptual design phase of the systems engineering lifecycle.

1.4. DISSERTATION LAYOUT

The following literature review (Section 2) discusses challenges of design evaluation and concept selection and the potential for integrating a 'Computing With Words' (CW) paradigm with Fuzzy Cognitive Maps (FCM) to overcome them. Several popularly used methods are discussed along with their advantages and limitations. The background survey identifies a knowledge gap within the design evaluation body of literature. It is from this knowledge gap that the motivation and opportunity for the presented research was obtained. Section 3 presents a theoretical introduction of the mathematical constructs used to develop the evaluation models. A brief introduction to fuzzy logic, fuzzy inference systems, FCMs and the CW paradigm is presented. Section 4 presents a novel method, based on fuzzy cognitive maps, for conceptual design evaluation that combines intuitive, cognitive mapping techniques with formal, quantitative analysis. A proof of concept for the proposed approach is presented in Section 5 by applying the proposed framework to the design and development of a hybrid energy system. Section 6 presents a retrospective study on the mission-mode selection problem for the Apollo program. This study was conducted mainly as a validation effort. Section 7 discusses and analyzes the results of the investigative studies, reviews the strengths and weaknesses of the AVM framework, and concludes the dissertation with an outlook on avenues of future research.

2. LITERATURE REVIEW

A considerable body of literature exists in the field of decision analysis. Nearly all engineering decision problems are MCDM problems. As discussed in Section 1.1.3, design evaluation is an MCDM problem. MCDM methods are modeling techniques for performing trade-offs between multiple, competing criteria in order to arrive at the best compromise solution. Multi-criteria decision-making requires balancing a set of attributes against each other to arrive at a compromise that provides the solution with the highest overall value. As shown in Figure 2.1, MCDM methods are typically classified into two main categories: Multiple Attribute Decision Making (MADM) methods and Multiple Objective Decision Making (MODM) methods.
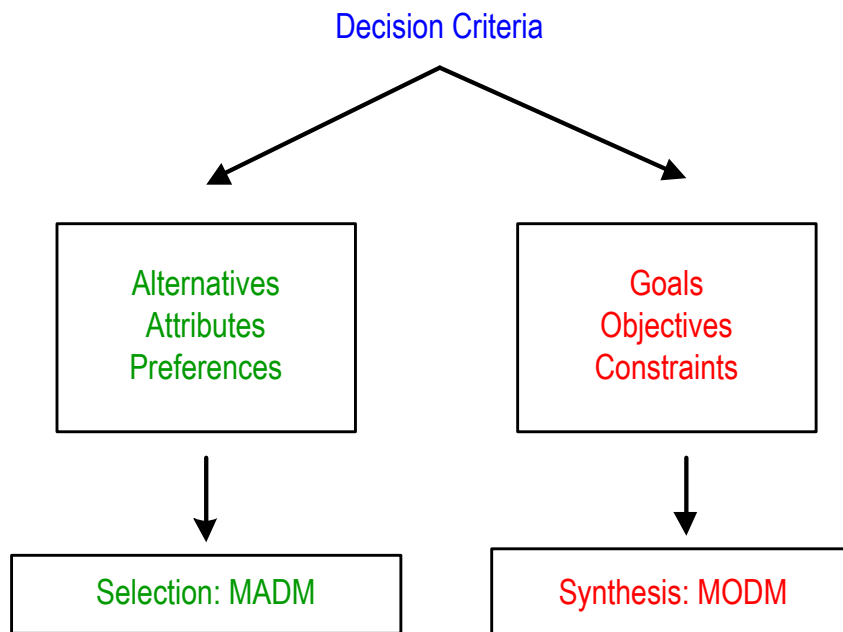
Figure 2.1. Types of Multi-Criteria Decision Making Methods

MADM problems consist of choosing one from a course of actions, in the presence of multiple, conflicting attributes, using the decision makers' preferences as determinants; their objective is selection. MADM methods have three main aspects, a set of decision criteria, a ranking of the decision criteria based on the decision maker's preferences, and a decision aggregation process. The decision alternatives in such problems are described by their attributes. MODM problems, on the other hand, involve the generation of the best solution by considering the tradeoffs between a set of interacting design constraints. Both design objectives and constraints are generally described by continuous functions. MODM techniques are used for synthesizing the best or optimal solution. The key difference between the two classes of methods lies in the decision space [13]. The decision space of MODM problems is continuous and the number of potential solutions is theoretically infinite. MADM problems have a finite and discrete decision space. The evaluation of feasible system concepts during the early design phases is an MADM problem where design alternatives are generated prior to evaluation and selection. Each candidate alternative is evaluated individually using a combination of analytical tools and an ordinal ranking of alternatives is created based on the extent to which each system concept attains the stakeholders' value objectives.

2.1. CONCEPTUAL DESIGN EVALUATION MODELS

Decision-making techniques used during the conceptual design phase are a combination of analytic and heuristic procedures. These techniques have a few major objectives; they all aim to structure a decision-making problem to facilitate analysis, to achieve the best balance between multiple objectives, to identify and quantify sources of

uncertainty and to incorporate subjective judgments. The presence of multiple stakeholders adds the aspect of group decision-making to conceptual design evaluation that the MADM techniques must handle. Relevant background literature on decision-making and design evaluation approaches, used during the conceptual and preliminary design phases, is presented in the next few subsections.

Design changes carried out late in the design lifecycle have serious impacts in terms of cost and other program objectives. As stated in Section 1.1.2, good decisions made during the conceptual design phase lead to better quality designs, and increase the likelihood of meeting budgetary and schedule-related goals. Many decision-support approaches have been developed for conceptual design evaluation. These models primarily follow two design evaluation schools of thought [10].

2.1.1. Alternative-Focused Evaluation Methods. Designs can be evaluated in two primary ways depending on the basis of evaluation. Alternative-focused evaluation methods make direct comparisons between two competing concept alternatives. The comparisons are made based on a pre-selected set of desirable design attributes. The best concept is selected from a set of alternatives, which are usually provided by the stakeholders themselves. This ensures that the analysis always focuses directly on those system concepts that are of interest to the stakeholders; this is a significant advantage of this form of design evaluation methods. However, this approach has its limitations. Since the stakeholders' value objectives do not form part of the evaluation criteria, there is no course for determining whether the concept alternative fulfils the stakeholders' expectations from the system. The methodology may in itself be capable of identifying the best alternative from the set of system concepts, and yet, be unable to reveal whether

the system delivers the stakeholders' expected value. The lack of an explicit link between design attributes and stakeholder value expectations, limits the decision maker's ability to identify design concepts that better deliver the intended value [14].

2.1.2. Value-Focused Evaluation Methods. Keeney [10] proposed Value-Focused Thinking (VFT) as a means to incorporate stakeholder objectives and value expectations into the decision-making process. Using VFT concept alternatives are evaluated using the stakeholders' value objectives, and through a process of iterative refinement, designs that better deliver the stakeholders' value are generated. Under the VFT approach stakeholder value is modeled in the form of attribute utility functions. Values are aggregated using the construct of Multi-Attribute Utility Theory (MAUT). Value focused design generation and evaluation models have been implemented extensively in the software domain [15-17]. A case for the use of stakeholder value objectives in systems architecting as a mechanism for making objective decisions about architectural trade-offs and for predicting how well candidate architectures will meet customer expectations was made by [11]. A survey of MADM approaches for evaluating potential system concepts and selecting the most appropriate one is presented next.

2.2. MULTI-ATTRIBUTE DECISION MAKING METHODS

A number of techniques have been proposed to capture a decision maker's preferences and use them to discriminate between alternatives. Preferences are modeled using two main techniques, either in the form of preference weights assigned to the attributes of interest, or as utility functions that quantify the value of attaining a stakeholder's goals in relation to the risk they are willing to undertake to obtain that

value. Weight based approaches utilize preference rankings elicited from the decision maker to weigh and rank alternatives based on multiple criteria. These weighted preference measures are aggregated to generate a final preference value. Various weight elicitation approaches have been proposed such as the eigenvalue approach, logarithmic least-squares approach and the least squares approach [18]. Other methods like the swing weighting and tradeoff weighting approaches assigns weights based on the decision maker's assessment of how much each criterion translates into overall system value. These techniques preserve the ratio scale properties of the decision maker's assessments and are commonly referred to as ratio weighting methods [19].

2.2.1. Quality Function Deployment. Quality Function Deployment (QFD) is a tool used to incorporate the customer's 'voice' into every stage of the product lifecycle [20, 21]. It was developed first in the Kobe Shipyard of Mistubishi Heavy Industries, Ltd., in Japan in the 1960s [20]. The QFD approach works by linking the customer's requirements with the technical performance measures of the product with varying strengths. In particular, the QFD method aims to capture the above information in a single matrix diagram known as the 'House of Quality', to facilitate inter-disciplinary dialogue about the problem. Figure 2.2 shows the principal components of a 'House of Quality'. A ranking of the technical performance measures attributes is derived from the customer's prioritization of the requirements. Interrelationships between attributes and possible sources of conflict are identified and recorded. The strengths of the QFD lie in its ability to exact an articulation and prioritization of the customer's needs. It provides designers with an improved understanding of the customer's expectations and enables the comparison of design alternatives.
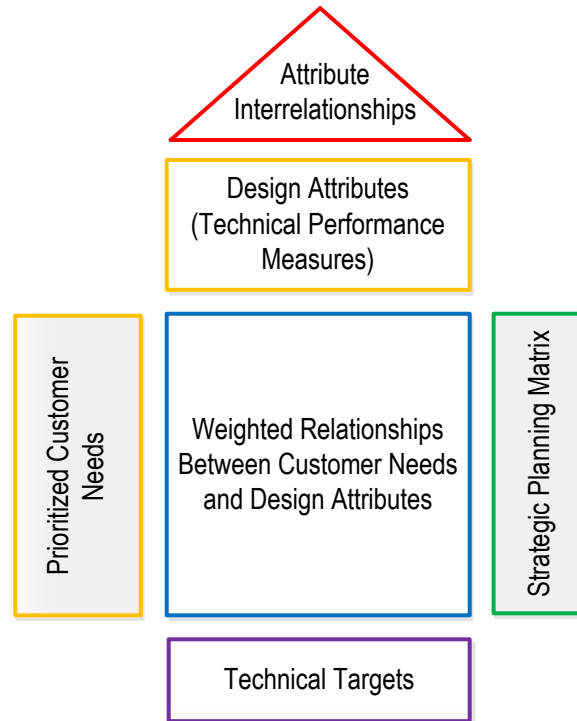
Figure 2.2. Components of the QFD House of Quality

The limitations of traditional QFD include the lack of a systematic process for ascertaining the customer's requirements and an ambiguous linking of needs with the TPMs. Also the crisp numerical rankings and relationship weights do not account for the uncertainty associated with translating customer requirements into technical attributes. Verma et al. [22] have proposed a fuzzy version of the QFD that uses fuzzy numbers to express the relative priority of requirements, as well as the mapping strengths, in order to capture the associated uncertainty.

2.2.2. Analytical Hierarchy Process. The Analytical Hierarchy Process (AHP) generates a ranked list of alternatives by performing pairwise comparisons of all needs for a given stakeholder [23-25]. This approach is especially useful in scenarios where the decision attributes are structured in a hierarchical manner, with the overall goal at the

highest level of the hierarchy, and the alternatives placed at the very bottom. Direct

relationships exist only between elements directly above or directly below each other in

the hierarchy. Figure 2.3 shows the goal-attribute-alternative hierarchy for a standard

AHP problem.
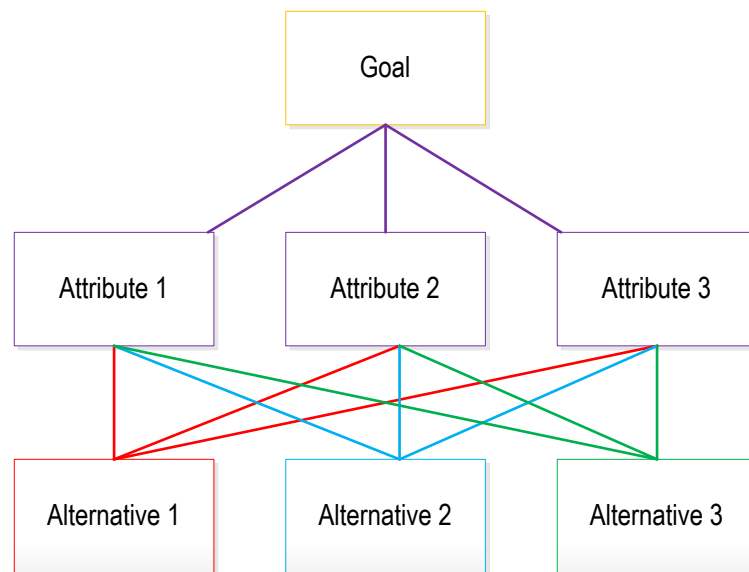
Figure 2.3. Hierarchical Relationship between Goals, Attributes and Alternatives in the
AHP

The AHP process consists of three primary steps: creation of a judgment matrix

containing pairwise comparisons of attributes at adjacent levels in the hierarchy,

computation of the eigenvectors of the judgment matrices, and the calculation of an

overall ranking vector. Saaty suggested a scale of 1 to 9 to assess the importance of one

criterion over another in the pairwise comparisons. Various techniques have been proposed for computing the weights of elements at each level in the hierarchy [18]. These weights are aggregated in a top-down fashion to obtain the composite weight of each alterative.

Even though AHP provides a composite ranking of alternatives that enables the comparison of alternatives on a one-to-one basis, it has several limitations. One of its primary drawbacks is the assumption of severability between elements at the same level in the hierarchy. A second limitation is the strict hierarchical structure of the attribute relationships that does not account for dependence within a level, and feedback across levels. Pairwise comparisons have to be performed for every possible combination of attributes and for a problem of large dimensions; this may lead to inconsistency and computational intractability. A large number of redundant pairwise comparisons may lead to inconsistency in the stakeholder assessments [26].

2.2.3. Analytical Network Process. The analytic network process (ANP) was proposed by Saaty [27] to overcome the limitations of the AHP in dealing with dependence and feedback among the decision criteria. The ANP is the general form of the AHP that overcomes the restriction of hierarchical structure of the AHP. It has been applied to project selection [28], product planning, strategic decision and optimal scheduling problems [29]. ANP uses the same fundamental prioritization process based on pairwise comparisons of elements as the AHP. However, unlike the hierarchical structure of the AHP, the ANP uses networks of clusters that contain the elements. Figure 2.4 shows the networked structure of a generic ANP problem with feedback and interdependence. It is not necessary to specify levels in an ANP decision structure.

Elements within one cluster are not required to have an influence on elements from other clusters. The requirements for pairwise comparison of elements within a cluster continue to be the same as the AHP along with all its associated objections as discussed in Section 2.2.2.
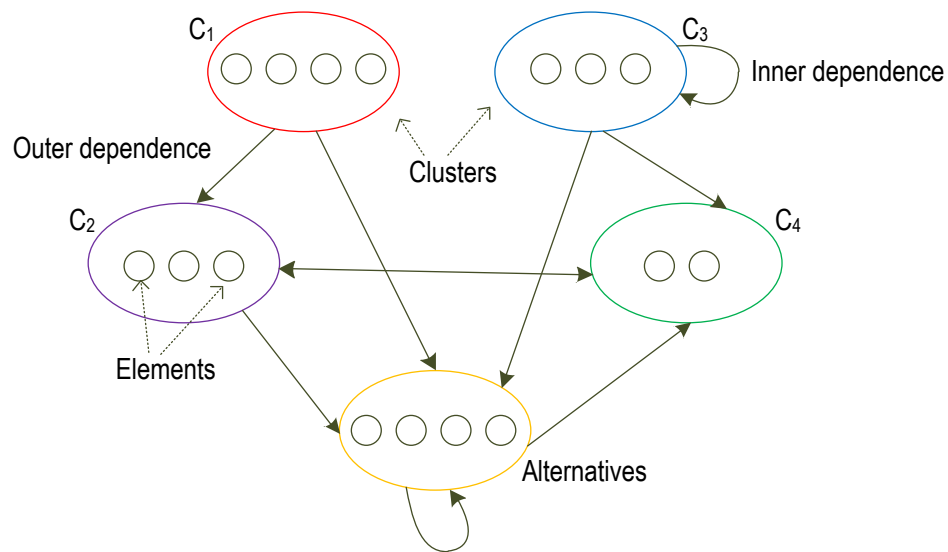
Figure 2.4. The Networked Decision Structure of the ANP

2.2.4. TOPSIS. Technique for Ordered Preference by Similarity to the Ideal Solution (TOPSIS) is another widely used decision-making and performance analysis technique; it was proposed by Hwang & Yoon in the early 1980s [30]. The goal of TOPSIS is to determine the relative advantages of alternatives by comparing them to a positive ideal solution and a negative ideal solution. The positive ideal solution is the one where each objective has its best performance values by any alternative for each attribute,

while the negative ideal solution has the worst performance values. Attributes are normalized and weighed based on the decision makers' preference information. The rational for selection is to maximize the proximity of the chosen alternative to the ideal solution and minimize the proximity from the negative-ideal solution. Proximity is measured by computing the Euclidean distance i.e., the square root of the sum of the squared distances along each axis in the "attribute space". Relative closeness is calculated using the positive ideal distance and the negative ideal distances.

$$d_i^+ = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^+\right)^2}, i = 1,\ldots,m \tag{1}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2}, i = 1,\ldots,m \tag{2}$$

Where, d_i^+ and d_i^- are the Euclidean distances of the ith alternative from the positive ideal and negative ideal solutions, respectively. The attribute values for each alternative i, their positive and negative ideal values are denoted by v_{ij}, v_j^+ and v_j^-. Relative closeness is given by,

$$rc_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{3}$$

A high relative closeness means a higher rank for the alternative being evaluated. TOPSIS suffers from the problem of inconsistent ranking. Since the ideal distances are calculated using the normalized values of attributes, any change in the attribute values or removal of attributes from the ranking process can alter scores and change the ranking of the alternatives [31]. Various extensions of TOPSIS have been proposed including a fuzzy TOPSIS that operates using fuzzy input values [32, 33].

2.2.5. Multi-Attribute Utility Theory. Multi-Attribute Utility Theory (MAUT) is one of the most widely applied MCDM techniques for assessing a discrete set of alternatives [6, 34, 35]. MAUT is a methodology based upon expected utility theory [36] that is used for structuring the decision maker's preferences on a numerical scale representing the utility or value they associate with an evaluation criterion. The decision maker's expected utility functions are used for scoring alternatives on a set of attributes. The overall utility is calculated by adding the product of the expected utilities of outcomes, with their probabilities. The basic premise of MAUT is to develop a conjoint 'measure of attractiveness' of an alternative by aggregating the individual utilities of each evaluation criterion. Many variations of the MAUT aggregation functions have been proposed [37]. The most widely used operator for aggregating individual utilities is the linear weighted operator. Linear aggregation greatly simplifies the computational complexity of the technique, but its use is subject to the condition that attribute utilities are preferentially independent. This assumption is usually very hard to meet without outright ignoring the effects of dependence and feedback among the criteria. Real-life problems rarely ever exhibit independence of underlying criteria and concepts. Obtaining accurate utility values and probabilities of outcomes add to the cognitive and computational complexity of this approach.

2.2.6. Joint Probability Decision Making Technique. The Joint Probability Decision Making (JPDM) approach uses multivariate probability theory to estimate the probability of simultaneously satisfying a set of criteria [38]. Univariate probability distributions, provided by the user, are combined to generate a joint probability distribution. Each univariate distribution provides the likelihood of the associated

criterion being satisfied by the selected alternative. A combined overall probability known as the 'Probability of Success' indicates the ability of an alternative to satisfy all the customer's criteria. This technique places a heavy cognitive load on the decision maker. The outcome of this technique of evaluating design concepts is the likelihood that a design alternative satisfies the customer's requirements. It does not reveal how 'well' the design alternative performs on the customer's value objectives.

2.2.7. Fuzzy Logic Based MCDM Techniques. Numerous Fuzzy methods methods have been developed in recent years to solve multi-criteria decision analysis problems with fuzzy attributes and goals [39-41]. The use of fuzzy set theory in conjunction with traditional MCDM approaches was developed in order to better handle uncertainties in the decision criteria. In the presence of high levels of ambiguity, crisp numerical representations of decision maker preferences do not adequately capture the uncertainty in the decision criteria. The imprecise information available in the early design phases is better represented linguistically; traditional MCDM methods cannot translate such information into good architectural decisions [42]. One of the initial attempts to incorporate fuzzy measures for design evaluation during the conceptual design phase of the systems engineering lifecycle was made Verma et al., [22, 42, 43], who modified and extended the traditional QFD method and Pugh's concept evaluation approach [44] to incorporate fuzzy preference measures to account for the uncertainty in information during conceptual design. Liqing et al., [45] developed a fuzzy ranking approach for design evaluation which assessed the product performances based on the customer's partial and global preference relations. Chen [33] extended the traditional TOPSIS technique to solve group decision-making problems in a fuzzy environment.

Fuzzy positive and negative ideal solutions were defined in order to calculate the relative closeness measure for each alternative.

