Knowledge-Intensive Collaborative Decision Support for Design Processes: A Hybrid Decision Support Model and Agent

Xuan F. Zha*
Design and Process Group, National Institute of Standards and Technology, Gaithersburg, MD 20899, USA
Ram D. Sriram
Design and Process Group, National Institute of Standards and Technology, Gaithersburg, MD 20899, USA
Marco G. Fernandez, Farrokh Mistree
System Realization Laboratory, Georgia Institute of Technology, Atlanta, USA

*Corresponding author, e-mail: xfzha@ieee.org

***Abstract*—**This paper proposes a hybrid decision support model within a multi-agent framework to facilitate integration and collaboration for design decisions in decision-based design. The hybrid decision model integrates the compromise decision support problem technique (cDSP) and the fuzzy synthetic decision model (FSD) to quantitatively incorporate qualitative design knowledge and preferences of designers for multiple, conflicting attributes stored in a knowledge repository so that a better understanding of the consequences of design decisions can be achieved from a more comprehensive perspective. The focus of this work is on the provision of a hybrid decision model and framework for improved cooperative design decision support. The novelty of the work is in combination of different models for making collaborative design decisions in both objective and subjective nature, in particular the fuzzy negotiation mechanism using the hybrid decision model. The developed hybrid decision model and framework are generic and flexible enough to be used in a variety of decision problems. Finally, the proposed hybrid decision model and framework are illustrated with applications in collaborative concept evaluation and selection in product family design for mass customization.

***Index Terms*—** Decision-based design, design decision support, hybrid, decision model, collaborative decision-making mechanism, fuzzy negotiation, autonomous decision agent, and multi-agent framework

1. INTRODUCTION

Design of complex engineering systems is increasingly becoming a collaborative task among designers or design teams that are physically, geographically, and temporally distributed. Collaborative design task essentially involves decision-making processes that require evaluation, comparison and selection of design alternatives as well as eventual optimization from a systematic perspective. For example, a product development team is generally composed of representatives from marketing, business development, engineering, and production. Those team members utilize various decision-making techniques and design criteria to develop and evaluate various design alternatives. Increasing design knowledge and supporting collaboration among designers or other decision-makers (e.g. customers) to make intelligent decisions can increase design efficiency and result in higher quality designs. Achieving a knowledge-intensive design support system is hampered by at least the following factors:

- Existing product design and decision knowledge modeling and support schemes have deficiencies in their representational capabilities. Very few provide explicit representations of the design decision and rationale as part of a comprehensive product design knowledge representation, which could not be directly used for design decision support. These issues reinforce the need for consensus among product development software developers and users regarding the content and form for more comprehensive representation of design knowledge including design decision knowledge.
- Models or methods, algorithms for making design decisions in both objective and subjective natures are not unified and seamlessly integrated. Currently available algorithms for optimization and constraint satisfaction have weaknesses; more rigorous algorithms tend to be too slow, heuristics, and too unreliable. It is therefore needed to develop a hybrid decision support model under an integrated framework to facilitate the seamless integration of objective and subjective aspects in collaborative design decisions.
- Current design decision support systems suffer one or more of the following drawbacks: a heavy dependency on the preferences, experience and knowledge of designers; no built-in ways for decision-making knowledge

representation; no efficient mechanisms to share, exchange, and reuse the decision knowledge; no efficient mechanisms to coordinate decision activities, provide advisory services, and explain the results and what-ifs. Thus, an intelligent decision tool that can provide efficient coordination and decision-making mechanisms for designers is still needed.

Designers distributed geographically and organizationally in global economies worsen the above problems. Multiple firms coordinate to develop and exchange product specifications and design decisions, and to reach compromised decisions by negotiations. In these situations, designers cannot rely on informal discussion to make joint decisions and resolve differences or conflicts in product design, or to combine separate contributions to the same product definition and in-process decision. The following challenges for product specifications and design decisions arise from the above problems:

- Specify more accurately which as-generated alternatives and evaluation and selection of them satisfy the design requirements, and which do not. This enables tools to incorporate the same interpretation of product specifications and design decisions made more reliably and accurately.
- Provide a structured and formalized comprehensive decision representation and framework for modeling the characteristics of multidisciplinary and multi-objective decision problems both in subjective and objective natures, which can handle qualitative and quantitative knowledge.
- Develop a sound, practical trade-off based decision model that can quantitatively incorporate qualitative knowledge and preferences for multiple, conflicting attributes stored in a design knowledge repository so that a better understanding of the consequences of design decisions cannot be achieved from a more comprehensive perspective.
- Establish a hybrid decision model and a comprehensive collaboration framework which may integrate more individual decision techniques such as the compromise decision support model, decision involving uncertainty (e.g., fuzzy systems), and intelligent agents to solve decision problems and help designers coordinate in making rapid and more intelligent decisions during the collaborative design process.