Fuzzy MCDM methods use membership function shapes to represent the decision criteria, both attributes and goals. Treating decision criteria as fuzzy numbers allows the influence of uncertainties to be included in the decision-making process, leading to solutions that are more robust. The advantages of fuzzy MCDM approaches include computational tractability and robustness of the results in the presence of ambiguity. However, fuzzy MCDM methods present the output of the computation in the form of fuzzy numbers, which have to be approximated to the closest linguistic expression for interpretability. This approximation leads to a loss of information and increases vagueness of the results [46]. This has the undesirable effect of reducing the decision space as compared with traditional MCDM techniques.

2.2.8. Bayesian Networks. A Bayesian Network represents probabilistic relationships between decision criteria using an acyclic graphical structure [47]. Bayesian networks can encode expert knowledge in domains where information is uncertain or incomplete. Besides modeling the probabilistic relationships between attributes, Bayesian networks can also represent causal links between the decision criteria. Uncertainties are modeled using conditional probabilities obtained from subjective expert knowledge or past data where available. Bayesian networks have been used for tradeoff analysis in systems engineering during the conceptual design phase [14], [48]. Their principle limitation is the need for obtaining reliable conditional probabilities, which can lead to computational intractability [49], and may place a significant cognitive burden on the decision maker.

2.2.9. Fuzzy Cognitive Maps as Decision Support Tools. Fuzzy Cognitive Maps (FCM) are signed digraphs used for representing causal reasoning [50]. They were proposed by Kosko as an extension of Axelrod's cognitive maps [51]. FCMs have the ability to represent and reason with partial levels of causality between the graph's nodes or concepts. FCMs have the ability to model dependence and feedback effects, and to make explicit the complex dynamics between any two variables in a decision problem. They can handle ambiguous information and simulate the behavior of a complex system through a recurrent feedback. Multiple FCMs can be easily combined using a simple weighted average of their connection weight matrices. This enables FCMs to handle problems of large dimensionalities without becoming mathematically intractable. Various modifications of the simple FCM have been proposed to enhance their ability to handle nonlinear relationships between the concepts, and to model temporal effects on concept values [52-56].

2.3. KEY OBSERVATIONS FROM THE LITERATURE REVIEW

Conceptual design evaluation is a complex multi-criteria decision making problem. Successful application of a MCDM model for design evaluation is subject to a few key conditions, which if not met, can decrease the reliability of the outcome. These include consistent and reliable preference elicitations by the decision maker, modest number of decision criteria, and manageable uncertainty. Architecture evaluation problems during conceptual design rarely ever meet all or most of these prerequisites [2].

Preference elicitation techniques generally assume linearity of, and severability between decision criteria. Nonlinear relationships between decision criteria can be

modeled by a very small subset of techniques such as the MAUT. However, even these become computationally intractable as the problem's dimensionality increases. Complex system architecting problems quite often have large sets of design attributes, which exhibit nonlinear behavior with respect to each other. Another issue in generating consistent preference elicitations is that of multiple stakeholders. Reconciling the preferences of multiple stakeholders to generate utility or value measures for a group decision-making problem requires a common representation scheme and an aggregation function capable of combining disparate preference scales.

In general, uncertainty can be classified into randomness, vagueness, and ambiguity [57]. Uncertainty, during the early design phases, arises because of insufficient system related information and ill-defined stakeholder needs. This type of uncertainty is primarily due to imprecision or ambiguity. During conceptual design the most accessible and reliable source of information is the experience base of the human evaluators, but the subjective and qualitative nature of this information further adds to the ambiguity inherent in the design evaluation process. Popular MCDM methods handle uncertainty in primarily one of two ways: by determining probabilities or by using fuzzy measures to represent uncertain information. Probabilistic approaches use conditional probabilities that maybe based on the subjective beliefs of an expert or on historical data. However, historical data is rarely available for unprecedented complex systems and generation of a large number of conditional probabilities using subjective expert input is neither simple nor reliable. While fuzzy set theoretic approaches can better handle ambiguous information without putting a heavy cognitive burden on the decision maker, they suffer from an inability to discriminate between alternatives that are close to each other on the

linguistic evaluation scale. The price for computational simplicity and a robust outcome is a reduction in the interpretability of results.

A systematic methodology is needed to identify the appropriate decision criteria, account for their complex and nonlinear interrelationships, properly represent diverse information sources in a common format, and aggregate this information into a consistent overall evaluation while handling the ambiguity that exists during the conceptual design phase.

2.4. PROPOSED APPROACH

Due to their ability to handle imprecise information, coupled with the capability to model causality and feedback effects among the criteria, FCMs have been chosen to model the stakeholders' value objectives in this research. Most fuzzy approaches rely on fuzzy arithmetic to perform the numerical computations. Such evaluation schemes present the final output in fuzzy numeric forms, which are neither easily interpretable, nor believable, and need to be approximated to the closest linguistic expression causing a loss of information.

"Computing with Words" is a methodology which uses words and natural language propositions to reason and compute with [58]. The inspiration for the CW approach is the human ability to reason and make decisions using perceptions instead of crisp measurements. In recent years, CW has been gaining traction in the decision-making community because it allows a more human-like formulation of decision models. The CW methodology represents a paradigm shift from techniques that manipulate numbers and symbols. The principal rationales for computing with words have been

defined as, [59]: insufficient precision in the values of decision variables, precision is unnecessary, or if a concept is too complex for numerical description. The CW methodology can be used to create and improve current techniques for decision-making where information is scarce or imprecise and the use of numbers is not essential. Thus, MADM during the conceptual design phase can be seen as a natural application for CW techniques.

In order to compensate for the loss of information and interpretability that occurs while computing with fuzzy arithmetic operators, the 2-tuple linguistic representation model was chosen as a common computational format [46]. This symbolic computation model has been shown to avoid the information loss and distortion that occurs with regular fuzzy set theoretic approaches [46].

3. THEORETICAL BACKGROUND

This section presents a brief overview of the fundamental principles of possibility theory. Fuzzy set theory, fuzzy cognitive maps, the 2-tuple linguistic representation and Ordered Weighted Averaging (OWA) operators are discussed.

3.1. FUZZY SET THEORY

Most MCDM techniques work with quantitative inputs. However, many real world problems cannot be assessed in quantitative terms. In such situations, qualitative or linguistic descriptions can better express the problem. According to Zadeh [58], fuzzy logic is the machinery that facilitates computing with words. Inputs in linguistic forms can be transformed into linguistic outputs by using fuzzy mathematical transformations, such as IF-THEN rules, fuzzy weighted averages, fuzzy Choquet integrals, etc. The four rationales for using CW discussed in Section 2.4.1 also apply to the linguistic representation of information. For example, when articulating the "aesthetics" of a vehicle, words like "beautiful", "ordinary" and "ugly" known as a "linguistic term set", can convey the evaluation better than any numeric values. The first consideration, while defining a linguistic term set, is the selection of the appropriate level of *granularity*. Granularity is the level of discrimination that is appropriate for representing the ambiguity in a qualitative variable. Numerically, it is the number of membership functions needed to characterize a linguistic term.

In fuzzy set theory, a linguistic attribute is represented by a membership function. Membership functions can have many different shapes, though the most popularly used are the triangular and trapezoidal membership functions [60]. Table 3.1 shows the

representation schemes for trapezoidal and triangular membership functions. Each

trapezoidal membership function is represented by a set of four values called a 4-tuple of

the form (*a, b, c, d*). Here, *a* and *d* are the lower bounds of preference, and *b* and *c* are the

higher bounds within which the membership value reaches its highest grade. Triangular

membership functions are a special case of trapezoidal functions where $b = d$. They are

represented by using a 3-tuple of the form (*a, b, c*).

Table 3.1. Membership Function Representation

Membership function type	Representation scheme	Example
Trapezoidal	4-tuple	(0.2, 0.4, 0.6, 0.9)
Triangular	3-tuple	(0.25, 0.5, 0.75)

Let *u* denote a linguistic variable, say *height*, which is decomposed into a set of

linguistic terms, $T(u)$. Let the numerical value of *T* range from [0,180] cms.

$$T = \{t_0 : short, t_1 : Average, t_2 : Tall\} \tag{4}$$

Triangular membership functions representing the linguistic term set, *T* of the linguistic

variable height are shown in Figure 3.1. Based on the above scheme, it is possible to

represent any set of terms that describe a linguistic input or output. Users define

membership functions based on their experience and expertise, or they may be generated

using optimization procedures if past data is available [61-63].
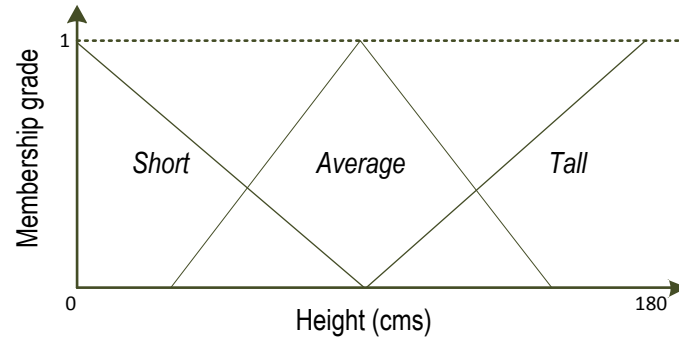
Figure 3.1. Triangular Membership Functions for the Linguistic Variable
$T(Height) = \{short, average, tall\}$

Trapezoidal and triangular membership functions have been deemed quite
adequate for representing subjective user-defined linguistic assessments since such
assessments are approximate to begin with, and it may be impossible and unnecessary to
obtain more accurate values [64].

The process of mapping crisp numbers into fuzzy sets is known as fuzzification.
Fuzzified numbers are represented by a membership grade in each linguistic term of its
term set. Defuzzification is the mapping of output sets into crisp numbers. For the
variable *height* this would mean converting the term *short* or *tall* into a crisp value in the
range [0, 180] cms.

3.2. 2-TUPLE LINGUISTIC REPRESENTATION MODEL

The 2-tuple linguistic representation [2TLR] is a symbolic computational model
for linguistic aggregation [46]. Linguistic information is represented using a pair of
values called linguistic 2-tuples. Each 2-tuple consists of a linguistic term and a symbolic
translation denoted as (s, α), where *s* is a linguistic term and *α* is a numeric value

representing the value of the symbolic translation. The result of the symbolic

transformation, β, is used as the basis for computation with the 2-tuples.

3.2.1. Symbolic Translation Functions. Linguistic transformation functions

for converting 2-tuples into their symbolic form, β, and vice versa are given by the

following definitions [46]. Here β is the result of a symbolic aggregation operation of the

indexes of a set of labels assessed in a linguistic term set, *S* and *i* lie within the semi-open

interval [0.5; 0.5).

3.2.2. Definition 3.1. Let $S = \{s_0, \ldots, s_g\}$ be a linguistic term set and $\beta \in (0, g)$

then the equivalent 2-tuple is obtained with the mapping, $\Delta : [0, g] \rightarrow S \times [-0.5, 0.5)$

given by the following expression:

$$\Delta(\beta) = (s_i, \alpha), \ with \begin{cases} s_i, i = round(\beta) \\ \alpha = \beta - i, \alpha \in [-0.5, 0.5) \end{cases}, \tag{5}$$

Here, *round( )* is the usual rounding operation. The inverse of the Δ function can

be used to obtain the β value from the 2-tuple representation. Figure 3.2 shows a 2-tuple

represented graphically on a set of triangular membership functions. If the 2-tuple is

represented as (s_2, α_2) where $\beta = 1.8$ is the value of the symbolic aggregation operation

then the 2-tuple representation of that value is $(s_2, -0.2)$.

3.3. ORDERED WEIGHTED AVERAGING OPERATORS

The most commonly used fuzzy aggregators are the *min* and *max* aggregators.

However these aggregators cannot model decision maker preferences that are

intermediate to the logical AND and OR. Ronald R. Yager introduced a new aggregation

technique called the Ordered Weighted Averaging (OWA) operators, which are capable

of modeling a wide range of aggregation preferences.
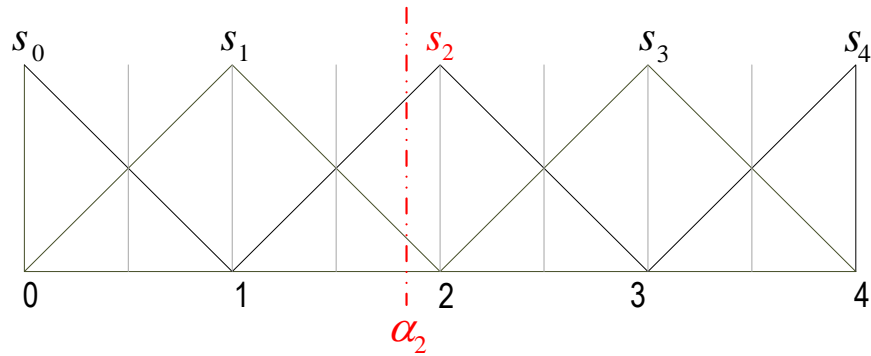
Figure 3.2. Graphical Representation of a Fuzzy Linguistic 2-Tuple $\left(s_2, \alpha_2\right)$

3.3.1. Definition 3.2. An OWA operator of dimension n is a mapping $F : R_n \rightarrow R$,

that has an associated weight vector,

$$w = \left(w_1, w_2, \ldots, w_n\right)^T \tag{6}$$

such that $w_i \in [0,1]$, $1 \leq i \leq n$, and $w_1 + w_2 + \ldots + w_n = 1$. Furthermore,

$$F(a_1, \ldots a_n) = w_1 b_1 + \cdots + w_n b_n \tag{7}$$

where b_j is the jth largest element of the bag $< a_1, \ldots, a_n >$.

OWA operators are unique in the aspect that a particular aggregate a_i is not

associated with a particular weight w_i, but rather a weight is associated with a particular

ordered position of aggregate. The reordering of the aggregate values is a key step in this

process. In order to classify OWA operators with regard to their location between the 'AND' and 'OR' operators, Yager introduced a measure of *orness*, associated with any weight vector *w* as follows [65],

$$orness(w) = \frac{1}{n-1}\sum_{i=1}^{n}(n-1)w_i \tag{8}$$

The *orness* of any weight vector *w*, is always in the unit interval. The closer the weight vector is to a logical OR or *max* operation, the closer its measure is to one; while the nearer it is to an AND or *min* operation, the closer its value is to zero. Generally, an OWA operator with a majority of the larger weights near the top will be an *or-like* operator with $orness(w) \geq 0.5$. This reason for this is evident from the fact that the sorted aggregate vector has the attributes with the higher values at the top. These values are weighed higher than the attributes with lower values closely resembling the maximization operation. On the other hand, when most of the higher weights are towards the bottom of the weight vector, the OWA operator will be *and-like*.

In [65], Yager suggested an approach for the aggregation of criteria weights guided by a regular non-decreasing quantifier Q. If Q is a Regular Increasing Monotone (RIM) quantifier then the aggregated value of an alternative $x = (a_1, \dots a_n)$ is given by $F_Q(a_1, \dots a_n)$, where F_Q is an OWA operator derived from Q. RIM quantifiers can be used to generate the OWA weights using the following expression,

$$w_i = Q\left(\frac{i}{n}\right) - Q\left(\frac{i-1}{n}\right) \tag{9}$$

The standard degree of *orness* associated with a Regular Increasing Monotone (RIM) linguistic quantifier Q is given by the area under the quantifier as [65],

$$orness(Q) = \int_0^1 Q(r)dr \qquad (10)$$

Consider the family of RIM quantifiers, $Q_\alpha(r) = r^\alpha$, $\alpha \geq 0$, an example of which is shown in Figure 3.3. The *orness* for a generic RIM quantifier is given by the expression,

$$orness(Q_\alpha) = \int_0^1 r^\alpha dr = \frac{1}{\alpha + 1} \qquad (11)$$

Here, $orness(Q_\alpha) < 0.5$ for $\alpha > 1$, and $orness(Q_\alpha) > 0.5$ for $\alpha < 1$.
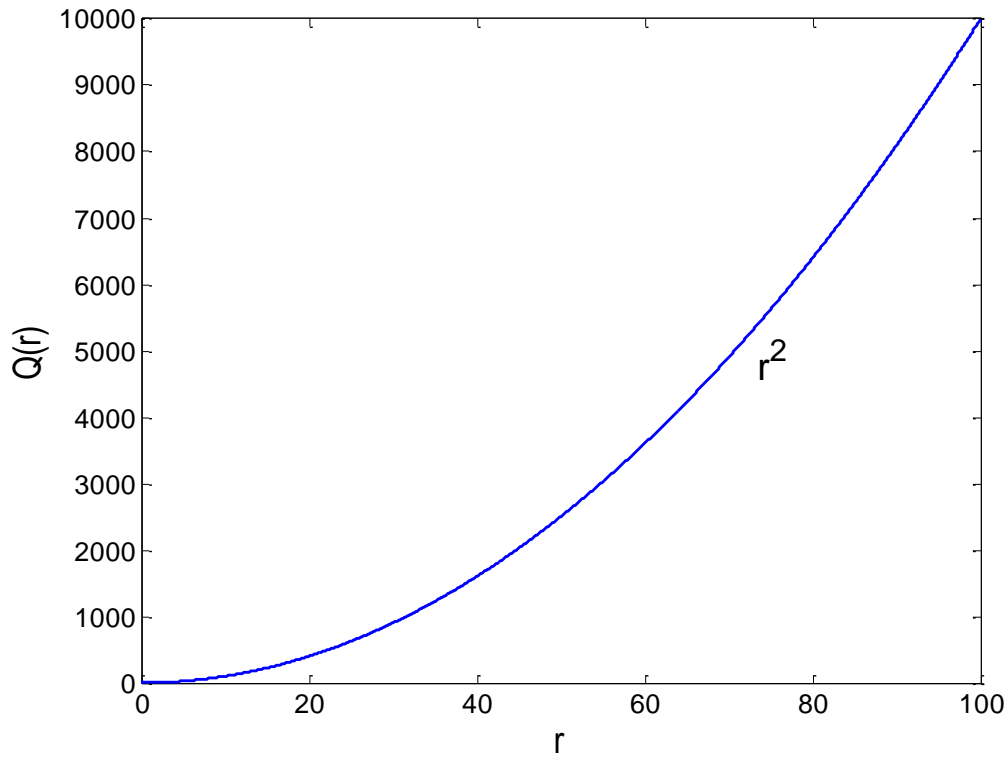
Figure 3.3. Regular Increasing Monotone Quantifier, r^2

3.3.2. Linguistic Ordered Weighted Averaging Operator. Let S be a set of 2-tuples, $S = \{(s_1, \alpha_1), \ldots, (s_n, \alpha_n)\}$ and $V = (v_1, \ldots, v_n)$ be an associated ordered weighting vector that satisfies: 1) $v_i \in [0,1]$ and 2) $\sum w_i = 1$. The OWA operator for dealing with linguistic 2-tuples is computed as [46],

$$F^{OWA}\left((s_1, \alpha_1), \ldots, (s_n, \alpha_n)\right) = \Delta\left(\sum_{j=1}^{n} w_j \cdot \beta_j^*\right) \tag{12}$$

where β_j^* is the jth largest of the β_i values.

3.4. FUZZY COGNITIVE MAPS

Fuzzy cognitive maps are an intelligent modeling methodology for complex systems, which originated from the combination of Fuzzy Logic and Neural Networks. An FCM describes the behavior of an intelligent system in terms of concepts; each concept represents an entity, a state, a variable, or a characteristic of the system [50]. The nodes of the FCM represent concepts. Let C be the set of concepts.

$$C = \{C_1, C_2, \ldots, C_n\} \tag{13}$$

The arcs of the FCM represent the causal links between the concepts and are denoted by the tuple $\left(C_i, C_j\right)$. The direction of the arc represents the direction of the causality between concept C_i and concept C_j. The set of all arcs in the FCM is denoted by,

$$A = \left\{C_i, C_j\right\}_{ji} \subset C \times C \tag{14}$$

Each arc is associated with a fuzzy weight w_{ji} that represents the strength of the causal relationship between the concepts connected by the arc. The fuzzy weight matrix

$W_{n \times n}$ represents the weights of all the arcs within the FCM, where each element of the weight vector lies between, $w_{ji} \in [-1,1]$. The bipolar interval represents positive or negative relationships between two concepts. Concept C_i causally increases C_j if the weight value $w_{ij} > 0$ and causally decreases C_j if the weight, $w_{ij} < 0$. A zero weight indicates no causal effect between concepts. The sign of the weight indicates whether the relationship between concepts is positive $\left(C_j^{W_{ij}} \to C_i \right)$ or negative $\left(C_j^{W_{ij}} \to \sim C_i \right)$, and the value of the weight indicates the strength of the causal influence of concept C_i on concept C_j. Graphically, an FCM is a signed graph with feedback, consisting of nodes and weighted interconnections as shown in Figure 3.4. This graphical structure of an FCM allows forward and backward propagation of causal influences between the interconnected nodes. Expert knowledge of the causal relationships and the direction of influence are modeled in the form of signed fuzzy numbers.
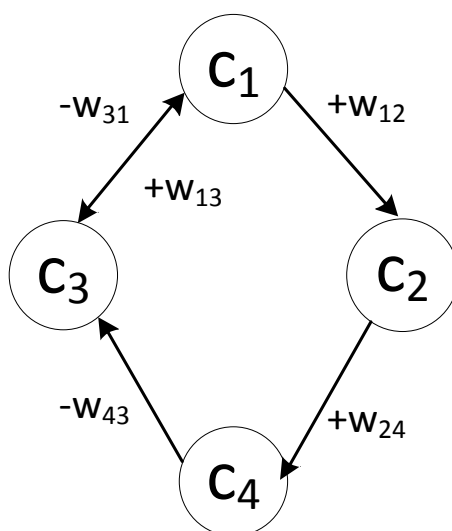
Figure 3.4. A Simple Fuzzy Cognitive Map

The activation levels for the concept nodes in an FCM are calculated using the recurrent relation,

$$a_i^{t+1} = f\left(\sum_{j=1, j\neq i}^{n} w_{ji} a_j^t\right) \text{ for } i = 1, \ldots, n. \tag{15}$$

where a_i^{t+1} is the value of the concept C_i at step t+1, a_j^t the value of the concept at step t, w_{ji} is the fuzzy weight from concept C_j to C_i and $f : R \rightarrow V$ is a threshold function which normalizes the activations. Commonly used normalization functions are the sigmoid function and the hyperbolic tangent function.

$$f(x) = \frac{1}{1+e^{-\lambda x}} \tag{16}$$

$$f(x) = \tanh(x) \tag{17}$$

Here, $\lambda > 0$ determines the slope of the sigmoid function.

4. THE ARCHITECTURE VALUE MAPPING APPROACH

A novel design evaluation approach, which uses fuzzy cognitive maps as a reasoning aid and computes with information encoded in the linguistic 2-tuple format, is presented. This approach is intended to be used during the conceptual design phase of the systems engineering lifecycle when the decision space is large, and the stakeholders' needs and objectives are ill defined and ambiguous. This approach applies the notion of 'hierarchical reduction of ambiguity' to derive the design evaluation attributes, and utilizes a linguistic representation scheme to aggregate non-homogenous information. The AVM approach graphically represents the design evaluation problem in the form of a causal reasoning diagram and explicitly links the stakeholders' value objectives to conceptual architecture attributes. Attribute interrelationships are modeled using FCMs as discussed in Section 3.4. The activation levels of the attributes and the influence weights of the FCM are may be elicited from the decision maker in linguistic terms or generated from past data where available. Information available in disparate forms is transformed into the 2-tuple fuzzy linguistic representation. This symbolic representation of information allows the FCM to compute using linguistic terms as input and overcomes the loss of information that occurs while computing with fuzzy numbers. The 2-tuple representation allows greater output resolution and makes it possible to distinguish between two very similar outcomes. This novel type of FCM has been developed specifically for the purpose of this research and is labeled the Symbolic Computation FCM or SC-FCM. The overall attribute scores are aggregated using decision maker risk preferences by encoding these in OWA operators.

This section starts with a description of the Architecture Value Mapping (AVM) approach which includes the mathematical model for dynamic analysis of the architecture value maps and the information aggregation functions. This is followed by the presentation of a framework for implementing the AVM approach during the conceptual design phase.

4.1. SYMBOLIC COMPUTATION-FUZZY COGNITIVE MAP

In order to make use of fusion operators on qualitative information Li and Xianzhong [66] have proposed an extension to Herrera and Martinez's 2-tuple linguistic model. Using the extended model, various mathematical operators for 2-tuples have also been proposed. In order to avail of these operators for computing with qualitative information, the extended version of the 2-tuple representation is used for this research. The modified mapping that transforms the range of the 2-tuple to a [0, 1] scale is presented below.

4.1.1. The Extended 2-Tuple Representation. The symbolic translation Δ when $\beta \in [0,1]$, is defined as,

$$\Delta(\beta) = (s_i, \alpha) \text{ with } \begin{cases} s_i, & i = round(\beta \bullet g) \\ \alpha = \beta - \dfrac{i}{g}, & \alpha \in \left(\dfrac{-1}{2g}, \dfrac{1}{2g} \right) \end{cases} \tag{18}$$

where $S = \{s_0, s_1, \ldots, s_g\}$ and $g+1$ is the granularity of the term set S. Here $s_0 = 0$ and $s_g = 1$. Let the weight matrix W of the FCM be,

$$W = \begin{bmatrix} w_{11} & \cdots & w_{n1} \\ \vdots & \vdots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{bmatrix} \tag{19}$$

w_{ij}, $i, j = 1, 2, \ldots n$, is the weight associated with the arc connecting the concept node i with concept node j. Here W is also the adjacency matrix of the FCM. The presence of a weight indicates a connecting arc between the corresponding elements of the matrix. The value of the weight is the strength of the connecting link and the sign of the weight indicates the direction of causality. Using the 2-tuple fuzzy linguistic representation each weight can be represented by a 2-tuple.

$$w_{ij} = (s_{ij}^w, \alpha_{ij}^w) = \beta_{ij}^w \tag{20}$$

where, s_{ij}^w is a linguistic term from the linguistic term set $S^w = \{s_0^w, \ldots, s_g^w\}$, α_{ij}^w is a numerical value expressing the value of the symbolic transformation. The weight matrix expressed in the 2-tuple symbolic representation becomes,

$$B = \begin{bmatrix} \left(s_{11}^w, \alpha_{11}^w \right) & \cdots & \left(s_{1n}^w, \alpha_{1n}^w \right) \\ \vdots & \vdots & \vdots \\ \left(s_{n1}^w, \alpha_{n1}^w \right) & \cdots & \left(s_{nn}^w, \alpha_{nn}^w \right) \end{bmatrix} = \begin{bmatrix} \beta_{11}^w & \cdots & \beta_{1n}^w \\ \vdots & \vdots & \vdots \\ \beta_{n1}^w & \cdots & \beta_{nn}^w \end{bmatrix} \tag{21}$$

where $\beta_{ij}^w \in [0,1]$ and $i, j = 1, 2, \ldots, n$. The concept activation vector is also represented by means of a 2TLR vector as below,

$$\begin{aligned} A &= \{a_1, a_2, \ldots, a_n\} \\ &= \left\{ \left(s_1^a, \alpha_1^a \right), \left(s_2^a, \alpha_2^a \right), \ldots, \left(s_n^a, \alpha_n^a \right) \right\} \\ &= \{\beta_1^a, \beta_2^a, \ldots, \beta_n^a\} \end{aligned} \tag{22}$$

4.1.2. Evaluating the Value of a Concept using the SC-FCM. Using the above constructs the value a_j^t of each concept node at time t is calculated by the following equation,

$$\sum_{i=1}^n w_{ij} a_j^t = \sum_{i=1}^n \beta_{ij}^w \otimes \beta_{ij}^a \tag{23}$$

The product operation for the extended 2-tuples is defined as follows,

$$
\begin{aligned}
\left(s_i,\alpha_i\right)\otimes\left(s_j,\alpha_j\right) &= \Delta^{-1}\left(\left(s_i,\alpha_i\right)\times\left(s_j,\alpha_j\right)\right) \\
&= \Delta^{-1}\left(s_i,\alpha_i\right)\times\Delta^{-1}\left(s_j,\alpha_j\right) \\
&= \beta_i\times\beta_j \\
&= \frac{\Delta\beta}{n+1}
\end{aligned}
\tag{24}
$$

From this definition the activation levels for the concept nodes in a SC-FCM can be calculated using the following relation,

$$
{}^{t+1}a_j = \Delta\left(k_1 \sum_{j=1,j\neq i}^{n} {}^t\beta_{ji}^{w}\otimes{}^t\beta_{j}^{a} + k_2\,{}^t\beta_{j}^{a}\right) \text{ for } i,j=1,\ldots,n.
\tag{25}
$$

where a_i^{t+1} is the value of the concept C_i at step t+1, a_j^t the value of the concept at step t, β_{ji} is the symbolic fuzzy linguistic weight from concept C_j to C_i. Nonlinear attribute relationships that cannot be combined using the linear weighted aggregation function, can be modeled by using the OWA operators described in the Section 3.3. Non-monotonic nonlinear relationships between attributes can be mapped via a rule based fuzzy expert system.

4.1.3. Combining Qualitative and Quantitative Values. The SC-FCM can operate with information in disparate forms, both qualitative and quantitative inputs. The transformation of quantitative inputs into the 2TLR format is show in Figure 4.1. Various transformation functions for converting fuzzy sets, intervals, and probabilistic inputs into the 2TLR format are discussed in depth in [67].
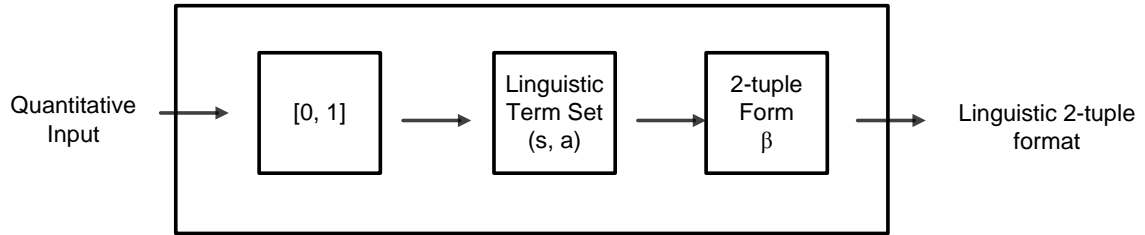
Figure 4.1. Steps for Transformation of Quantitative Input into the 2TLR Format

The first step of the transformation is normalizing the numerical input into a [0, 1] scale. A fuzzy term set for the numerical input is defined over a [0, 1] support range. The membership grade for the numerical input in the fuzzy term set is computed. Finally the following transformation is applied to convert the membership value to its corresponding β value. A detailed description of the approach with examples can be found in [68].

4.1.4. Incorporating Group Decision Preferences. Most real world decision problems have more than one stakeholder with whose needs and objectives must be considered while making design decisions. Hence, a provision for combining the inputs of multiple stakeholders needs to be made. Most conceptual design evaluations in systems engineering are carried out by teams of experts from various disciplines. For achieving an appropriate assessment of the architecture variant, inputs of subject matter experts from all the disciplines involved in the system design need to be considered. The experts use their experience and domain expertise to individually assess and evaluate the design options. There are number of benefits of this group evaluation approach, such as a better understanding of the problem, thorough exploration of MOEs, better evaluation of concepts and increased acceptance of the group's decision. However, aggregating these diverse opinions into a single preference function is a challenge. Assessments provided by various stakeholders are normalized to a common linguistic term set known as the

Basal Linguistic Term Set (BLTS). These preference weights are then combined using a simple weighted average operator. The weights w represent the relative importance of the experts. Here w_i is the weight assigned to each expert. When the inputs of all experts are given equal consideration, $w_i = 1$.

$$Weighted\ Average\big((s_1, \alpha_1), \ldots, (s_n, \alpha_n)\big) = \Delta \left(\frac{\sum_{i=1}^{n} \beta_i w_i}{\sum_{i=1}^{n} w_i} \right) \qquad (26)$$

4.2. THE AVM APPLICATION FRAMEWORK

To find the best solutions, it is essential to state with precision the rules by which the concepts will be created and judged. Figure 4.2 shows the main steps of the decision evaluation framework using the AVM approach. The very first step is the definition of evaluation attributes and specification of their relative importance to the decision maker.

4.2.1. Deriving the Design Evaluation Attributes. Firstly, there is a need to define the set of objectives on which the systems engineer can base his design decisions. As a preliminary step, the Stakeholders' Value Objectives (SVO) are derived from the need statement and requirements definition; these are highest level design evaluation criteria. Using a process of stepwise reduction of abstraction, MOEs and MOPs are derived from the SVOs. MOEs reflect the ability of a system to accomplish its primary objectives effectively. At the lowest level in the system attribute hierarchy are the MOPs which are design dependent attributes. Each MOP is directly associated with a design parameter and a complete set of design parameters constitute a design alternative.
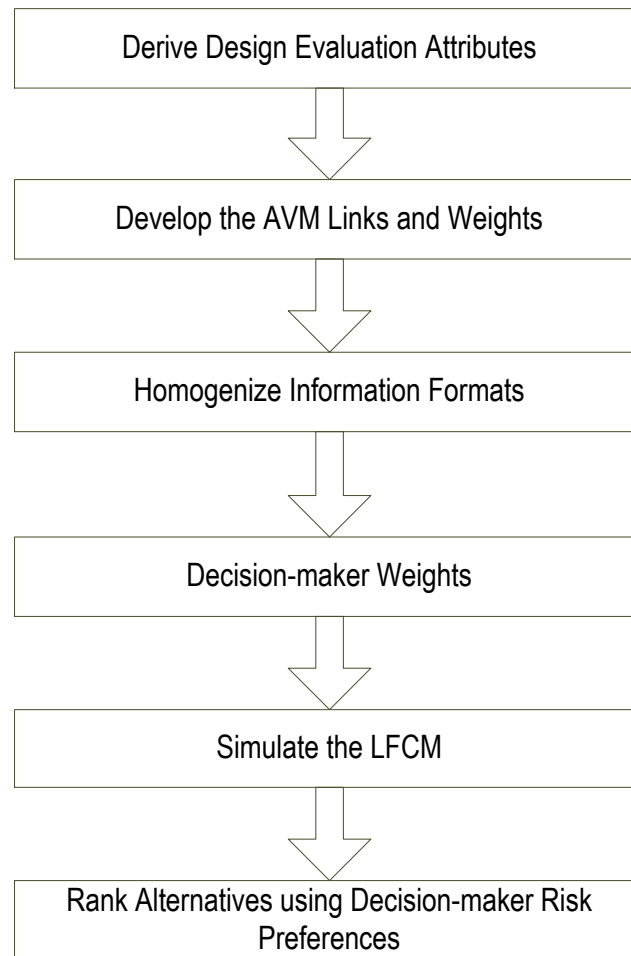
Figure 4.2. The AVM Framework

Figure 4.3 shows the hierarchy of design evaluation criteria from the general SVOs to the specific MOPs. The hierarchical reduction of abstraction in design evaluation criteria is depicted in Figure 4.4. A design alternative is considered 'satisfactory' based on how well it satisfies the design evaluation criteria. Thus, design features can be identified that directly influence the selected MOEs and MOPs. Using the proposed design evaluation process those design features that have a net positive impact on all the design attributes can be selected for further refinement.
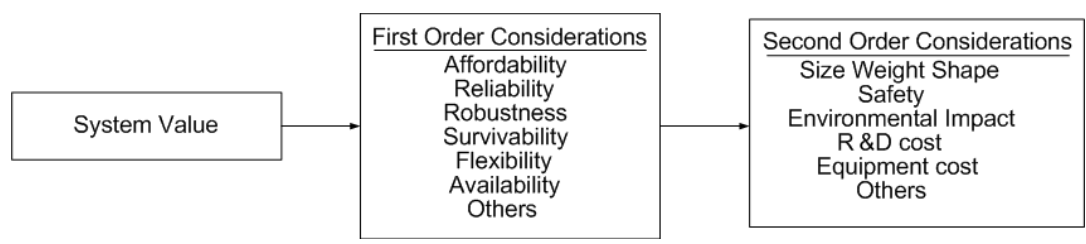
Figure 4.3. Hierarchy of Design Attributes
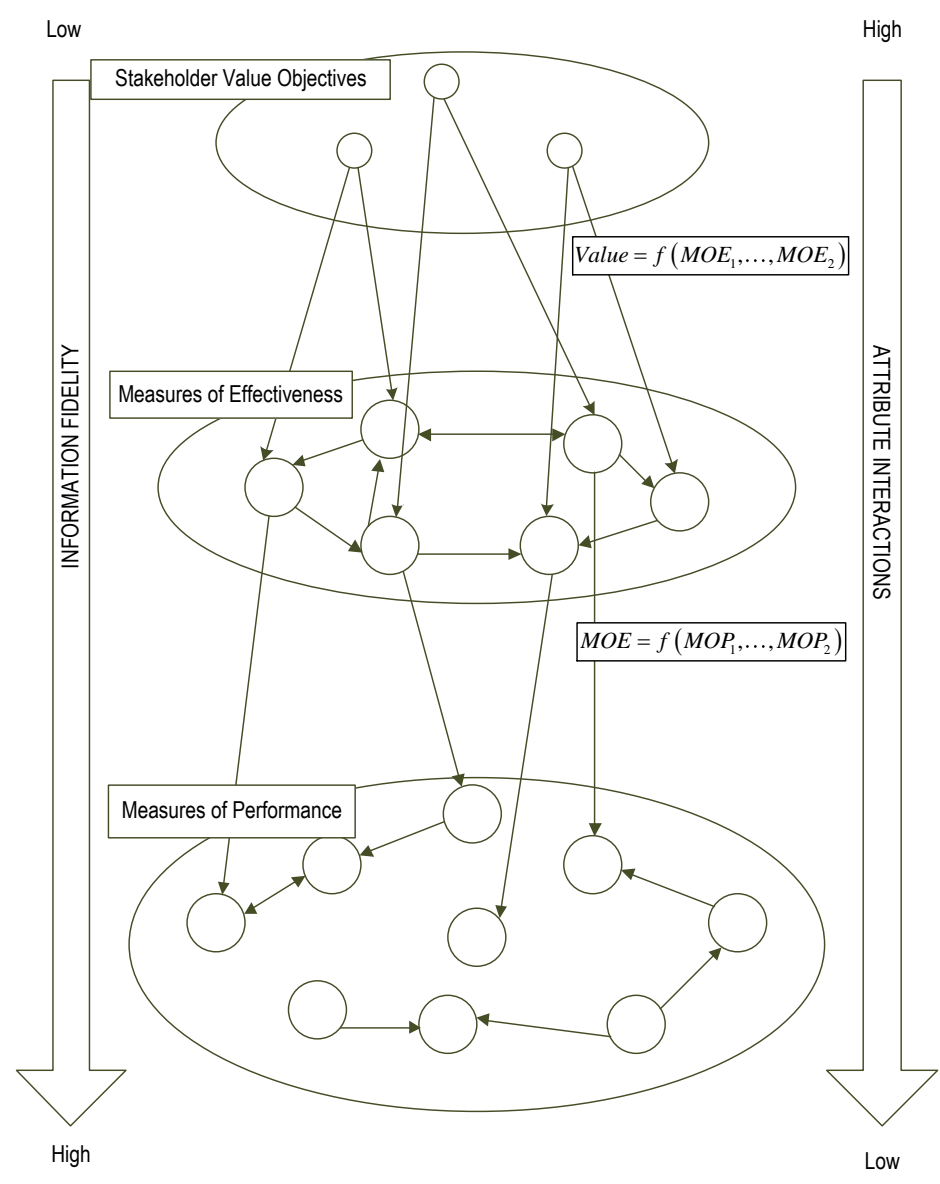
Figure 4.4. Derivation of Design Evaluation Attributes Using Hierarchical Reduction of Ambiguity

Once the design attributes have been derived, the AVM framework can be applied for conceptual design evaluation. The primary objective of this process is to develop a framework, which assists decision makers in exploiting their own capability and expertise to perform evaluations and make rational decisions. The value model is developed by the primary stakeholders of the system. This includes all potential beneficiaries and users of the system. The systems engineering team and project management teams along with subject matter experts must all form the working group. Between eight to12 members are recommended to ensure maximum utility of the decision making process [69].

4.2.2. Develop AVM Links and Weights. After the design evaluation criteria have been derived through an iterative process of stepwise reduction of ambiguity, the AVM is generated in consultation with key decision makers and stakeholders. Relationships between the SVOs, MOEs and MOPs are identified and mapped along with the direction of influence of the attribute connections.

4.2.3. Homogenize Information Formats. Information available in different Formats can be converted into the 2TLR form using the procedure described in Section 4.1.3. Qualitative attributes are directly converted to their linguistic term sets while numerical values are mapped to the closest linguistic term along with a symbolic translation value that prevents loss of information due to generalization.

4.2.4. Elicit Decision Maker Preference Weights. Each decision maker selects a preferred linguistic term-set and provides qualitative inputs for the attribute initializations and their influence weights. Each stakeholder may specify his assessment of the connection weights and node initializations on a unique linguistic term set. The linguistic term sets for different decision makers are normalized to a common BLTS. The

choice of the size of the basic term set is entirely subjective and maybe selected to minimize the number of transformations necessary.

4.2.5. Simulate the SC-FCM. The FCM is simulated until it converges to a fixed equilibrium point. In certain cases, the FCM will cycle between a fixed set of final values. This is known as a limit cycle attractor and in such a case the weights will have to be reevaluated and adjusted accordingly. The SW-FCM can be used to perform different types of analyses, both, on the input and output values and the topology of the AVM itself. Static analyses focus on a topological analysis of the AVM structure. A centrality measure can be computed for all the AVM's nodes, which provides an understanding of the most important concepts, which possess maximum influence over the concept's value. Centrality is the sum of all incoming and outgoing connections to and from a node. Dynamic analyses include scenario analysis and sensitivity analysis, which are discussed next.

4.2.5.1 Scenario analysis. Scenarios are constructed with combinations of uncertain input attributes, in order to assess the performance of the design concept under a wide range of future states. Design concepts that deliver high stakeholder value in the maximum number of future scenarios are the most desirable.