.
There have been many research efforts on the development of intelligent design decision support systems including collaborative decision support systems (Suh 1990, Tong and Sriram1992, Shen et al. 2001, Sriram 2002, Rosen et al. 2000, Panchal et al. 2002, Xiao et al. 2001, Gerhard et al.2000), but the challenges above are still not well addressed. Earlier studies focused on integrating reasoning mechanisms in design support systems (Gero 1990, Tong and Sriram1992). Recent studies focus on decision system or task structures, unified data and knowledge modeling and representation, concentrating on how these are integrated (Allen et al. 1992, Gerhard et al. 2000, Li et al. 2006, Zha et al. 2003a, b). Latest research indicates a trend towards semantic data and knowledge modeling for better interoperability of integrated decision support systems (Schoop et al. 2002, Chiu et al. 2005). Rather than attempting to design a new algorithm without weaknesses - a task that is difficult if not impossible - some researchers have been working on ways to organize algorithms so that they can suppress their respective weaknesses through cooperation, and together achieve what separately they might not (Talukdar et al. 1998, Zha et al. 2003a). Section 2 gives a comprehensive review of related work on the design decision support.

This paper aims to address the challenges above with a knowledge-intensive collaboration paradigm including a unified, hybrid decision support model for decision-based design and a knowledge-supported decision support framework. The developed model and framework aims to serve as a basis for the seamless integration of stakeholders and decision-makers involved in the collaborative decision-based design process. Design decision modeling in this paper refers to analyzing subjective as well as objective design conditions, generating design alternatives, and choosing the most appropriate one among them (see Section 3). A high level of interoperability for integrated design decision making reduces the cost of decision, increases reliability, opens opportunities for innovation, and provides stronger competition in the international marketplace. This paper covers the aspects of decision modeling within the above scope, such as decision support process, decision-based design, decision taxonomies, interconnections of decision models (a hybrid decision model), performance evaluation, and a multi-agent collaboration framework. It does not address more detailed topics such as decision process models, alternative generation models, and other agents in the framework. The approaches of this paper will be applied to these topics and the wide product lifecycle decision support in future work, see Section 7.

The organization of this paper is as follows. Section 2 reviews the previous research related to design decision support and current status. Section 3 discusses the design decision support process and decision-based design. Knowledge intensive decision support for design processes is highlighted. Section 4 proposes a hybrid decision mode that integrates the compromise decision support problem model (cDSP) and the fuzzy synthetic decision model (FSD). Section 5 presents a knowledge supported decision agent within a multi-agent collaborative decision support framework. Section 6 provides an application of the proposed hybrid decision model in the concept evaluation and selection stage and two case studies. Section 7 summarizes and concludes the paper and gives future work.

2. LITERATURE REVIEW

Design decision support problems necessitate the search for superior or satisfacing (Simon 1996, Simon 1976) design solutions, especially in the early stages of design, when all of the information needed to model a system comprehensively may not be available. Current research in design decision support (particularly pertaining to decision-based design) is focused on enabling decision technologies to assist product designers to make decisions during the design process (Rosen et al. 2000, Mistree et al. 1995, Fernández et al. 2002a,b), where the primary emphasis is on support for information management related to decision-making. The principles and methods developed from game theory, decision and risk analysis, and utility models are incorporated into the design process for complex systems, where consistency is necessary at all levels of decision making in order to resolve conflict and intransivity, and to facilitate negotiation and optimization. Generally, the literature on design decision support including integrated, collaborative decision support can be classified into the following categories (Jiao and Tseng 1998): multi-criteria utility analysis (Seepersad et al. 2002, Fernández et al. 2001), fuzzy set analysis, probability analysis, integrated design analytic methodology, and the information content approach (Suh 1990, 1998). The following review is focused on the first four approaches, due mostly to their current popularity or potential for collaborative decision support.