4.2.5.2 Sensitivity analysis. Sensitivity of the final ranking of alternatives, to change in parameter values is determined by holding all other parameters constant and varying only the parameter of interest. A robust ranking of alternatives will remain unchanged in the face of changing parameter values.

4.2.6. Rank Alternatives Using Decision Maker Risk Preferences. Overall scores for the concept alternatives are generated using the decision maker's risk taking preferences. Decision maker risk attitudes can be encoded in the form of OWA operators as discussed in Section 3.3. Three important types of OWA operators that reflect three different types of decisions are: the *max* operator, the *min* operator and the weighted average operator.

$$F^* : W^* = \{1, 0, \ldots, 0\} \text{ and } F^* (a_1, \ldots, a_n) = \max \{a_1, \ldots, a_n\} \tag{27}$$

$$F^* : W^* = \{0, 0, \ldots, 1\} \text{ and } F^* (a_1, \ldots, a_n) = \min \{a_1, \ldots, a_n\} \tag{28}$$

$$F^* : W^* = \{1/n, 1/n, \ldots, 1/n\} \text{ and } F^* (a_1, \ldots, a_n) = \frac{a_1 + \ldots + a_n}{n} \tag{29}$$

Based on Yager's definition of the *orness* measure for OWA [70], it can be interpreted as a degree of risk acceptance. The value of *orness* lies in the interval [0, 1]. A small value of *orness* indicates a risk avoidance attitude while a large value illustrates a greater acceptance of risk. If a RIM quantifier is used to derive the OWA weights, then aggregate weights can be calculated using Equation (9) from Section 3.3. The *orness* function of the aggregate weights for a RIM quantifier is given by Equation (11) where α can be used to model different types of risk preferences. An $\alpha > 1$ represents an *orness* < 0.5, which is an indicator of a pessimistic or risk averse decision. An $\alpha = 1$, implies an *orness* $= 0.5$ which illustrates a neutral risk attitude and a Laplace decision. An $\alpha < 1$, indicates an *orness* > 0.5 which is representative of a risk taking nature or an optimistic decision.

The AVM approach can be used to evaluate concept variants in relative terms and study the impact of variations in the input values by aggregating their effects using the

causal relations between them. This approach can assist the decision maker to identify design aspects that best serve the stakeholder's objectives. The hierarchical reduction of abstraction helps the decision maker to expose the implicit attribute connections that play an important role in the development of a successful system. The working of AVM approach was verified and validated by means of two case studies, design of a hybrid energy system and mission-mode selection for the Apollo program. These are presented in the forthcoming sections.

5. APPLYING THE AVM APPROACH TO CONCEPTUAL ARCHITECTURE EVALUATION OF A HYBRID ENERGY SYSTEM

Rising fuel prices, government backed incentives in the form of feed-in tariffs and tax rebates, and a growing concern for the environment are leading to greater adoption of renewable sources of power in new generation planning [71]. Distributed generation resources (DGR) include renewables like photovoltaic (PV) systems and wind energy, and modular stand alone systems like fuel cells and microgenerators; DGRs are emerging as attractive alternatives to large centralized utility-owned power generation and distribution systems. Revenues from Renewable Distributed Energy Generation Systems (RDEGS) are projected to increase from $50.8 billion in 2009 to $154.7 billion by 2015 [71]. Hybrid Energy Systems (HES) comprise primarily of two or more modular generating systems that may include a combination of renewable and nonrenewable energy sources, used together to provide increased system efficiency as well as a greater balance in energy supply [72]. Such systems may operate in a 'grid-tied' mode or use backup storage technologies to operate completely independently from the grid. They may be sized from a few kilowatts for small residential systems up to tens of megawatts for large commercial and industrial applications [73].

Consumers have a wide selection of choices in planning small scale generation systems to meet local energy needs, either as alternatives or supplements to the centralized grid. Generation technologies popularly used in HES include fuel cells, PV systems, wind turbines, biomass generators, micro-turbines, engine/generator sets, and electric storage systems. Consumer need may be motivated by a combination of personal value considerations, for instance, concern for the environment and a desire to minimize their carbon footprints, or by more practical needs such as a remote location with an

unreliable or nonexistent grid supply. The selection of an appropriate portfolio of renewable and non-renewable energy sources is a MCDM problem that involves finding the most reasonable compromise among numerous economic, political, and environmental attributes.

Traditionally, maximizing performance to maximize financial gain has been the sole focus of energy planning methodologies [74]. The viability of renewable and distributed energy generation was generally assessed based on cost related benefits alone. Despite their numerous benefits, power from renewable sources still costs more than that from fossil fuel sources. However, this price does not reflect the hidden environmental and health costs of power from conventional systems [73]. Hybrid energy systems are socio-technical systems with multiple stakeholders with conflicting value objectives. The nature of such systems does not justify a single objective optimization approach. Deregulated power markets, the changing political landscape, and increased consumer awareness of the health and environmental costs of fossil fuel based power necessitate the redefinition of planning objectives and the inclusion of many more complex attributes into a planning scenario. More sophisticated MCDM techniques are called for that can accurately model multiple stakeholder preferences, simulate dynamic feedback effects within the criteria, and incorporate uncertainty into the planning scenarios.

5.1. CASE STUDY: HYBRID ENERGY SYSTEM DESIGN FOR A GENERIC MIDWESTERN DAIRY FARM

Increasing mechanization of farm operations have led to a continuing increase in their use of electrical energy. A generic Midwestern dairy farm was considered for the implementation of a hybrid energy system to supply its energy needs. The objectives of

the study were to determine the best renewable resource portfolio based on the stakeholders' value expectations, and to illuminate the rationale behind the ranking and selection of acceptable plans. The stakeholders wished to become self-sufficient with regards to their day-to-day energy needs while reducing their carbon footprint, and to reduce their dependence on an increasingly unreliable power grid. The system was to be designed to operate in a grid-tied mode to ensure uninterrupted supply of power in the event of unavailability of the renewable resource. A detailed description of the problem and planning scenarios follows. Since the performance of renewable energy resources depends significantly on the local environmental conditions, a site-specific analysis was performed by setting the Midwestern US as the location for implementing the HES.

5.1.1. Problem Formulation. Conceptual architecture alternatives for the HES were generated as part of a pre-feasibility analysis. The components of the HES and their specifications were determined based on the average daily load of the farm and locally available renewable resources. System performance and effectiveness attributes (MOEs and MOPs) and the stakeholders' value objectives (SVO) were selected based on the stakeholder's stated needs and objectives. Selected feasible concept alternatives were evaluated over a set of uncertain future scenarios that were identified a priori.

5.1.2. Load Description. Daily energy consumption of U.S. dairy farms varies between 40,000 kilowatt-hours (kWh) to 220,000 KWh per annum depending on the herd size [75]. The average energy consumed per animal is lesser for large scale operations due to increased efficiencies of scale. Milk-processing operations consume the bulk of the power while lighting and ventilation systems utilize the remainder [75]. The peak demand occurs twice a day when milking tasks are performed. Figure 5.1 shows the load
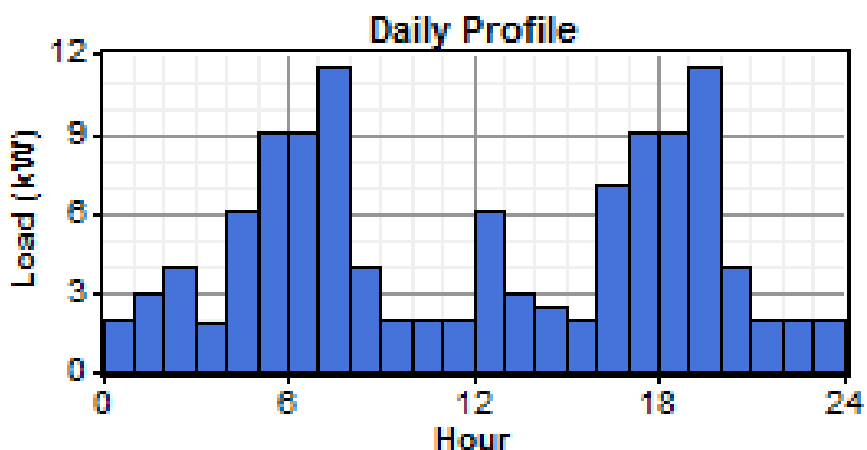
Figure 5.1. Daily Load Profile of a Generic Dairy Farm

profile of a small 60 animal farm. The data for this load profile was obtained from a University of Wisconsin study [76]. For simplicity of analysis, seasonal variations in the load profile were not modeled and the same average daily load profile was used for all days of the year. The farm averaged an energy consumption of 116kWh/d with a 20kW peak power demand. An hourly load variation of 20% and daily load variation of 15% were assumed. The total annual energy consumption and energy consumed per cow are listed in Table 5.1.

5.1.3. Renewable Resources Options. The farm had three main types of renewable resources available for use in energy production – solar, wind and biomass.

Table 5.1. Energy Consumption of a Generic Small Scale Dairy Farm

Number of Cows	Total Annual Electricity Consumption (kWh)	Annual Electricity Consumption per Cow (kWh/cow)
60	41,975	700

The availability and energy potential of the solar and wind resources were determined using historical weather data obtained from the NASA Surface Meteorology and Solar Energy website [77]. The data used for a rural location in central Missouri

    5.1.3.1 Solar radiation. The monthly averaged insolation data for a central Missouri location with 38° 38′ 53″ N latitude, 90° 12′ 44″ W longitude was obtained from the NASA Surface Meteorology and Solar Energy online repository [77]. The annual average of daily radiation for that location was 4.086 KWh/m2/day. The monthly variation in insolation averaged over a period of 22 years is shown in Figure 5.2.

    5.1.3.2 Wind resource. Data for monthly average wind speed for the were obtained from the National Climatic Data Center [78]. The annual average of wind speeds for central Missouri was 4.381 m/s. This is an average of 30 years of data collected between the years 1978 – 2008.
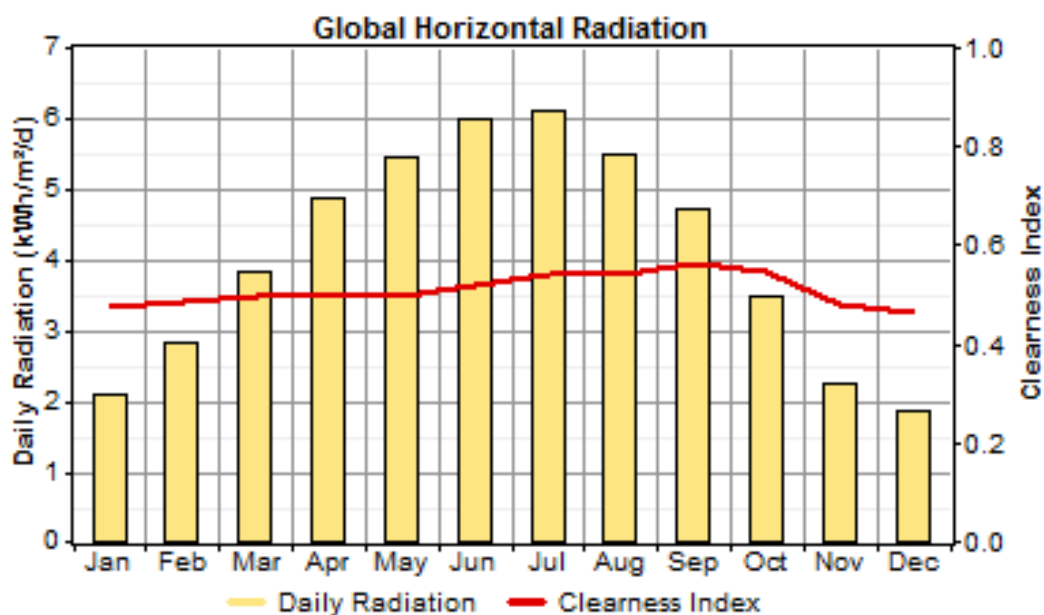
Figure 5.2. Annual Average Solar Radiation Incident on a Horizontal Surface

Figure 5.3 shows the monthly variations in wind speed over the period of a year. Missouri ranks among the top 25 states in the United States in terms of wind resource availability. It has a power potential equal to 63 percent of the state's electricity use [78].
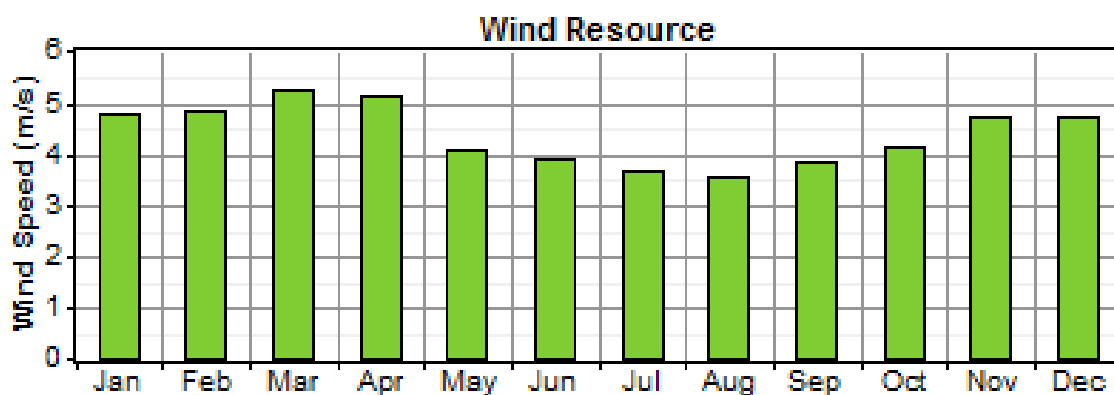
Figure 5.3. Monthly Average Wind Speeds for Central Missouri

5.1.3.3 Biogas resource. Farm-scale anaerobic digestion is used to manage cattle waste and generate biogas which can be used as a fuel source on the farm. Besides providing a fuel source, this technology has the added benefits of eliminating waste, preventing soil and water pollution, and producing manure for use as a fertilizer. The solid byproducts of the biodigestions process can be used as an additional source of income. However, the high cost of biodigesters makes biogas production financially infeasible for dairy operations with fewer than 300 cows [79]. Based on this assessment, a biogas based renewable energy system was not considered for this case study.

5.1.4. System Components. With biogas being ruled out as a power resource, the options considered for the farm HES were wind and solar in conjunction with the power grid. A power converter device was also required for converting the DC power output of the solar system into AC. Table 5.2 lists the sizes of the system components being considered for the farm HES. The HES's components were a PV module, wind turbine and power converter. Brief descriptions of each of these components are given in the following sections.

5.1.4.1 Photovoltaic systems. Recent improvements in the conversion efficiency of PV panels have made solar energy systems much more affordable. Government subsidies and tax-breaks have also helped in furthering the appeal of solar power as a renewable energy resource. The state of Missouri offers a $2 per watt rebate for farm-scale PV installations and state net-metering laws allow solar electricity producers to sell their energy back to utilities [80]. A 30% federal tax credit is also available to qualifying systems. Capital, and replacement costs for PV panels were specified were specified at $7/We and $6.5/We respectively [81]. Very little maintenance is necessary for the PV panels. Operations and maintenance (O&M) costs over a 20 year system life are low enough to be neglected and were set as 0 for this study. PV module sizes considered were 0kW, 10kW and 20kW. State and federal subsidies were deducted from the initial cost specifications to arrive at the actual capital and replacement costs.

5.1.4.2 Wind energy systems. A generic wind turbine of 20kW rating was considered for this study. Since the availability of energy from a wind turbine is significantly impacted by prevailing wind speeds, a minimum of 0 and maximum of 3 turbines were considered. Cost of one unit was considered to be $29,000 and replacement

Table 5.2. Search Space Alternatives

Components				
	PV (kW)	Wind Turbine (20 kW)	Converter (kW)	Grid (kW)
Sizes/numbers	0 10 20	0 1 2 3	0 10 20	1000

and maintenance costs were also kept at the same amount [82]. O&M costs are taken as $100/yr for a lifetime of 15 yrs. The power curve for the generic turbine is shown in Figure 5.4.
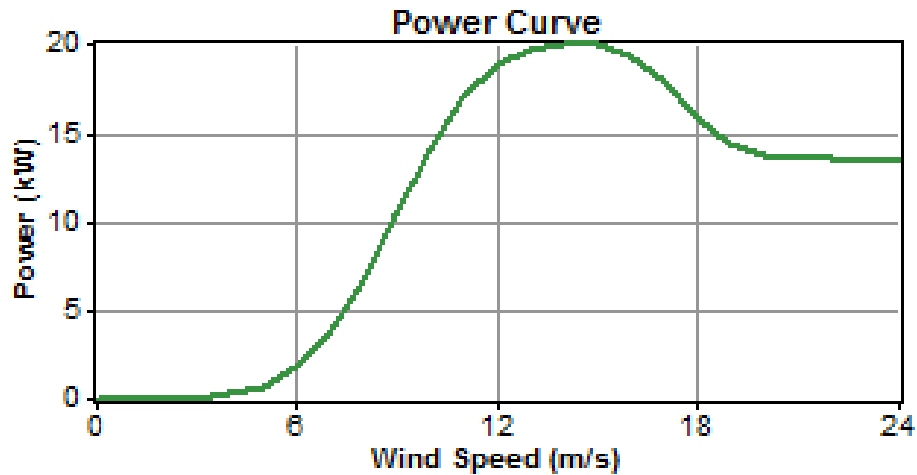
Figure 5.4. Power Curve of a Generic 20kW Wind Turbine

5.1.4.3 Power converter.   In order to allow the DC supply from the PV system to be used to serve the AC load, a power converter is required. The converter is only used in system alternatives that include a PV module. A generic converter with 90% efficiency and a lifetime of 15 yrs was considered. Converter sizes included were 0kW, 10kW and 20kW. The converter costs are taken as $1000/kW capital and replacement. O&M costs were taken as $100/yr.

5.1.5. Generation of Alternatives. Feasible component configurations for the HES were generated using the HOMER® Micropower Optimization Model [83]. HOMER is a modeling tool developed by the U.S. National Renewable Energy Laboratory (NREL) to assist in the design of micropower systems and to facilitate the comparison of power generation technologies based on their technical and economic merits. For the purpose of this study, HOMER was used to search through the design tradespace for feasible design configurations. The top four concept alternatives selected for evaluation using the AVM approach are shown in Table 5.3. The next step is the identification of the AVM's attributes. These include the architecture's performance and effectiveness attributes (MOE's and MOP's), and the SVO.

Table 5.3. Feasible System Architecture Alternatives

Configuration	Grid (kW)	PV Module (kW)	Wind Turbine (kW)	Converter (kW)
C1	1000.00	0.00	0.00	0.00
C2	1000.00	0.00	2.00	0.00
C3	1000.00	10.00	0.00	10.00
C4	1000.00	10.00	2.00	10.00

5.1.6. Model Parameters.   To formulate the architecture value map the first step

is developed by linking the value objectives to the system attributes most likely to

influence the value measures. The performance attributes are in turn linked with the

design features that determine the extent to which the system alternative satisfies these

attributes. The attributes and value measures for the HES value map are listed in Table

5.4. Figure 5.5 shows the AVM for the hybrid energy system.

Table 5.4. AVM Attributes for the Hybrid Energy System Architecture Evaluation

Specific Need	Key System Objectives	Solution-Neutral Attributes: Measures of Effectiveness	Solution-Specific Attributes: Measures of Performance
Hybrid energy system for a small scale dairy farm	1. Overall cost 2. Energy security 3. Socio-environmental impact	Expenses Costs avoided Flexibility Reliability Social impact Environmental impact	Total capital cost Maintenance costs Operating costs Grid sales earnings Grid purchase avoided Percent change in cost of energy Percent change in net present cost System availability System capacity Aesthetics Noise levels Land use impact CO_2 emissions SO_2 emissions NOX emissions
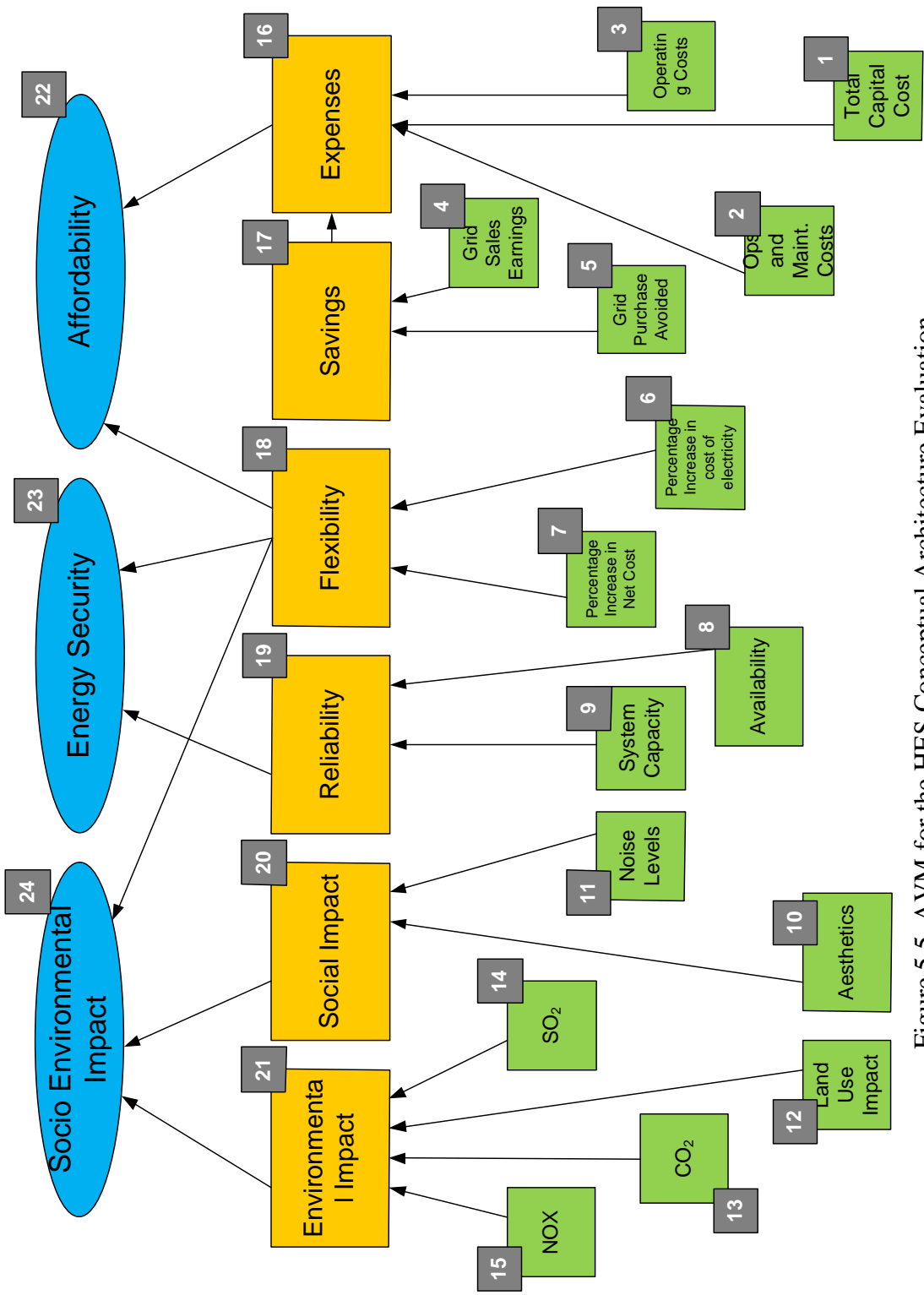
Figure 5.5. AVM for the HES Conceptual Architecture Evaluation

The quantitative and qualitative attributes for each scenario are calculated using the HOMER planning package or determined using subjective judgments obtained from the literature. The customer's highest value objectives from the system are an affordable and secure power supply with minimal social and environmental impact.

5.1.7. Attribute Descriptions. Expenses were assessed as a direct influence of capital costs, maintenance costs and operating costs, with capital costs being assigned the most significant influence weight. Savings were modeled as a combination of the cost avoided by not purchasing power from the grid and the earnings from selling excess energy back to the utility. Energy security was dependent on the reliability and flexibility of the system. Flexibility was defined as the added cost of adjusting to future scenarios. Percent change in cost of electricity and percent change in the over system net present cost were determined to have the highest impact on flexibility. A system configuration with high flexibility would be able to cope with uncertain futures with a smaller increase in cost and vice versa. The availability of the system configuration and its capacity factor were used to assess reliability. Since actual system availabilities depend on component make and specifications, this attribute was modeled as a fuzzy linguistic input. The availability of system with multiple sources of power operating in parallel is higher than the availabilities of the individual components. Thus the linguistic assessment of availability was based on the number of generating technologies used in a given system configuration, with more generating resources being associated with higher reliability. The capacity of a system alternative is directly related to its renewable fraction. Renewable resources have a much lower capacity factor than fossil fuel based power plants. The capacity factor is a measure of the productivity of a power production facility.

It compares the plant's actual production over a given period of time with the amount of power the plant would have produced if it had run at full capacity for the same amount of time. A higher renewable fraction was interpreted as a measure of lower system capacity.

One of the major reasons given as an objection to wind turbines is their visual impact on a landscape. The noise generated from the turbines is also cited as an issue for concern. Both these factors along with the land use impact of renewable generation technologies are used to assess the social impact of the HES configurations. Emissions of CO_2, SO_2 and NO_x gases were utilized as a direct measure of the system's environmental impact.

5.1.7.1 Economic parameters and policies. Assuming the project's lifetime to be 30 years and yearly interest rates are taken as 8%. A \$2 subsidy for every We of installed PV capacity offered by state of Missouri is used to compute the capital costs for the PV modules. A further 30% federal tax credit is applied to both the PV and wind turbine costs. Base electricity price was set at \$0.115/kWh. This is an average of the nearly \$0.2/kWh price for the North-Eastern and Western states on the higher end, and the 0.9/kWh of the Midwestern states on the lower end [84]. Table 5.5 summarizes the economic parameters used for this case study.

5.1.7.2 Net-metering. Even though the U.S. does not a federally mandated net-metering policy, various states have passed laws that allow customers to offset electricity costs by selling excess electricity back to the utilities. The Missouri net-metering law went into effect on January 1, 2008 [80]. Any clean power system of 100kW or smaller is eligible for net-metering under this plan. Customers receive energy credits on their monthly power bills for any excess power generated. These credits carry over during the

Table 5.5. Summary of Economic Parameters and Policy Assumptions

Economic Parameters	Assumption
Project lifetime	30 years
Annual interest rate	8%
Federal tax credit for renewable technologies	30% FTC on capital cost of wind and solar systems
State subsidies	$2/We of installed PV systems
Base electricity price	$0.115/kWh

annual billing cycle. For this case study it assumed that under a net-metering policy a customer is permitted to sell excess power back to the utility at a pre-negotiated rate. A selling price of $0.025/kWh is assumed for grid sales of renewable energy.

   5.1.8. Uncertain Future Scenarios. The performance of the selected architecture alternatives was assessed over a set of uncertain future scenarios. Uncertain attributes are factors that are likely to change in future and have a significant influence on the system's performance. Such attributes may include load growth, fuel prices, or regulatory changes. Possible values for the uncertain attributes are pre-specified. Uncertainties in electricity price, wind speeds and load growth were selected to generate future scenarios. Increase in loads of 8% and 12% are assumed to model load growth uncertainty. The load profile was not modified as the load was increased, but rather kept constant in shape and scaled in size. Electricity prices in the U.S. have increased at the average rate of 3.5-4.5%/yr for the last decade [84]. Three different prices of electricity reflecting this uncertainty were chosen for this study. The efficiency and productivity of a wind turbine significantly depend on the wind's speed. Wind speed variations are modeled by means of three different annual average wind speeds. Tables 5.6 and 5.7

Table 5.6. Future Values of Uncertain Attributes

	Future Value - 1	Future Value - 2	Future Value - 3
Load growth	116 kWh/d	128 kWh/d	140 kWh/d
Electricity price	$0.115/kWh	$0.15/kWh	$0.2/kWh
Wind speed	3.5m/s	4.38m/s	6m/s

Table 5.7. Future Scenarios for Evaluating System Architecture Concepts

Scenario Number	Load Growth kW/d	Electricity Price $/kW	AverageWind Speed m/s
S1	116.40	0.12	4.38
S2	116.40	0.12	3.50
S3	116.40	0.12	6.00
S4	116.40	0.15	4.38
S5	116.40	0.15	3.50
S6	116.40	0.15	6.00
S7	116.40	0.18	4.38
S8	116.40	0.18	3.50
S9	116.40	0.18	6.00
S10	125.28	0.12	4.38
S11	125.28	0.12	3.50
S12	125.28	0.12	6.00
S13	125.28	0.15	4.38
S14	125.28	0.15	3.50
S15	125.28	0.15	6.00
S16	125.28	0.18	4.38
S17	125.28	0.18	3.50
S18	125.28	0.18	6.00
S19	129.92	0.12	4.38
S20	129.92	0.12	3.50
S21	129.92	0.12	6.00
S22	129.92	0.15	4.38
S23	129.92	0.15	3.50
S24	129.92	0.15	6.00
S25	129.92	0.18	4.38
S26	129.92	0.18	3.50
S27	129.92	0.18	6.00

show the uncertain future values of the three attributes and the future scenarios respectively. Future scenarios consist of various permutations of the uncertain attributes. A total of 27 uncertain future scenarios were considered for this study.

5.1.9. Analysis of Alternatives. Two decision-makers with conflicting value objectives were considered for assigning the connection weights of the HES architecture value map. Figure 5.6 shows the AVM with its connection weights as rendered by Pajek® [85]. Details of the decision-maker expertise, the number of terms in their linguistic term-sets and the weights assigned to the AVM connections are shown in Tables 5.8 and 5.9 respectively.
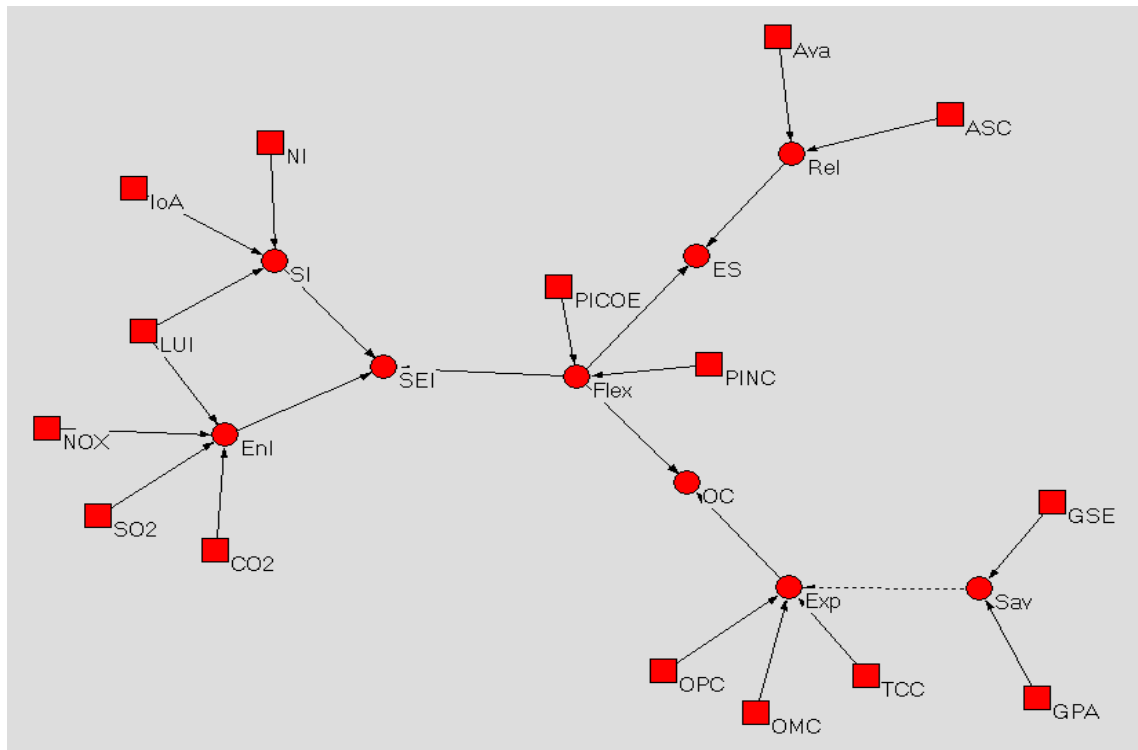
Figure 5.6. Architecture Value Map of the HES as Rendered by Pajek [73].

Table 5.8. Aggregated Weights in the 2-Tuple Linguistic Representation

Causal Node	Effect Node	Aggregated Symbolic Weight		Direction of Influence
		Linguistic 2-tuple	Beta	
1	16	$\left(s_{11}^{15}, 0.0049\right)$	0.7906	+
2	16	$\left(s_{4}^{15}, 0.0049\right)$	0.2906	+
3	16	$\left(s_{4}^{15}, 0.0049\right)$	0.2906	+
4	17	$\left(s_{11}^{15}, 0.0049\right)$	0.7906	+
5	17	$\left(s_{8}^{15}, 0.0013\right)$	0.5844	+
6	18	$\left(s_{11}^{15}, 0.0049\right)$	0.7906	-
7	18	$\left(s_{8}^{15}, 0.0013\right)$	0.5844	-
8	19	$\left(s_{13}^{15}, -0.0006\right)$	0.9279	+
9	19	$\left(s_{11}^{15}, 0.0049\right)$	0.7906	+
10	20	$\left(s_{4}^{15}, 0.0049\right)$	0.2906	+
11	20	$\left(s_{11}^{15}, 0.0049\right)$	0.7906	+
12	20	$\left(s_{8}^{15}, 0.0013\right)$	0.5844	+
12	21	$\left(s_{11}^{15}, 0.0049\right)$	0.7906	+
13	21	$\left(s_{11}^{15}, 0.0049\right)$	0.7906	+
14	21	$\left(s_{11}^{15}, 0.0049\right)$	0.7906	+
15	21	$\left(s_{11}^{15}, 0.0049\right)$	0.7906	+
17	16	$\left(s_{13}^{15}, -0.0006\right)$	0.9279	-
16	22	$\left(s_{13}^{15}, -0.0006\right)$	0.9279	-
18	22	$\left(s_{11}^{15}, 0.0049\right)$	0.7906	-
18	23	$\left(s_{11}^{15}, 0.0049\right)$	0.7906	+
18	24	$\left(s_{11}^{15}, 0.0049\right)$	0.7906	+
19	23	$\left(s_{3}^{15}, -0.0049\right)$	0.2094	+
20	24	$\left(s_{13}^{15}, -0.0006\right)$	0.9279	+
21	24	$\left(s_{6}^{15}, -0.0130\right)$	0.4156	+

Table 5.9. Decision-Maker Characteristics

	Decision-Maker 1 (DM1)	Decision-Maker 2 (DM2)
Expertise level	High	Moderate
Term-set granularity	7	5
Linguistic terms for assigning connection weights for the AVM	{Very Low, Low, Moderate, High, Very High}	{Very Low, Low, Moderately Low, Moderate, Moderately High, High, Very High}

5.1.10. Discussion of Results. The AVM inputs are normalized and transformed into the 2TLR format using the transformation functions presented in Section 4.13. The AVM was then simulated using MATLAB scripts. Overall scores for each of the three key system attributes were obtained for each alternative in each scenario – a total of 108 values. Figures 5.7, 5.8 and 5.9 show the performance of the architecture alternatives based on the value attributes. The data points are the symbolic value of the 2-tuple representation and have been superimposed on the basic linguistic term set, in order to show their linguistic values. The results indicate that the proposed decision making technique has an ability to quantify the value delivered by a proposed system configuration. Concept C2, which was a combination of a wind turbine operating in a grid tied mode, has a higher value associated with energy security and overall cost. Concept C3 and C4 both include PV modules and have a lower value in terms of cost.

Concept 1 which consists entirely of the grid supply without any renewable component has high value in terms of cost but performs poorly on energy security. In case of an outage the customer will lose power entirely since concept 1 does not include any alternative generation options.
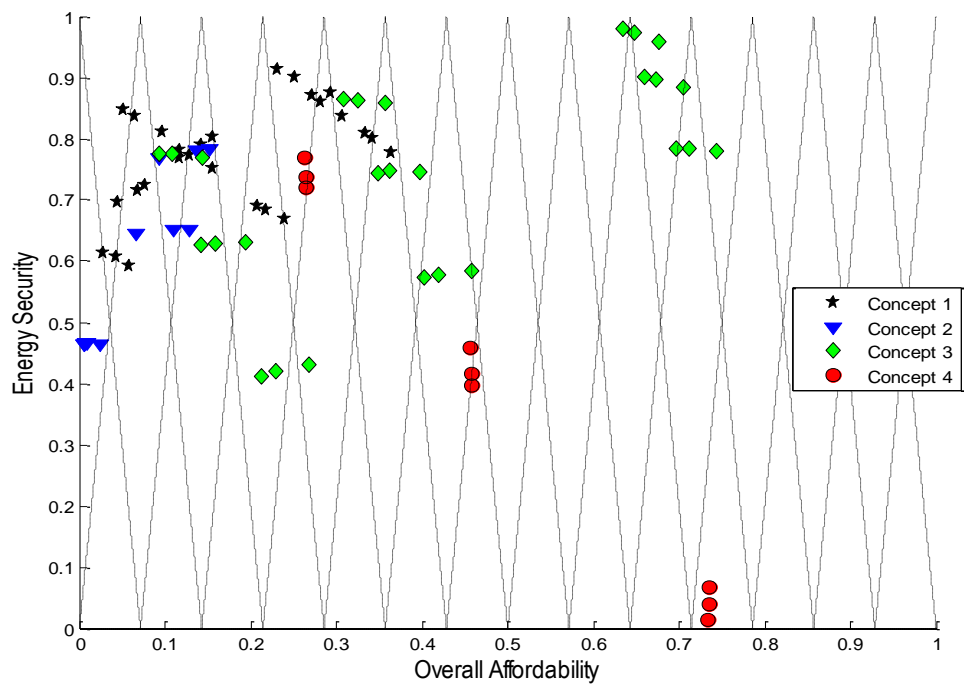
Figure 5.7. Overall Affordability vs Energy Security
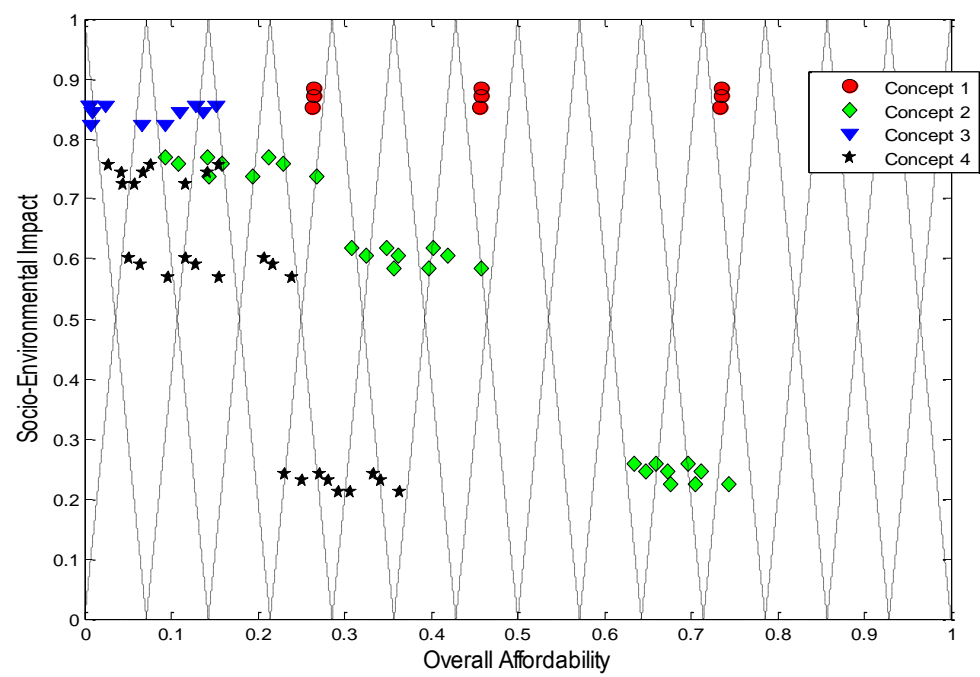
Figure 5.8. Overall Affordability vs Socio-Environmental Impact

It can be seen from Figures 5.7 and 5.9 that economic factors favor conventional systems while environmental factors favor renewable systems. PV systems are the least feasible due to high initial cost and long payback periods. Concept 4 performs best on the socio-environmental impact measure. This can be attributed to a greater portion of the energy being supplied by renewable sources which dramatically decreases emissions. Concept 2 has the best value performance for all three key system attributes on the highest number of scenarios.
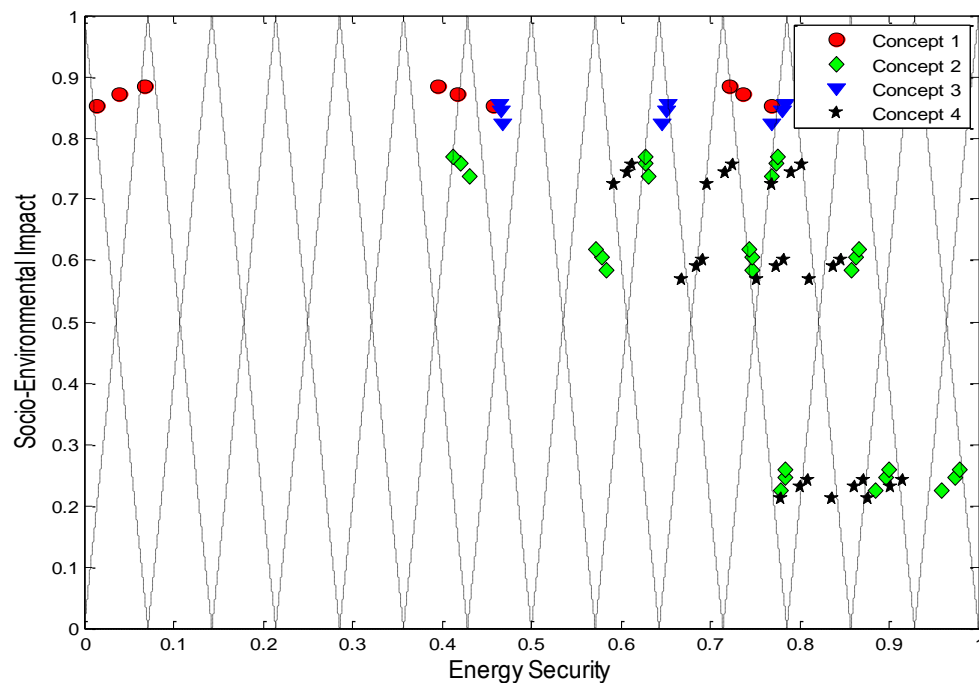
Figure 5.9. Energy Security vs Socio-Environmental Impact

Figure 5.10 shows the performance of all four concepts alternatives on all three key system attributes. The results indicate that for central Missouri use of wind resource

is more economical than solar energy. Solar systems become feasible only in case of high electricity prices and poor wind resource availability. A further reduction in PV module costs will make a concept 4 the best value based on the KSA. Such a system would have very low socio-environmental impact and offer superior energy security.