Multi-criteria utility analysis, originally developed by von Neumann and Morgenstern (1947), is an analytical method for evaluating a set of alternatives, given a set of criteria. It has been applied widely in the areas of engineering and business for decision-making (Hwang and Yoon, 1981). Thurston (1991) has applied this technique to the material selection problem, where alternatives are evaluated based on utility functions that reflect the designer's preferences for multiple criteria. Similar work by Fernández and co-authors (2001) addressed the difficulties associated with resource selection for rapid prototyping by synthesizing the selection Decision Support Problem with utility theory. Mistree et al. (1993, 1995) modeled design evaluation as a compromise Decision Support Problem (cDSP) and employed goal-programming techniques to make superior compromise decisions. While mathematical programming and utility analysis enhance algorithm-rigorous optimization modeling, such methods require the expected performance with respect to each criterion to be represented in a quantitative form. They are not appropriate for use in the early design stages, where some qualitative (*i.e.*, intangible) design criteria, are involved and difficult to quantify (Thurston and Carnahan, 1992, Fernández et al. 2001). The AHP mechanism proposed by Saaty (1991) is widely recognized as a useful tool to support multicriteria decision-making (MCDM) problem.

Fuzzy analysis, based on fuzzy set theory (Zadeh, 1965), is capable of dealing with qualitative or imprecise inputs from designers. It does so by describing the performance of each criterion with linguistic terms, such as "good," "poor," and "medium," and has proven to be quite useful in decision-making problems with multiple goals or criteria (Zimmermann, 1987; 1996). Wood and Antonsson (1989) have demonstrated its viability in performing computations with imprecise design parameters in mechanical design. Wood *et al.* (1990) compared fuzzy sets with probability methods and concluded that the fuzzy analysis approach is most appropriate when imprecise design descriptions abound, while a probability analysis approach is best suited for dealing with stochastic uncertainty. Thurston and Carnahan (1992) revealed that the fuzzy analysis approach is useful and appropriate at very early stages of the preliminary design process. Knosala and Pedrycz (1992) utilized the Analytic Hierarchy Process (AHP) method (Saaty 1991) to construct membership functions for the performance and weight of each criterion, and then applied the fuzzy weighted mean of the overall evaluation to ranking alternatives. Carnahan et al. (1994) represented evaluation results and weights regarding each criterion with linguistic terms and ranked alternatives based on the fuzzy weighted mean of distance from a fuzzy goal. While the fuzzy analysis approach excels in capturing semantic uncertainty via linguistic terms, it requires discreet deliberation in dealing with crisp information specifically. A domain-specific method is needed to "fuzzify" each tangible criterion whose evaluation is naturally estimated as an ordinary real variable. Another challenge is the incomparability/compatibility among various criteria (Wang, 1997; Siskos et al., 1984), which necessitates mechanisms to be capable of converting various types of performance evaluation with respect to different criteria to a common metric so as to allow for the specification of suitable membership functions for these.

Design evaluation usually involves both tangible and intangible criteria, along with quantitative and qualitative performance measures. This necessitates a hybrid approach for combining the quantitative, normative problem structuring capabilities of operations research techniques with the qualitative, descriptive problem-solving approaches used in artificial intelligence research. For example, Maimon and Fisher (1985) presented a robot selection model using integer programming and a rule-based expert system. Considerable research efforts have been devoted to fuzzy goal programming for modeling mathematically the imprecise relationships implicit in fuzzy goals and soft constraints (Gui 1993, Allen et al. 1992). However, these efforts mostly model a particular aspect of uncertainties in design evaluation, such as inexact relationships, imprecise information, and uncertain information (Knosala and Pedrycz 1992). It is difficult for a fuzzy goal-programming model to consider all sources of uncertainty coherently during the preliminary stages of design (Carnahan et al 1994). In addition, computational complexity is a key issue, especially if a large number of design alternatives and criteria are involved (Wang 1997; Boender et al 1989).