5.1.11. Overall Concept Ranking. An overall rank for the concept alternatives was generated using Ordered Weighted Averaging (OWA) operators which allow the risk taking preferences of decision makers to be incorporated into the overall ranking of concept alternatives. The *orness* measure of the OWA operator represents risk attitudes of the decision-maker. OWA weights for aggregating the KSA scores into an overall ranking can be derived using the *orness* values. For this problem, the KSA scores were aggregated using three different sets of OWA weights representing three different risk attitudes as shown in Table 5.10. Table 5.11 lists the final ranking of the concept alternatives in all 27 future scenarios. Concept 2 delivers the highest value in terms of the customer's key system attributes even under different decision-maker risk taking preferences.
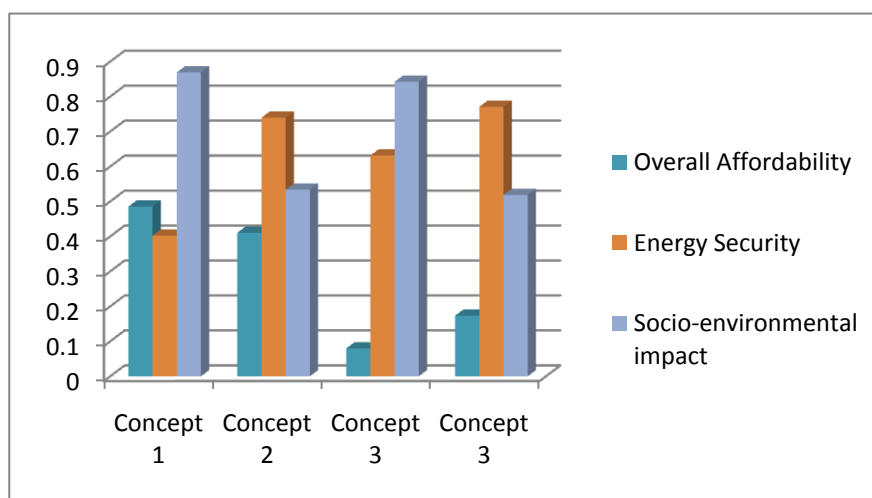
Figure 5.10. Performance of Concept Alternatives on Stakeholders' Value Objectives

Table 5.10. OWA Weights for Modeling Risk Taking Attitudes

Risk taking attitude	*Orness* measure	OWA weight vector
Pessimistic	0.3	[0.0770, 0.3112, 0.6117]
Laplace	0.5	[0.3333, 0.3333, 0.3333]
Optimistic	0.7	[0.6245, 0.2160, 0.1595]

Table 5.11. Highest Ranked Concept Alternatives in All 27 Scenarios

Scenario	Pessimistic Rank	Laplace Rank	Optimistic Rank
	Highest Ranked Concept Alternative		
S1	2	2	2
S2	1	1	1
S3	2	2	2
S4	2	2	2
S5	1	2	4
S6	2	2	2
S7	2	2	4
S8	2	2	1
S9	2	2	2
S10	2	2	2
S11	4	4	4
S12	2	2	2
S13	2	2	2
S14	1	4	4
S15	2	2	2
S16	2	2	4
S17	2	4	1
S18	2	2	2
S19	2	2	2
S20	4	4	4
S21	2	2	2
S22	2	2	2
S23	1	4	4
S24	2	2	2
S25	2	2	4
S26	2	1	1
S27	2	2	2

6. VALIDATION STUDY: MISSION MODE SELECTION FOR THE APOLLO PROGRAM

The AVM framework makes use of subjective judgments to evaluate the concept variants. Hence, the validity of this approach depends upon its ability to generate outcomes that mirror expert expectations. To verify the working of the approach, it was applied to a retrospective study of the mission-mode selection problem for the Apollo program. Since the results of this study are well known, this study verified that the AVM approach can be used to make value judgments and differentiate between conceptual architectures based on their ability to satisfy stakeholder value objectives. The Apollo program was a benchmark problem in the discipline of systems engineering, and historical records [86-90] have shown that the selection of the mission-mode was the deciding factor that went on to determine the success of the Apollo program. It was the most critical decision made during the early design phases and had a significant impact, not only, on the design of the system components, but also, on the schedule and program risks [91]. Previous research in systems engineering has used the selection of the Lunar-landing mode as a decision-making problem. The mission-mode selection problem clearly demonstrated the importance of the decisions made during the early stages of system design. The outcome of this problem has been thoroughly researched and well documented. Thus, this problem was determined to be most appropriate for the verification and validation of the AVM framework. This chapter summarizes the mode comparison study for selecting the best mission mode for a successful manned lunar landing.

6.1. PROBLEM DEFINTION

President John F. Kennedy laid down the need for the Apollo program in his historical speech to a joint session of Congress, on May 25th 1961. Rising to the challenges issued by then recent Soviet successes in the space race, Kennedy set down the primary objective of the Apollo program as the manned lunar landing of and return a United States Citizen before the end of the 60s decade. The SVOs identified from the need statements are: human lunar landing and return, crew survival and a one decade time limit.

6.1.1. Functional Breakdown. Figure 6.1 shows a solution neutral functional decomposition of the lunar-landing mission. The major functions that will be required to achieve the system's objectives are identified. Identifying these functions is the precursor to the characterization of system attributes that determine the value of a candidate solution. By listing the objects and mechanisms associated with each function it becomes possible to develop an initial skeleton of a system's physical architecture.

6.1.2. Identification and Definition of Attribute Measures. The value mapping process starts with delineation of system attributes that specifically contribute to its overall performance. The solution-neutral system attributes are derived from the SVOs using an iterative process of decreasing abstraction and increasing specificity. From the solution-neutral measures of effectiveness, the measures of performance are obtained which are further decomposed into solution specific design attributes. The MOEs and MOPs for the mission mode selection problem are listed in Table 6.1. Five high-level MOEs are derived from the stakeholders' value objectives. These attributes determine 'how well' a system achieves its key objectives. Each MOP has a one-to-one mapping

with a specific architecture option. Thus, depending on their values, the 10 MOPs

explicitly define a particular mission mode. Both the attributes and the mission mode

alternatives were derived from an exhaustive study of the referred documents [90-92].
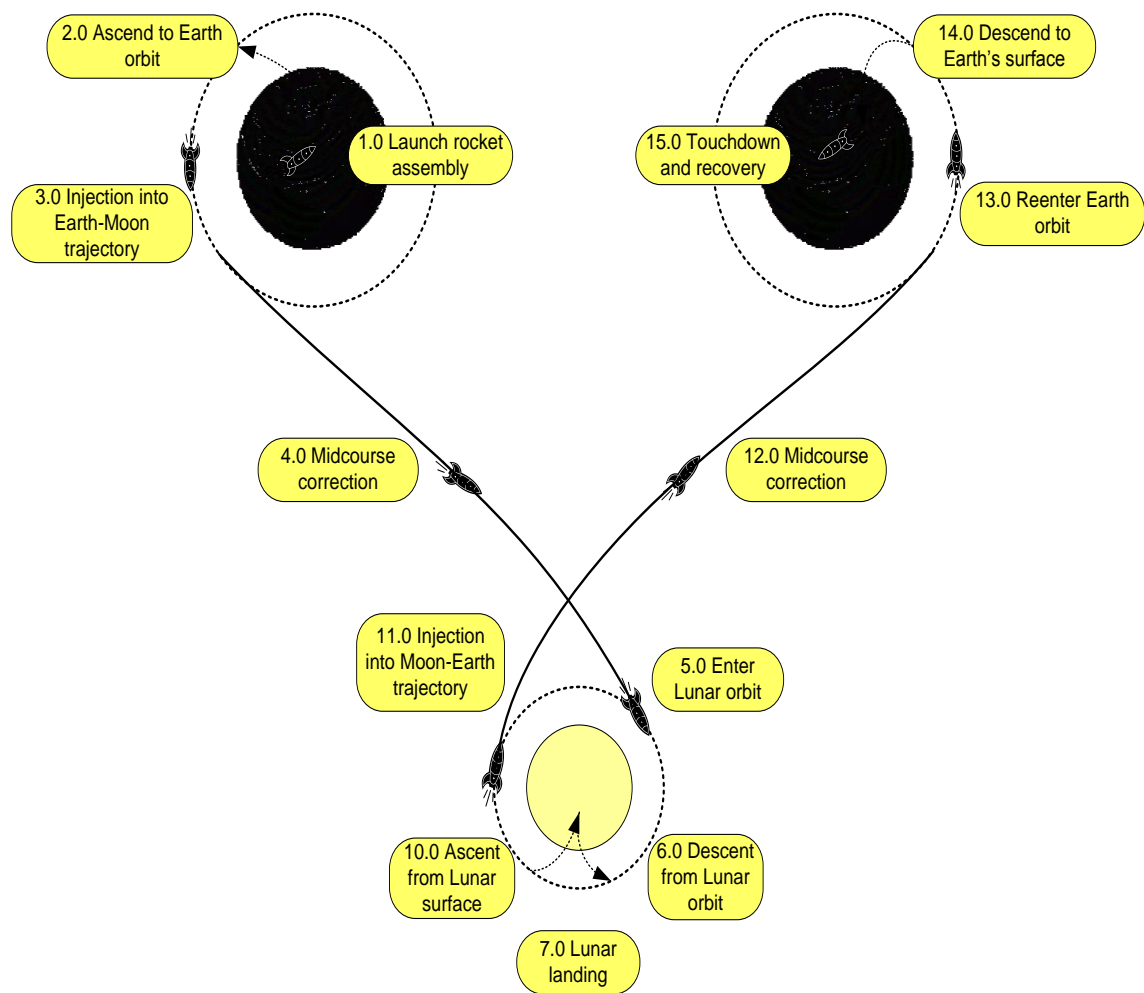
Figure 6.1. Functional Flow Diagram of the Apollo Mission Modes

6.1.3. Solution Definition. One of key constraints for selecting the mission

mode was minimum disruption of the development contracts that were already underway

such as the Saturn rockets and the Apollo spacecraft consisting of the command and

service modules.

Table 6.1. Measures of Effectiveness and Measures of Performance for Mission Mode
Selection

Specific Need	Value Objectives	Solution-Neutral Attributes: Measures of Effectiveness	Solution-Specific Attributes: Measures of Performance	Architecture Options
Manned lunar landing and return of a US citizen by the end of the 1960s decade	1. Human lunar landing and return 2. Crew survival 3. 10-year deadline	Mission mode realizability Risk of mission loss Mission safety Schedule risk Cost	Weight margin Fuel storability EOR risk LOR risk Stability of Lunar landing Degree of visibility Design modularity Mission mode operational risk Developmental difficulty Structural cost	Initial injected weight Fuel type Earth Orbit Rendezvous configuration Lunar rendezvous configuration Lunar touchdown module weight Customizability of Lunar Landing vehicle Functions per vehicle Total maneuver risk Estimated time to first flight Booster size

In keeping with these constraints, multiple mission mode concepts were considered for the Apollo program. Figure 6.2 summarizes the major trajectories to and from the moon for each of the 4 candidate mission modes. Four of these that have been included in this study are:

1. Earth Orbit Rendezvous – using the Saturn C-5 launch vehicle and present Apollo Command Module(C-5 EOR)

2. Lunar Orbit Rendezvous using the Saturn C-3 launch vehicle and the Apollo Command Module(C-4 LOR)

3. Direct Ascent using the Nova or Saturn C-8 launch vehicles and the Apollo Command Module(Nova DA)

4. Direct Ascent using the Saturn C-5 launch vehicle and a smaller modified command module (C-5 DA)

As can be seen, many of the phases are common to all candidate modes. However, certain phases are unique to each mode and have been used to assess mode performance. Table 6.2 shows the morphological matrix for the 4 mission modes being considered for selection. The architectural options for each of the performance attributes are listed.

6.1.4. Developing the AVM. The causal relationships and feedback effects between the MOEs and MOPs were determined from the analysis presented in the mission mode selection studies [91-92]. Figure 6.3 shows the influences and the directions of influence between the attributes. The reasoning process is illustrated by means of an example: The Apollo spacecraft was already under contract at the time these studies were performed.

Table 6.2. Morphological Matrix Linking the MOPs with the Architectural Options

Measures of performance	Architecture Option	Unit	Mission Mode Concept Variants			
			C-5 Lunar Orbit Rendezvous	C-5 Earth Orbit Rendezvous	Nova Direct Ascent	C-5 Direct Ascent
Weight margin	Initial injected weight	lbs	80,000-150000	90,000 per launch x 2-300000	238,000-300000	190,000-300000
Fuel storability	Fuel type		Primarily storable	Cryogenic & storable	Primarily cryogenic	Cryogenic & storable
EOR risk	Earth Orbit Rendezvous configuration		Lowest	Highest	Moderate	Moderate
LOR risk	Lunar rendezvous configuration		Moderate	Low	Low	Low
Stability of Lunar landing	Lunar touchdown module weight	lbs	22,000-35,000	50,000-70,000	80,000-100,000	60,000-84,500
Degree of visibility	Customizability of Lunar Landing vehicle		High	Moderate	Low	Low
Design modularity	Functions per vehicle		Lowest	Moderate	Highest	Highest
Mission mode operational risk	Total maneuver risk		0.595	0.73	0.81	0.645
Developmental difficulty	Estimated time to first flight		Nov 1965 – March 1966	+6 months	+17 months	March 1966
Structural cost	Booster size		C-4	C-5	Nova	C-5
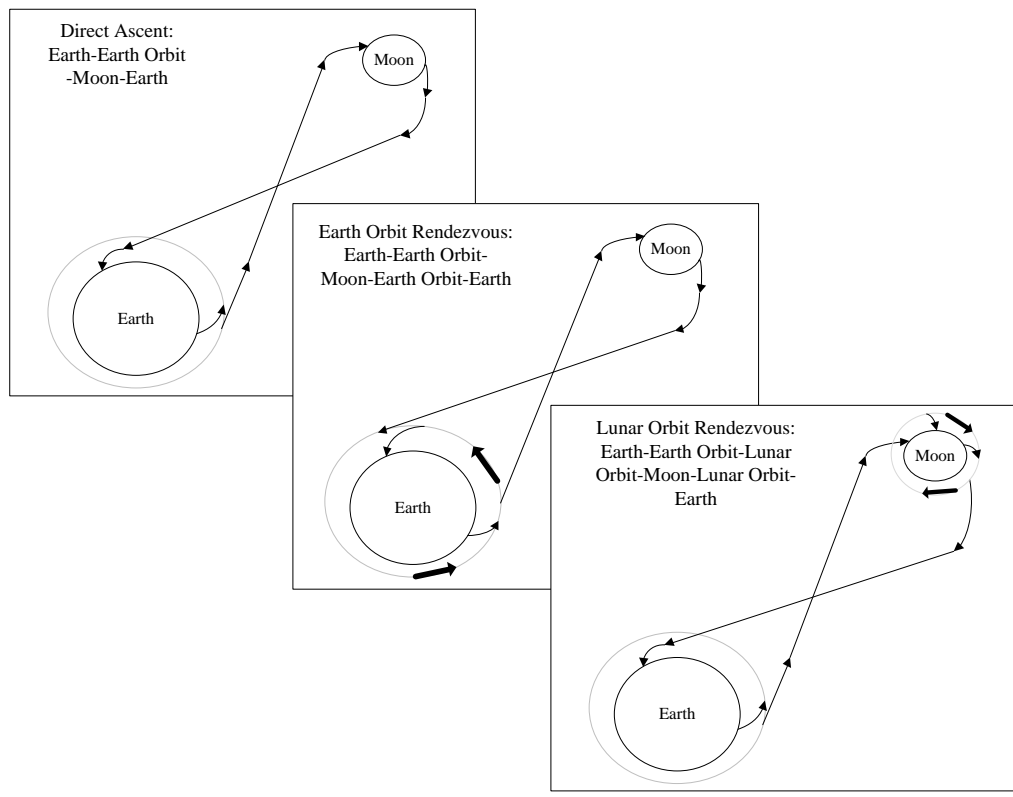
Figure 6.2. Possible Mission-Mode Trajectories [5]
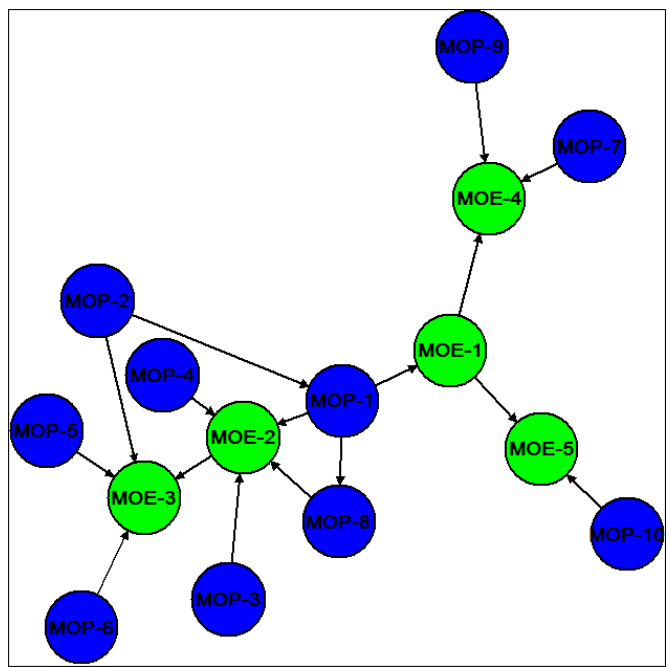
Figure 6.3. Architecture Value Map for Mission-Mode Selection

A direct ascent approach would have required the modification of the Apollo command and service modules to prepare them for the high risk landing on the lunar surface. The complexity of the task would have an impact on the program schedule. Thus the Lunar landing configuration would have an impact on the schedule. Similar reasoning was used to develop the relationships between the other attributes in the AVM.

6.2. APPLYING THE SC-FCM MODEL

The SC-FCM evaluation model is applied to the AVM. The code for this problem was written using MATLAB [93] and the GraphViz [94] plotting tool. Inputs from three decision makers were used to create the final influence weight matrix and the concept activation matrix using information from numerous mission mode selection studies conducted by private contractors and NASA space flight centers [89]. The decision makers select appropriate semantic types for linguistic variables in accordance with Table 6.3 to assign the influence weights and the attribute initializations.

The basic linguistic term sets for both sets of criteria were set at a cardinality of 5. The attribute initialization linguistic term set, designated the 'Level of satisfaction' (LoS) term set, represents the level of satisfaction that the decision maker has with the attribute values for each concept variant. A term set with a granularity of 5 is chosen for the LoS variable, such that, LoS = {*Highly Satisfactory, Quite Satisfactory, Moderately Satisfactory, Somewhat Satisfactory, Not Satisfactory*}.

$$LoS = \left\{ s_0^{LoS}, s_1^{LoS}, \ldots, s_g^{LoS} \right\} \tag{30}$$

where $g = 4$ is the cardinality of the LoS term set. The strength of the connection weights

is represented by a term set of cardinality $h = 4$ given by CS = { *Highly Positive,*

Moderately Positive, Neutral, Moderately Negative, Highly Negative }

$$CS = \left\{ s_1^{CS}, s_2^{CS}, \ldots, s_h^{CS} \right\} \tag{31}$$

The membership functions for three different semantic terms sets described in Table 6.3

are shown graphically in Figures 6.4, 6.5 and 6.6.

Table 6.3 Concept Node Labels

Semantic Term Set	Number of linguistic	Linguistic variable	Illustration
A	3	Positive(s_0^3), Neutral(s_1^3),Negative(s_2^3)	Shown in Figure 6.4
B	5	Highly Positive(s_0^5), Moderately Positive(s_1^5), Neutral(s_2^5), Moderately Negative(s_3^5), Highly Negative(s_4^5)	Shown in Figure 6.5
C	7	Very Highly Positive(s_0^3), Highly Positive(s_0^3), Moderately Positive(s_2^7), Neutral(s_3^7), Moderately Negative(s_4^7), Highly Negative(s_5^7), Very Highly Negative(s_6^7)	Shown in Figure 6.6
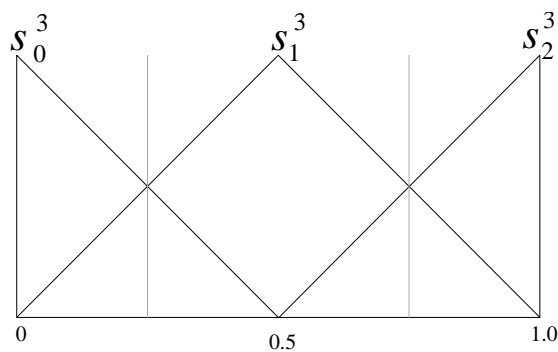
Figure 6.4. Semantic Term Set A of Cardinality 3
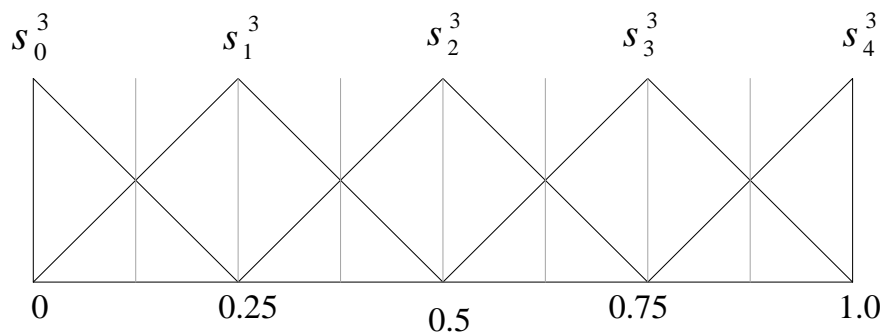
Figure 6.5. Semantic Term Set B of Cardinality 5
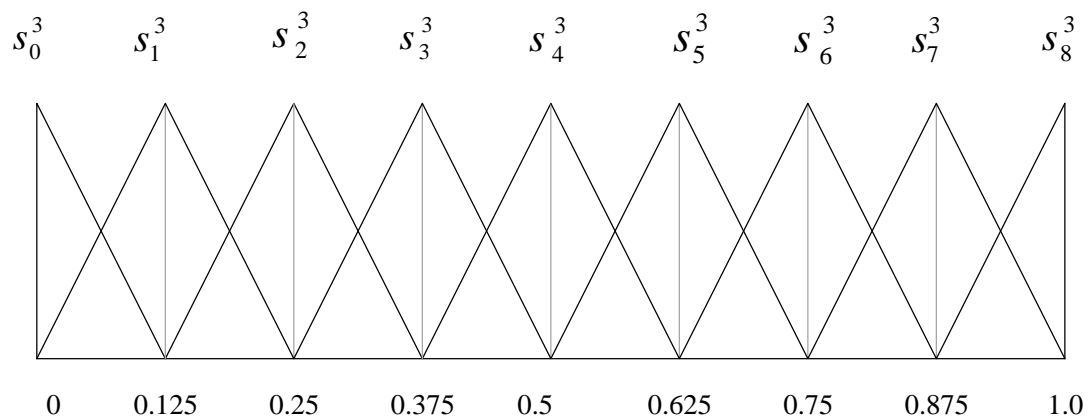
Figure 6.6. Semantic Term Set C of Cardinality 7

Semantic set 'B' is used as the basic linguistic term set and the decision maker weight assessments are converted into the BLTS to generate the connection matrix. The next step involves the creation of the linguistic weight evaluation based on the AVM connections. Based on an analysis of the nature of interactions and feedback within the attributes the following weight matrix was created for representing the connection strengths linguistically. The decision inputs from the three decision makers were aggregated into a common assessment value shown in Table 6.4.

Table 6.4. Aggregated Influence Weights

Causal Node	Effect Node	Aggregated Symbolic weight	Polarity
1	5	$(s_4^5, 0.1)$	+
2	3	$(s_4^5, 0)$	+
1	4	$(s_3^5, 0)$	+
6	1	$(s_4^5, 0)$	+
6	2	$(s_1^5, 0)$	-
7	3	$(s_0^5, 0)$	-
6	13	$(s_1^5, 0)$	-
8	2	$(s_3^5, 0)$	+
9	2	$(s_3^5, 0)$	+
10	3	$(s_3^5, 0)$	+
11	3	$(s_3^5, 0)$	+
12	4	$(s_2^5, 0)$	-
13	2	$(s_3^5, 0)$	+
14	4	$(s_3^5, 0)$	+
15	5	$(s_4^5, 0)$	+

The initial assessments of the three concepts are generated by first converting the quantitative inputs into a [0, 1] range. For example, the lander weight has a range of 20000 to 100000 lbs. This range is converted to a [0, 1] value which is then evaluated over the LoS membership function. The qualitative inputs are evaluated directly on the linguistic term set of LoS. Attribute evaluations are performed on a common linguistic term set shown in Figure 6.5. The penultimate step in the assessment process is simulation. The SC-FCM is simulated until it converges to a fixed equilibrium point.

Figure 6.5 shows the final converged values of the five measures of effectives for each of the mission mode alternatives. The LOR mode has the highest overall ranking for 4 of the 5 MOEs. The final converged values of the MOEs for all four concept alternatives are presented in Table 6.5. Fuzzy swing weights for the 5 MOEs were defuzzified and normalized on a scale of [0, 1]. The overall weighted value of the architectural alternatives is computed using the 2-tuple weighted average operator.
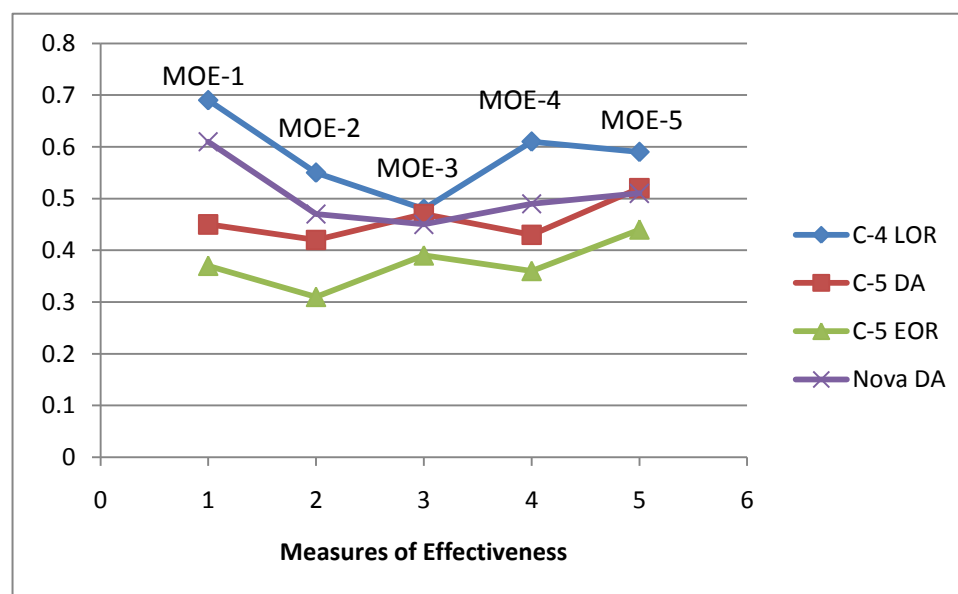
Figure 6.5. Final Converged Values of the MOEs

Table 6.5. Final Attribute Values from the FCM Simulation

Alternatives	Linguistic Representation				
	MOE-1	MOE-2	MOE-3	MOE-4	MOE-5
C-4 LOR	(QS,-0.06)	(MS,0.05)	(MS,-0.02)	(MS,0.11)	(MS,0.09)
C-5 EOR	(MS,-0.05)	(MS,-0.08)	(MS,-0.03)	(MS,0.-0.03)	(MS, 0.02)
Nova DA	(SS, 0.12)	(SS,0.06)	(MS, -0.11)	(SS, 0.11)	(MS,-0.06)
C-5 DA	(MS,0.11)	(MS,-0.03)	(MS,-0.05)	(MS,-0.01)	(MS,0.01)
Defuzzified Attribute Weights	0.357	0.2857	0.1786	0.1429	0.0357

6.3. ANALYSIS OF RESULTS

Once the AVM has been created and the final converged measures have been determined, a range of analyses can be performed to the study the behavior of the AVM and assess design concepts.

6.3.1. Static Analysis. Two primary types of analyses can be performed on the AVM. These include static analysis of the structure of the map. A centrality measure shows the role played by an attribute in the system. A large centrality measure indicates a higher importance and a low centrality reflects a lesser importance of the attribute. Centrality is computed by adding the total number of incoming and outgoing nodes in a map. The nodes of the camera AVM ranked based on a centrality measure are shown in the Table 6.6. Figure 6.6 depicts concept centrality a graphically. Risk of mission loss is the most important MOE based on its centrality measure while the weight margin is the most important MOP.

Table 6.6. Relative Significance of concepts in the domain

	Attributes	Centrality Measure
1	Mission mode realizability	3
2	Risk of mission loss	5
3	Mission safety	3
4	Schedule risk	3
5	Cost	2
6	Weight margin	4
7	Fuel storability	2
8	EOR risk	1
9	LOR risk	1
10	Stability of Lunar landing	1
11	Degree of visibility	2
12	Design modularity	1
13	Mission mode operational risk	1
14	Developmental difficulty	3
15	Structural cost	3

Based on the vertex degree, the Risk of mission loss and weight margin are identified as the key criteria in the AVM. The validity of this result is confirmed by the NASA reports that were consulted by for this study. The weight margin was a key mode comparison criterion in all of NASA's own mission mode selections studies. The weight margin has a wide ranging impact on multiple elements of the system. Sufficient fuel storage and redundant system components are determined by the weight margin. An adequate weight margin was very important for mission realizability and for reducing operational risk.
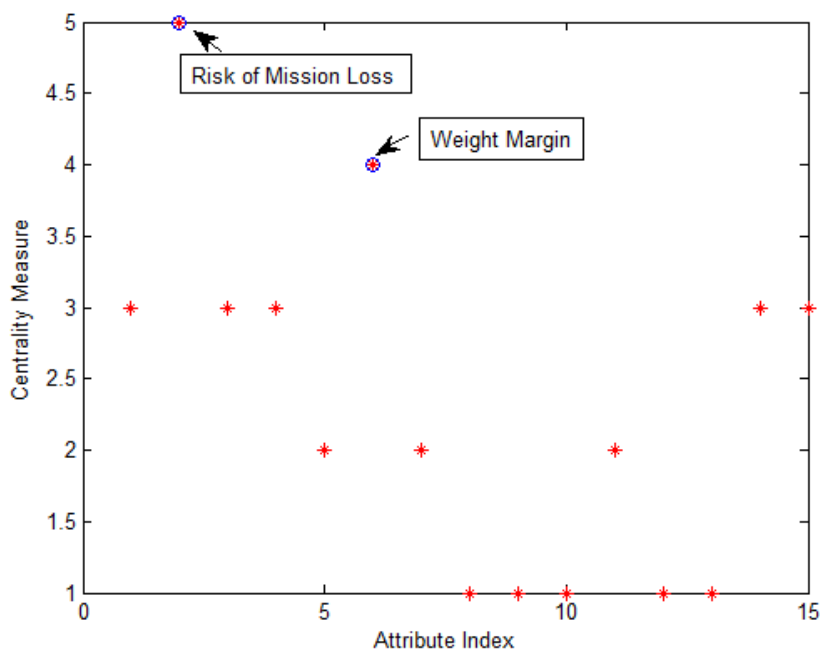
Figure 6.6. Concept Centrality

6.3.2. Dynamic Analysis. The final ranking of the alternatives is shown in Table

6.7. The C-4 LOR mode is ranked as the most satisfactory mission mode. This result is as

expected. The overall ranking of the LOR mode is 'Moderately Satisfactory' with a

Table 6.7. Final Overall Assessment Values for the Mission Mode Alternatives

Mission Mode Alternative	C-4 LOR	C-5 EOR	Nova DA	C-5 DA
Overall Symbolic Value	0.597	0.444	0.357	0.5205
Overall Linguistic Value	(Moderately Satisfactory, 0.097)	(Moderately Satisfactory, - 0.056)	(Somewhat Satisfactory, 0.107)	(Moderately Satisfactory, 0.02)

positive directional bias of 0.97 making it the alternative closest to a quite satisfactory ranking. The higher risk of the lunar rendezvous operation is mitigated by the favorable impact of the other measures. The separation of the re-entry vehicle and the lunar excursion module contribute to a highly satisfactory rating of most of the measures of performance. The Nova DA is the least recommended option. This can be attributed it is low satisfaction of schedule and risk criteria. Primarily, the need for the Nova rocket has an adverse impact on the schedule and the high weight of the lunar lander vehicle increases the risk of the lunar landing operation. Figure 6.7 shows the overall value of the four concept alternatives with C-4 LOR mode with the highest ranking.

Dynamic analysis of FCM can be carried out to study the behavior of the simulated system over time. As mentioned before, the system might stabilize to a fixed state, enter into a limit cycle, or a chaotic attractor. All of these possible behaviors can provide very important information for decision-making. The dynamic analyses can include an initial dynamic analysis to study the behavior of the simulated system, and a range of what-if analyses can be performed to study the sensitivity of the overall value to change in different values of interest. Complex relationships between concepts can be explored by holding some concepts values constant while allowing others to change. Figure 6.8 shows the results of a 'what if' analysis conducted by testing various feasible configurations of lunar lander weights. All other attributes were maintained at their previously assigned values. The lunar lander with the lowest feasible weight is the most desirable mission mode configuration. This can be explained by the greater landing stability of the LEM, which in turns increases crew safety.
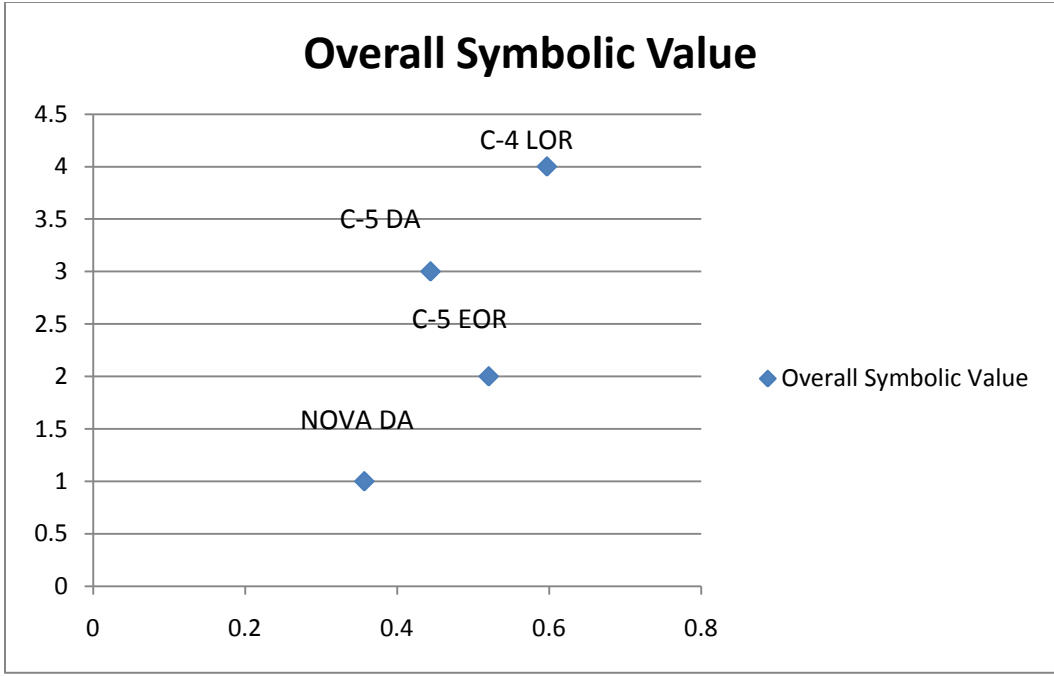
Figure 6.7. Overall Symbolic Value
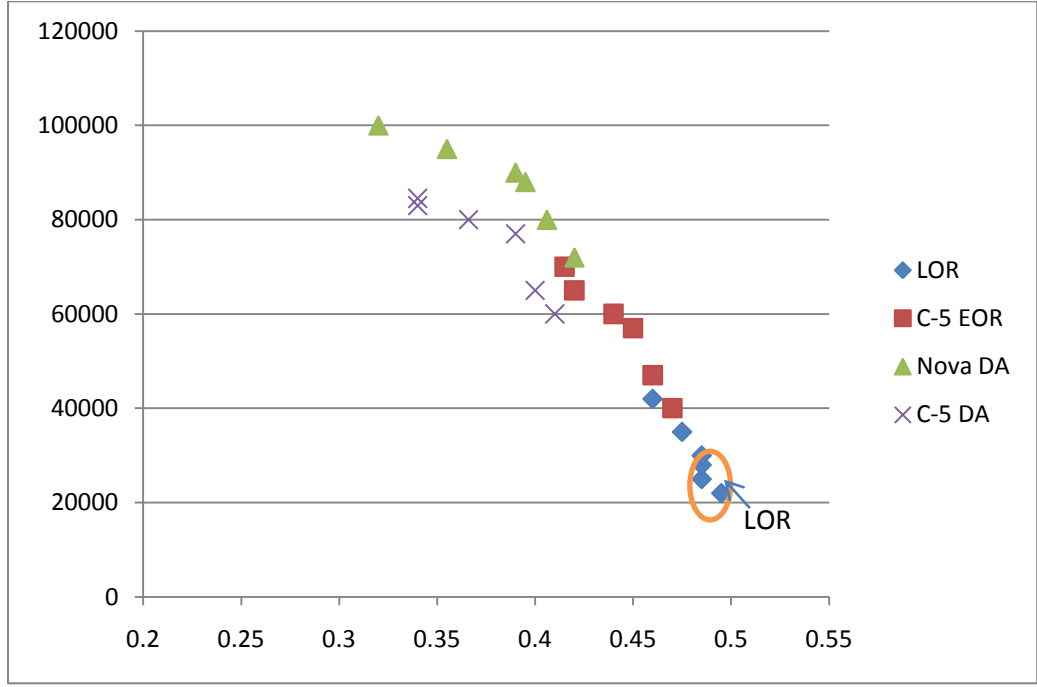
Figure 6.8. Lander Weight vs Mission Safety

6.4. COMMENTS ON VALIDATION

The traditional approach of formal, rigorous and quantifiable validation relies on the objectivity and rationality of available data. Engineering research based on mathematical models can be validated by comparing the predicted results with historically available information. However, this approach is problematic for design evaluation approaches, which depend on subjective and qualitative judgments of human experts to make their predictions. Since design evaluation methods do not fulfill the fundamental assumption of "objectivity of data", they cannot be validated mathematically.

To validate conceptual design evaluation methods rigorously, all proposed alternatives would have to be developed, and followed through their lifecycles. The time and cost involved render this course of action infeasible. Seepersad et al. [95] have proposed a relativist validation procedure appropriate for decision theory methods focused on open problems for which there may be many acceptable solutions. Based on the precepts of their approach a discussion of the attempts to validate the AVM framework is presented.

6.4.1. Structural Validity. The AVM approach is based on two principle constructs of fuzzy set theory, fuzzy cognitive maps and the 2-tuple linguistic representation. Both of these techniques have been tested and validated extensively in the literature. These constructs were integrated into the overall approach using the 2-tuple arithmetic operators. The internal consistency of the SC-FCM was evaluated and validated using various test cases.

6.4.2. Performance Validity. The usefulness of the method has been demonstrated for two distinct domains indicating its generality for conceptual design selection problems. The selection of the Apollo mission mode selection is appropriate for testing the method since it is a benchmark systems engineering problem that has been used to test other similar methods. Even though the value judgments used for this problem cannot be compared to other similar approaches, the final ordinal ranking of the mission modes is consistent with results reported in literature. The validity of a subjective design evaluation approach depends upon its ability to deliver results that are consistent with decision maker expectations. In that respect, the case studies demonstrated that AVM framework is useful in selecting designs that fulfill customer value objectives. This benefit is directly attributable to the underlying assumptions of the approach.

7. CONCLUSIONS AND FUTURE WORK

7.1. DISCUSSION AND REVIEW

The number of types of MCDM problems in engineering design is rivaled only by the number of MCDM approaches that have been developed to solve them. No single MCDM approach can claim to be universally applicable to all decision analysis problems. Selection of an appropriate MCDM approach for a decision problem is an MCDM problem in itself, and significant research has been devoted to this subject [96-98]. Different methods do not always lead to the same outcome, but this is not always an indication of a flawed decision process. The objective of multi-criteria decision analysis is not to come up with a unique solution, but to provide the decision maker with a deeper insight into the problem, an exact and explicit rationale for decision making, and reduced risk of making an uninformed decision.

According to Hazelrigg, a good design selection method should at a minimum provide a mathematically rigorous framework that can guarantee a self-consistent analysis of decisions independent of the context or discipline within which the decisions are made [99]. It is suggested that the AVM framework with its ability to derive the design attributes of a problem using a top-down stepwise reduction of abstraction, starting with the highest level system objectives, provides a domain independent methodology of formulating the decision structure of a design evaluation problem. The use of fuzzy set theoretic constructs to model attribute values and decision maker preference relations provides the systems engineer with the means to model ambiguous and incomplete information and use it to make design tradeoffs during the early design

stages. A review of the strengths and weaknesses of the AVM framework and a discussion of the conditions under which its application is recommended is presented.