To reflect customer preferences in multi-criteria design evaluation, the relative importance or weighting for each criterion has been considered by numerous evaluation procedures (Jiao and Tseng 1998). Frazell (1985) assigned weights to criteria on a 0-100 scale. Sullivan (1986) presented a similar method called the linear additive model, in which ranking is included. Huang and Ghandforoush (1984) offered another procedure for quantifying subjective criteria. They computed intangible criteria measures as the multiplication of the intangible criterion weights by the subjective customer rating. Dixon *et al.* (1986) measured the performance by degree of satisfaction, ranging from excellent to unacceptable, and combined this measure with priority categories of high, moderate, or low to evaluate the design. Nielsen *et al.* (1986) used factor-criteria to establish the level of importance of attributes. A priority level (absolutely necessary, important, or desirable) is indicated for each factor-criterion and is used to guide decision-making. The main drawback of these evaluation methods is that they ignore inconsistency on the part of the decision maker. The Analytic Hierarchy Process (AHP) was developed to deal with the decision-maker's inconsistency and to more accurately mimic the human decision-making process (Saaty, 1991). In AHP weights are determined by means of pair-wise comparisons between hierarchical decision levels. It has been proven to be a more rigorous procedure for determining customer preferences and has been approached from the fuzzy point of view by Boender *et al.* (1989). Carnahan *et al.* (1994) also proposed to "fuzzify" the weights subsequent to their having been obtained via AHP. However, they are not used for collaborative evaluation and selection in design decision.

There are also many other product feasibility and quality assessment tools that are useful for planning and evaluating the design concepts of products. Examples include quality function deployment (QFD) (Clausing 1994), concurrent function deployment (CFD) (Prasad 1996), the conceptual selection matrix (Pugh 1991), Taguchi's robust design method (Taguchi 1986), etc. Quality function deployment (QFD) provides a set of matrix-based techniques to quantify the organizational characteristics and identify qualities that would meet customer expectations and needs. While QFD addresses only qualitative aspects, CFD deals with total life-cycle concerns from a concurrent engineering perspective. The concept selection matrix initially proposed by Pugh (1991) is another matrix-based approach employed to quantify and measure product quality. It is based on a list of product and customer requirements. The purpose of Taguchi's robust design method is to reduce or control variations in a product or process (Taguchi, 1986). Depending upon the complexity and stage of a design, there could be a large number of iterations required. While these methodologies provide high-level guidelines for design evaluation, detailed supporting techniques are essential. Prasad (1996) also noted that 4Ms (models, methods, metrics and measures) are the core in integrated product development.

With the emergence of collaborative design, researchers are addressing enabling technologies or infrastructure to assist product designers to make decisions in the computer or network-centric design environment. Some techniques are intended to help designers collaborate or coordinate by sharing product and design information through formal as well as informal interactions, while others are geared towards conflict management (Sriram 2002, Rosen et al. 2000, Panchal et al. 2002, Xiao et al. 2001, Gerhard et al.2000, Tien 2003, Sriram et al. 2006). There are other approaches for solving the resolution of conflicts, i.e., Altshuller's (1999) concept of conflict resolution by change of used components or the algorithm for conflict elimination using TRIZ (Theory of Inventive Problem Solving) and DOE (design of experiment) (Hsing et al. 2001), etc. Most decision support systems can only calculate satisfaction levels and are based upon the mathematical programming, utility analysis and algorithm-rigorous optimization modeling principles and approaches (e.g., cDSP and game theory). They are data and information based, and thus cannot handle knowledge explicitly. They are more appropriate for quantitative (tangible) criteria but not for qualitative (intangible) criteria (difficult to quantify). There is a need for adding unique analysis and reporting features, including: the probability that a particular alternative is the best choice; assessment of the level of consensus for each alternative; guidance on what should be done next; and documentation of the entire decision making process. In early stages of design decisions are *ill structured* and often supported with scarce information. Multiple potential solutions and limited predictability all contribute to design complexity (Lambright and Ume, 1996). Moreover, significant functional and technical barriers often prevent the free flow or sharing and exchange of the necessary information and knowledge, especially for design decision making (Forgionne, 1994).

3. KNOWLEDGE INTENSIVE DESIGN DECISION SUPPORT

Decision-based design addresses the cognitive "structuring" of a design problem; the drive for innovation where the existing design "structure" or design solution space is ill-defined or insufficient; the need to reduce complexity by mapping to what we know; and the consistent use of decision technologies to optimize the decision-making capabilities within the design space that has been created (Sriram et al. 2006). Decision-making generally involves realizing a goal by analyzing subjective as well as objective conditions, generating alternatives, and choosing the most appropriate one among them. A generic decision support process can be described as having the following interactive aspects: intelligence, design, choice and implementation (Simon 1976). It involves several stages ranging from problem identification and classification, simplification of assumptions, data collection, model formulation, solution alternative generation, evaluation, selection, model verification and validation, and testing of the proposed solution to final implementation of the devised plan. Current research is focused predominantly on how knowledge support can aid the decision-maker during the design process.