7.1.1. Assumptions and Usage Guidelines. The AVM approach relies on the stakeholders' ability to articulate and prioritize their needs consistently. The problem formulation depends on the cognitive models of the decision makers and domain experts. Due to this reason it is recommended that this approach is most suitable for application in group decision making scenarios with adequate representation by stakeholders, systems engineers, and subject matter experts. A participatory decision process is best supported by this methodology. The use of a linguistic input representation scheme is only justified in situations where information is scarce and unreliable, and increased precision will not translate into a more precise decision. The conceptual design phase of the systems engineering design process with its large design search space and ill defined needs and objectives is most suited for the application of the AVM framework.

7.1.2. Strengths and Weaknesses. The main outcome of the AVM approach is a ranking of concept alternatives using the decision maker's risk preferences. Its strengths include an explicit graphical visualization of the decomposition of high level objectives into measurable lower level design attributes that helps facilitate an improved understanding of the design aspects that contribute to overall system value and make the decision analysis more transparent. This methodology allows decision makers to seamlessly integrate the views of multiple stakeholders, thus enabling decision making using group preferences. The AVM method allows dependence and feedback between evaluation criteria giving the systems engineer a means to incorporate real world complexity into the design evaluation process. Dynamic analysis of the AVM using

scenario and sensitivity analyses also help illuminate the design performance under various uncertain future scenarios, thus, increasing the decision maker's confidence in his decision. Its primary weaknesses lie in its reliance on subjective information provided by the user. A good decision will depend on the consistency and stability of the user specified value objectives. The AVM approach depends on expert knowledge to formulate the value map and generate the connection weights. Modeling linear monotonic increasing or decreasing relationships between the AVM's node attributes is computationally simple. However, nonlinear relationships between attributes have to be modeled by means of complex aggregation functions or rule based fuzzy expert systems. Both these methods have drawbacks associated with them; the former increases computational complexity while the latter adds another source of subjectivity to the aggregation process.

7.1.3. Comparison with Other MADM Techniques. Hazelrigg lists the desirable properties of a good design evaluation approach which include [99],

a. The method should provide a rank ordering of candidate designs

b. The method should rank alternatives based on the decision maker's preferences

c. It should permit comparison of alternatives under uncertainty

d. It should be independent of any specific domain or system

e. Presence of absence of alternatives should not alter the rank order of designs

f. The method should be self-consistent and logical, and it should make maximum use of available information for design alternative selection.

Using these criteria as a benchmark, a comparison can be made between the AVM framework and two of the most popularly used design evaluation methods for conceptual design, the AHP and the QFD. Hazelrigg's original assessments of the AHP and QFD over the proposed features are used for comparison with the AVM method. A rationalization for the claims made here regarding the AHP and QFD is provided by means of illustrative examples in [99]. The results of the comparison are shown in Table 7.1. A 'Y' indicates that the method satisfies the desired property, whereas an 'C' indicates that it does so only under specific conditions. 'N' indicates that the technique fails to satisfy the property to a satisfactory degree.

The first property requires the design evaluation method to provide a recommended design and preferably a rank ordering of all candidate design alternatives. It also states that the technique should explicitly state which the best design is and the rationale behind that analysis.

Table 7.1. Comparison of Properties of Design Selection Methods (Adapted from [99])

Design alternative evaluation method	Desirable Property from Hazelrigg's List					
	A	b	c	d	e	f
AHP	C	N	N	Y	N	Y
QFD	C	N	N	Y	Y	N
AVM	C	N	Y	Y	Y	Y

While the AVM methodology does generate an explicit ranking of the design alternatives based on the stakeholders risk preferences, it does not recommend one alternative as the best. The final decision of selection of a design concept from a set of suitable alternatives is left to the designer. The selection of a design alternative is governed by more than just stakeholder value objectives. Schedule, support and maintenance, manufacturability of the system concept are just some of the aspects that are not dealt with during the evaluation process. Allowing the designer to have the final say on concept selection is justified.

According to the second property, any method that imposes preferences on a decision maker is flawed. However, this recommendation overlooks the fact that the designer's knowledge and expertise notwithstanding, the final judgment of the system's success is made by the stakeholder. Hence, it is important to incorporate the stakeholder's value perceptions into the decision making process even if they impose design restrictions on the systems engineer. The second part of the same property states that any method that restricts the mathematical form of the decision maker's preferences is intrinsically flawed. In an ideal situation a design method would impose no constraints on the preferences. However, the very act of encoding design preference into a mathematical construct is bound to place constraints on their expression. The AVM methodology enables stakeholders to express their preferences using linguistic term set of their own choosing. However, the process of aggregating this information onto a common linguistic term set violates the second property.

The AVM approach has a clear advantage over the both the AHP and QFD in its ability to handle uncertainty, make effective use of information in multiple formats and

produce design evaluations that are robust to changes in the design attribute values. Neither the QFD nor the AHP can deal with ambiguity and risk in their traditional forms. One major drawback of the AHP is its problem with ranking instability. The presence of absence of design alternatives can alter the final ranking of the remaining alternatives. The use of a common representation scale allows designs to be evaluated without being impacted by the attribute value changes due to the addition or removal of design alternatives. While not a perfect solution, the AVM framework has a few significant advantages to offer the system designer during the nascent stages of the system design process.

7.2. FUTURE WORK

7.2.1. Extension of AVM Framework Scope.
The graphical structure of the AVM and the hierarchical process of deriving design attributes can be extended to encompass the risk assessment processes performed during conceptual design. The effect of extraneous attributes, such as those related to manufacturability, survivability, disposability, and maintainability, on the overall value delivered by the system should also be incorporated in the design evaluation analysis. These attributes do not directly impact the form or function of the system but they do impact how well the system performs with respect to the stakeholder's value objectives, not just during acquisition but also over the system's operational life.

7.2.2. Architecture Search using Evolutionary Algorithms.
In any large scale system, the design search space is vast making it hard for a system designer to explore all possible architecture variants. Automated architecture generation approaches have been used to generate populations of near optimal designs. Evolutionary algorithms based

multi-objective optimization has long been successfully used as design space exploration technique in many engineering disciplines [100-102]. However, a key constraint to the use of design search algorithms has been the difficulty of creating an objective function. It is suggested that the AVM technique can be used in conjunction with automated design evolution methods in lieu of an objective function. This can help overcome the problem of creating an objective function for fitness evaluation. Even though the AVM approach is a MADM methodology which selects from a set of predetermined architecture alternatives, it can be combined with a heuristic search algorithm such as a genetic algorithm to partially automate the design search process. As the design life-cycle progresses, the architectural representations can be changed to reflect the change in architectural models. The fuzzy attributes used to represent the linguistic preference relations of the decision maker at the system level, can be replaced by less ambiguous performance metrics to evaluate lower level designs. The combination of the two methodologies can allow a systems architect to quickly and efficiently search through a design space for a population of near optimal system architectures. A preliminary version of the design exploration methodology has been developed and tested and can be found in [100-101].

7.2.3. Decision Support Ontologies for Systems Engineering. The computing with words paradigm introduced by Zadeh [58] provides the foundations for processing non-numerical information in a human-like fashion. A computing with words system, such as the one proposed by this research, facilitates a symbolic representation of words and their relationships, and provides the mathematical constructs to reason with them. An ontology is a representation of the concepts and properties pertinent to a domain of

interest, as well as the relationships and the rules that govern them [103]. In this context, the integration of an ontology based approach with the CW paradigm is very appropriate. The need for design assessment ontologies in systems engineering has been discussed by Eric Honour, Ricardo Valerdi and others [104], [105]. These ontologies are intended to act as knowledge repositories for system information pertaining to the 'ilities' or value attributes.

The most accepted definition of an ontology is that by Tom Gruber, "A formal explicit specification of a shared conceptualization" [106]. In my opinion the properties of an AVM are highly analogous to the concepts and relations within an ontology. Similar to an ontology, the AVM 'explicitly' describes the concepts related to an application and their causal relationships. The AVM is also 'formally' described using a fuzzy mathematical representation that is machine readable and can be computed with. Finally, just like an ontology, the AVM is 'shared' in the sense that it is developed and agreed upon through a consensus between all stakeholders and decision makers involved in a project. The capabilities of the AVM framework can be enhanced by integrating it with the concept of ontologies to develop a Fuzzy Decision Support Ontology (FDSO) which can provide a meta-level description of the components of the AVM. This meta-representation will encapsulate the semantics, vocabulary, rules and axioms capable of modeling complex scenarios for modeling design evaluation problems. A high-level fuzzy definition ontology shown in Figure 7.1, can formally capture the semantics of fuzzy constructs such as linguistic term sets, linguistic variables and membership functions in a formal modeling language. Using these definitions a domain-specific instance of the DSO can be built to describe the fuzzy concepts and relationships, within

an AVM, in fuzzy terminology. This lower-level ontology will include decision-related information such as generic descriptors for system objectives, evaluation criteria (measures of effectiveness and measures of performance), and concept alternatives (design dependent parameters).
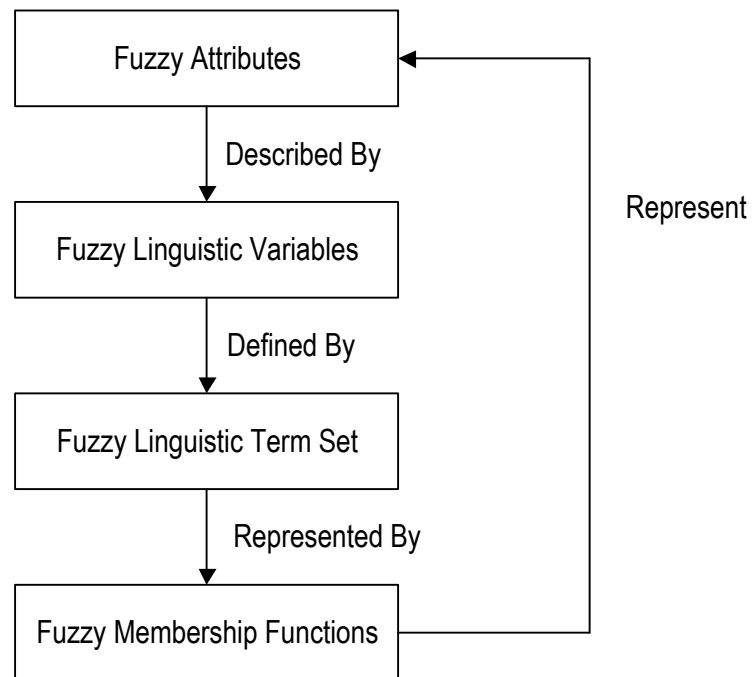
Figure 7.1. Ontology for Defining Fuzzy Constructs of an AVM

A decision support ontology developed using the AVM can support designers in quickly and easily generating architecture value maps by allowing a systematic capture of design knowledge and efficient reuse of solution-neutral attribute representations. Such a DSO can help save complex value maps and allow them to be reused to support reasoning during the conceptual design process. The DSO can help organize concepts and

properties into meaningful relationships which can provide common understanding of a problem domain. Evaluation models of common aspects of systems can be compared, contrasted and reused, greatly increasing efficiency and flexibility of the design evaluation process in systems engineering.

7.2.4. Decision Support Software. The usability of the AVM framework can be greatly enhanced by the development of a Decision Support Software (DSS). Such can tool can streamline the processes of attribute transformations, map generation, sensitivity and scenario analyses and increase the decision makers effectiveness in the decision making process.

The AVM approach evaluates and ranks potential system concepts based on stakeholders' perceptions of the value it delivers to them. It is a decision-support tool intended to assist the systems architect in making decisions that impact, not only a system's functionality, but also how well it achieves its objectives, i.e., the 'goodness' of the architecture. The goodness of the system architecture is dependent on the system's properties and features, and the manner in which they interact. The AVM framework is based on Keeney's value-focused thinking and does not use an explicit representation of the conceptual architecture. The architecture is implicit in the design parameters/options selected by the systems engineer based on their impact on the overall value delivered by the system.

To summarize, the AVM framework will enable system designers to successfully deliver reliable systems that fulfill the stakeholders' value expectations. The proposed approach provides the systems architect with multi-faceted capabilities which include the ability to handle ambiguous and incomplete information during the early design stages

without having to develop complex mathematical models that are too abstract to be used in practice. The proposed approach on fuzzy cognitive maps brings a novel approach for dealing with ambiguity and leveraging it to develop transparent evaluations of system architecture concepts using a value-focused approach.

APPENDIX: MATLAB SCRIPTS FOR 2-TUPLE TRANSFORMATION OPERATORS

A. Generate triangular membership functions for a fuzzy term set

```matlab
function termset = gen_termset(num_terms)
% Creating a custom term set
% Only applicable to triangular membership functions
term_indices = (1/num_terms).*[0 0:num_terms num_terms];
for i = 1:num_terms+1
termset(i,:) = term_indices(i:i+2);
end
```

B. Convert symbolic representation into its 2-tuple form

```matlab
function TTF = Beta2TTLR(Beta, n)
% Convert Beta to its 2-tuple form
TTF(1) = round((n+1)*Beta);
TTF(2) = Beta - (TTF(1)/(n+1));
```

C. Convert the 2-tuple into its symbolic form beta

```matlab
function Beta = TTLR2Beta(Two_Tuple_Form, n)
% Convert any two tuple back to its Beta form
Beta = (Two_Tuple_Form(1)/(n+1))+Two_Tuple_Form(2);
```

D. Generate and plot the basic linguistic term set

```matlab
%% GENERATE the BASIC LINGUISTIC TERM SET (BLTS)
n = 13; %Linguistic term sets
lbls(1) = 0;
for i=1:(n+1)
    lbls(i+1) = i/(n+1);
end
S = zeros(n+2,3); % 3 columns for triangular membership
functions
S(1,:) = [lbls(1) lbls(1:2)]; % First membership function
S(n+2,:) = [lbls((n+1):(n+2)) lbls(n+2)]; % Last membership
function
for i = 1:(n)
    S(i+1,:) = lbls(i:i+2);
end

%% PLOT THE BLTS
BLTS = S;
x = 0:0.0001:1; % Input for plotting BLTS
```

```matlab
y = zeros(n+2,length(x));
% Plotting the BLTS
for i = 1:n+2
    y(i,:) = trimf(x, S(i,:));
end
plot(x, y,':');
xlabel('Support');
ylabel('Membership Grade');
```

E. Calculate membership grade in the BLTS

```matlab
function MG_IN=BLTS_Fun(BLTS,IN_values,n)
% Membership grade of input vector in the BLTS
MG_IN = zeros(length(IN_values),length(BLTS));

for i = 1:length(IN_values)
    MG_temp = [];
    for j = 1:n+2
        MG_temp = [MG_temp trimf(IN_values(i), BLTS(j,:))];
    end
 MG_IN(i,:) = MG_temp;
End
```

F. Convert numeric data into the 2-tuple form

```matlab
function [TTF, Beta] = num2ttf(MG_IN,n)
% NUM2TTF - Transforms numeric input to the 2-tuple format
r = size(MG_IN,1);
TTF = zeros(r,2);
Beta = zeros(r,1);
for i = 1:r
Index = find(MG_IN(i,:))-1;
Index_Mat = zeros(1,length(MG_IN(i,:)));
Index_Mat(1,Index+1) = Index;

Sum_Membership_Grade = sum(MG_IN(i,:));
Product_Sum = Index_Mat.*MG_IN(i,:);
Beta(i) = (sum(Product_Sum)/Sum_Membership_Grade)/(n+1);

% TTF Transformation
term_index = round((n+1)*Beta(i));
alpha = Beta(i) - term_index/(n+1);
TTF(i,:) = [term_index, alpha];
End
```

G. Convert intervals into the 2-tuple form

```
function [TTF, Beta] = int2ttf(MG_IN_L,MG_IN_U,n)
% INT2TTF - Transforms numerical intervals into the 2-tuple
format
MG_IN = MG_IN_L+MG_IN_U;
r = size(MG_IN,1);
TTF = zeros(r,2);
Beta = zeros(r,1);

for i = 1:r
Index = find(MG_IN(i,:))-1;
% check for size of index, correct if not 4
if size(Index,2)==3
    ind = 3;
elseif size(Index,2)==2
    ind = 2;
else
    ind = 4;
end
MG_IN(i,(Index(1)+1):(Index(ind)))=1;
Index_Int = Index(1):1:Index(ind);
Index_Mat = zeros(1,n+2);
Index_Mat(i,Index_Int+1)=Index_Int;

Sum_Membership_Grade = sum(MG_IN(i,:));
Product_Sum = Index_Mat(i,:).*MG_IN(i,:);
Beta(i) = (sum(Product_Sum)/Sum_Membership_Grade)/(n+1);

% TTF Transformation
term_index = round((n+1)*Beta(i));
alpha = Beta(i) - term_index/(n+1);
TTF(i,:) = [term_index, alpha];
end
```

H. Convert a linguistic input into the 2-tuple form

```
function [TTF,Beta] = lv2ttf(LV,n,BLTS)
r = size(LV,1);
y = 0:.0001:1;

for i=1:r
MG_LV=trimf(y,LV(i,:));

for j = 1:(n+2)
MG_BLTS=trimf(y,BLTS(j,:));
gamma(j)=max(min(MG_LV,MG_BLTS));
TTFtemp(j,:) = [j-1,gamma(j)];
```

```
end

Product_Sum = sum(TTFtemp(:,1).*TTFtemp(:,2));
Beta(i) = (Product_Sum/sum(TTFtemp(:,2)))/(n+1);
term_index = round((n+1)*Beta(i));
alpha = Beta(i) - term_index/(n+1);
TTF(i,:) = [term_index, alpha];
end
```

I.   2-tuple arithmetic operations

```
function [Beta_out] =
TTLR_Operators(Beta_in,n,operator,sclr)

% Operators for extended 2-tuple linguistic representation
% proposed by Li et al.
% Beta_in: Input vector to perform operation on; one input
for negation and
%          minimum two for all other operations
% sclr: scalar input for scalar multiplication
% n: length of basic term set, cardinality = n+2, Final
term index = n+1
% operator: Number from 1-5 indicating the operation to be
performed
%          1 - Negation
%          2 - Addition
%          3 - Subtraction
%          4 - Multiplication
%          5 - Scalar multiplication

% Switch statement to choose operation
switch operator
    case 1
        [Beta_neg] = TTLR_negation(Beta_in);
        Beta_out = Beta_neg;
    case 2
        [Beta_add] = TTLR_addition(Beta_in);
        Beta_out = Beta_add;
    case 3
        [Beta_sub] = TTLR_subtraction(Beta_in);
        Beta_out = Beta_sub;
    case 4
        [Beta_prod] = TTLR_product(Beta_in);
        Beta_out = Beta_prod;
    case 5
```

```matlab
        [Beta_prod_scalar] =
TTLR_product_scalar(Beta_in,sclr);
        Beta_out = Beta_prod_scalar;
    end

% Operator functions
    function [Beta_neg] = TTLR_negation(Beta_in)
        % Negation
        Beta_neg = 0-Beta_in;
    end

    function [Beta_add] = TTLR_addition(Beta_in)
        % Addition
        Beta_add = 0;
        count = length(Beta_in);
        for i = 1:count
            Beta_temp1 = Beta_add+Beta_in(i);
            if Beta_temp1 < 1
                Beta_add = Beta_temp1;
            else
                Beta_add = 1;
            end
        end
    end

    function [Beta_sub] = TTLR_subtraction(Beta_in)
        % Subtraction
        % Check for length of Beta_in
        % Only two inputs at a time
        if length(Beta_in)~=2
            disp('Incorrect number of operands. Only two
operands allowed for this operation');
        else
            Beta_temp2 = Beta_in(1)-Beta_in(2);
            if Beta_temp2 > 0 && Beta_temp2 <= 1
                Beta_sub = Beta_temp2;
            elseif Beta_temp2 > -1 && Beta_temp2 < 0
                Beta_sub = TTLR_negation(-Beta_temp2);
            elseif Beta_temp2 > 1
                Beta_sub = 1;
            else Beta_temp2 < -1;
                Beta_sub = -1;
            end
        end
    end

    function [Beta_prod] = TTLR_product(Beta_in)
```

```matlab
        % Product
        % Check for length of Beta_in
        % Only two inputs at a time
        if length(Beta_in)~=2
            disp('Incorrect number of operands. Only two
operands allowed for this operation');
        else
            Beta_temp3 = Beta_in(1)*Beta_in(2);
        end
    end

    function [Beta_prod_scalar] =
TTLR_product_scalar(Beta_in,sclr)
        % Check for length of Beta_in
        % Only one inputs at a time
        if length(Beta_in)~=1
            disp('Incorrect number of operands. Only one
operand allowed for this operation');
        else
            Beta_temp4 = Beta_in*sclr;
            if Beta_temp4 >=0 && Beta_temp4 <1
                Beta_prod_scalar = Beta_temp4;
            else
                Beta_prod_scalar = 1;
            end
        end
    end

end
```

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