The main role of a designer is to apply scientific and engineering knowledge to find (generate, evaluate and select) the solutions to design problems, and then optimize those solutions within the framework composed of requirements and constraints set by physical, environmental and human-related considerations. Design can be viewed as the process of converting information that characterizes the needs and requirements for a product into knowledge about it. Based on the principle of decision-based design, the design equation can be expressed as follows (Mistree 1995): $\{K\} = T\ \{I\}$, where K is a knowledge output, I is an information input, and T is a transformation relationship, respectively. Thus, knowledge-intensive support becomes more critical in the design process and has been recognized as a key enabling technology for retaining competitive advantages in product development.

Generally, the problem of design decision (evaluation and selection) can be defined as follows: given a set of design alternatives, the designer or agent/system evaluates them and selects one among them that can best satisfy customer needs, meet design requirements and constraints, and fit the technical capabilities of a company. This paper proposes a knowledge-intensive design decision support scheme (KIDDSS), as depicted in Figure 1, in which the design decision support is exploited from the perspective of synthesis of design process modeling (DPM), knowledge management (KM), and decision support (DS). Figure 1 also shows a scenario of implementing the KIDDS from the perspectives of decision knowledge management (DKM), including knowledge generation and acquisition, codification, processing and utilization (reasoning), etc. The principles and methods developed from decision theories including game theory, utility theory, probability theory, fuzzy set theory, among others, play a key role in implementing KIDDS framework as they are incorporated into the design process (see Hazelrigg 1996 and Fernández et al. 2002b for discussion of some of these techniques).

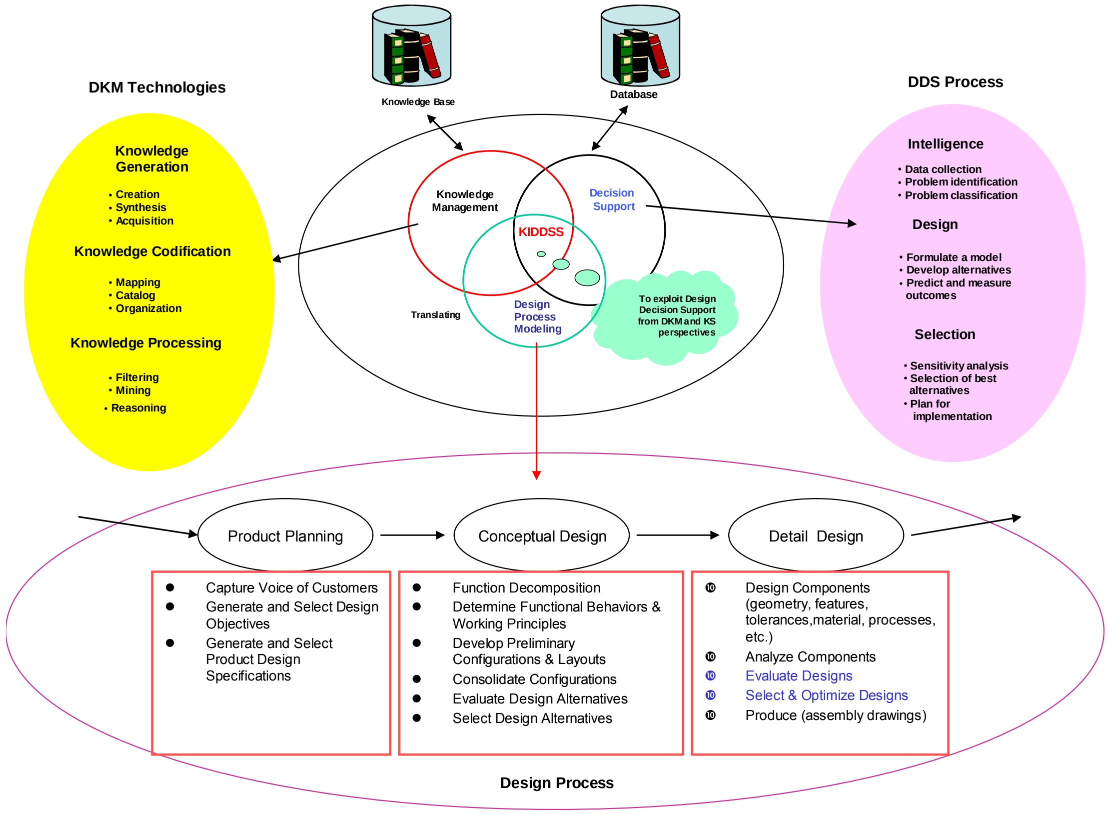


Figure 1: Knowledge-intensive design decision support scheme (KIDDSS)

The importance of developing fully automatic algorithms for choosing design options in the face of objective and subjective design criteria which often conflict are explained in the literature. The knowledge-intensive design decision support processes shown in Figure 1 underscore that it is also difficult to develop automatic algorithms for such situations. In next sections, instead, a suite of algorithms which work together in an integrated fashion are proposed to select design choices where there are potential conflicts in the design specifications. These algorithms are feeding into and supporting the larger vision of a design support environment.

4. THE HYBRID DESIGN DECISION MODEL: TECHNICAL DESCRIPTION

One of the important features of design is that the process of design is a decision-making process. Designers will be forced to choose actions in each refinement step of the design object. The final design is certainly definite and unambiguous. However, when designers choose an initial design solution or formulate the initial model, it always involves considerable uncertainties. By uncertainty, we mean that imprecision of the design problem has the nature of possibility. Formulated design goals and constraints are often subjectively estimated by designers. Conventional mathematical programming uses a certain objective function (or multi-goal function) and a set of certain constraints. Then designers must give precise values to each constraint or goal. Research into uncertainty in early design has been reported from the following two aspects (Gui et al 1993): 1) using case-based approximate reasoning to generate design solutions and 2) formulating the design problem in a fuzzy environment. We are interested in decision making model with the aid of computing support because a successful computer-based model for a design process depends largely on how many methods / models could be used to assist designers in design decision making. In this section, a hybrid decision model is proposed, which can integrate one or more decision-making techniques such as the cDSP, fuzzy systems, and fuzzy cDSP to solve complex design decision problems.

4.1 The Compromise Decision Support Problem Model (cDSP)

Decision support problems (DSPs) are generally formulated using a combination of analysis-based information and engineering judgment in the form of viewpoints, post solution sensitivity analysis, bounds, and context for decisions to be made. Two primary types of decisions are supported within the DSP technique: *selection* and *compromise*. Complex decisions are supported through their combination. The "selection" type decision actually includes evaluation and indication of preference based on multiple attributes for one among several feasible alternatives, while the "compromise" type decision involves the improvement of a given alternative through modification. Another aspect of the DSP technique that is particularly relevant to distributed collaborative design is the ability to express decisions that are linked together such as coupled and hierarchical decisions through combinations of selection and compromise DSPs (i.e., selection-selection, compromise-compromise, and selection-compromise, see Figure 2) (Xiao et al. 2002, Fernández et al. 2002b, Mocko 2006). These derived decision constructs are ideally suited for modeling networks of concurrent and sequential decisions that share information and knowledge.

In the compromise decision support problem model (cDSP), as shown in Figure 3, a hybrid of goal programming and mathematical programming is used to determine the values of design variables that satisfy a set of constraints and achieve as closely as possible a set of conflicting goals (Mistree et al. 1993, 1995). We will not embark on a through evaluation of the acceptability of conventional rigorous mathematical programming; nevertheless, it has at least two limitations: 1) a selected initial solution has much influence on the effectiveness and productivity of the program; 2) the true constraints or goals are often imprecise and subjective in nature rather than exact. For example, the boundary or performance constraints are usually not "hard" but very "soft". During the design process, the designer needs to start with approximate assessment of input variables/parameters. The value of mathematical precision is often reduced with increasing complexity of the system. Fuzziness could be introduced into the formulation of the cDSP by way of fuzzy numbers which are used to describe the design environment.

Fuzzy set theory has been widely used in conventional optimization methods so that the normal objective function and/or a set of constraints are a fuzzy field, which are assigned by membership functions. Thus, the model of fuzzy decision-making under constraints is formulated, and further, the so-called fuzzy compromise DSP (fuzzy cDSP) is attained (Allen et al. 1992), see Appendix A. Noted that using this approach, although the system or design problems modeled may be fuzzy, the solution is crisp. Compared to the conventional value-based decision making, the significance of this approach is that designers are no longer forced to give a precise description for relevant design variables and goals.

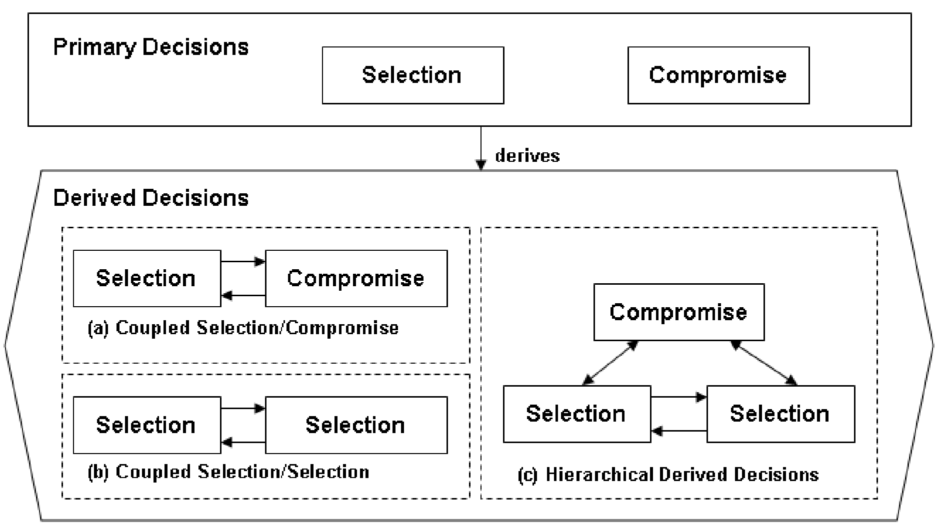


Figure 2: Primary and derived decisions

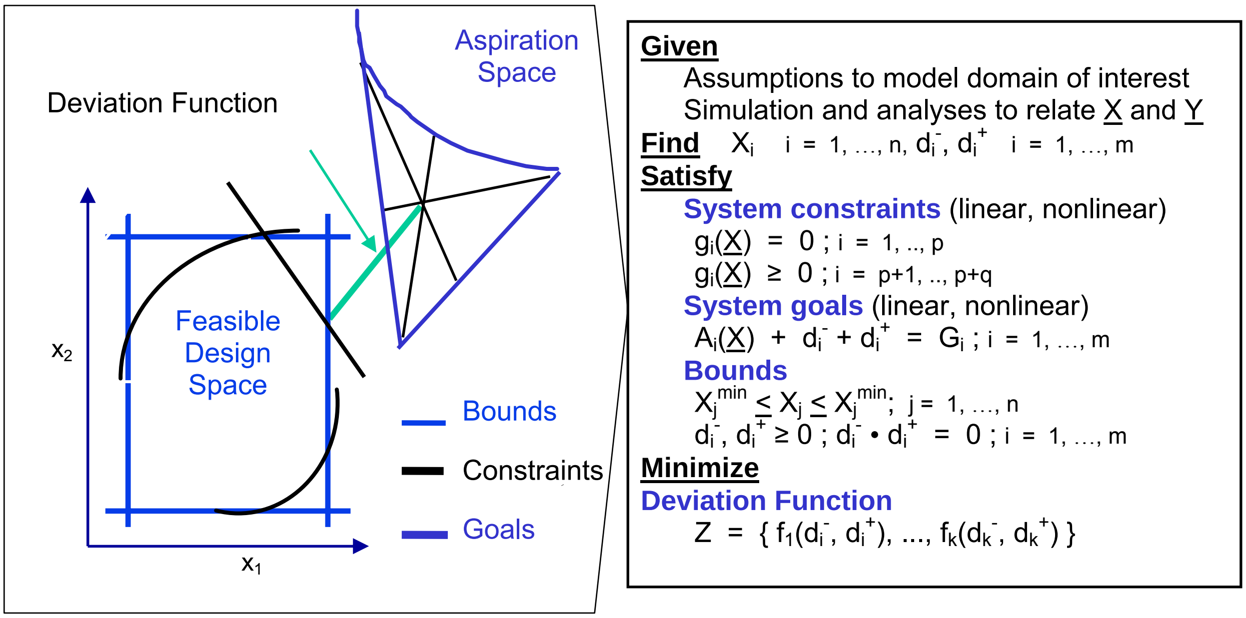


Figure 3: Compromise decision support model (cDSP)

4.2 Fuzzy Synthetic Decision Model (FSD)

As stated above, the design problem is to generate and select a family of design solutions (DS) that must satisfy a certain set of functional requirements (FR) and design constraints (DC). The relationships between function requirements, design constraints, and final design solutions can thus be represented as three fuzzy matrices *M* (FR×DS), *M* (DC×DS), and *M* (DS×DS). A critical step in the design process is to map a fuzzy set of requirements to a crisp set of design solution alternatives. To combine expert judgment and process-useful knowledge for fuzzy decision-making, we propose a fuzzy synthetic decision model (FSD) for fuzzy design comprehensive evaluation and selection in this section based on the improved fuzzy AHP, ranking algorithms and inference mechanisms for engineering design evaluation and selection.

4.2.1 Fuzzy Analytic Hierarchy Process

The AHP mechanism (Saaty 1991) provides a compositional approach to the multicriteria decision-making (MCDM) problem that is first structured into a hierarchy of interrelated elements and then a pairwise comparison of elements in terms of their dominance is elicited. The weights are given by the eigenvector associated with the highest eigenvalue of the reciprocal ratio matrix of pairwise comparisons. The pairwise comparison ratio used to compare the importance of criterion *i* and criterion *j*, that is w_i and w_j, is defined as:

$$a_{ij} = w_i / w_j \tag{1}$$

Considering a pairwise comparison matrix $A = [a_{ij}]$ and an importance index (weight) vector $W = [w_i]$, their relationship can be described according to:

$$AW = nW \tag{2}$$

When *A* is given, *W* and *n* are calculated as an eigenvector and an eigenvalue of *A*, respectively. The pairwise comparison matrix *A* must be examined for reliability of consistency, and the consistency index (CI) is calculated as:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{3}$$

where, $\lambda_{\max}$ is the maximum value of 0. If the value of *CI* is higher than 0.1, then the matrix should be reset by comparing importance again.

Most of current approaches compose the comparison matrix *A* in the AHP according to designer's or user's individual preferences only. In a collaborative design environment, negotiation should be flexible; design agents may change their offers according to their counter offers. Each agent has its own comparison matrix *A* and exchanges its matrix with other agents to cooperatively adapt to changes during the design process. Thus, the comparison matrix *A* should be built dynamically. To this end, this paper combines fuzzy membership functions with the AHP to pursue the preference of designers or agents dynamically, and as a result, the fuzzy comparison matrix *A* is generated. This will also be used in fuzzy negotiation for design collaboration.

4.2.2 Fuzzy Ranking, Evaluation and Selection for Design Alternatives

We treat design evaluation as a fuzzy multicriteria decision-making problem, in which the fuzzy ranking of design alternatives is carried out by evaluating a set of design alternatives against a set of design criteria. For example, the linguistic terms "very low," "low," "fairly low," "medium," "fairly high," "high," and "very high" themselves constitute a fuzzy evaluation set. A set with *m* design alternatives A={a_1, a_2,...,a_m} is to be evaluated by the fuzzy evaluation set in terms of *n* criteria $C=\{C_1,C_2,...,C_n\}$. The fuzzy rating $\widetilde{r}_{ij}$ to criterion C_j for alternative a_i is characterized by the membership function $\mu_{\widetilde{R}_{ij}}(\widetilde{r}_{ij}), \widetilde{r}_{ij} \in R$, and a set of weights $\widetilde{W} = \{\widetilde{w}_1, \widetilde{w}_2, ..., \widetilde{w}_n\}$ is fuzzy linguistic variables characterized by the membership function $\mu_{\widetilde{W}_j}(\widetilde{w}_j), \widetilde{w}_j \in R^+$. Consider the mapping function $g_i(\widetilde{z}_i): R^{2n} \to R$ defined by:

$$g_i(\widetilde{z}_i) = \sum_{j=1}^{n}(\widetilde{w}_j \widetilde{r}_{ij}) / \sum_{j=1}^{n}\widetilde{w}_j \tag{4}$$

where, $\tilde{z}_i = (\tilde{w}_1\tilde{w}_2...\tilde{w}_n, \tilde{r}_{i1}\tilde{r}_{i2}...\tilde{r}_{in})$. Define the membership function $\mu_{\widetilde{Z}_i}(\widetilde{z}_i)$ by

$$\mu_{\widetilde{Z}_i}(\widetilde{z}_i) = \overset{\circ}{\wedge}_{j=1,...,n}\mu_{\widetilde{W}_j}(\widetilde{w}_j) \overset{\circ}{\wedge}_{k=1,...,n}\mu_{\widetilde{R}_{ik}}(\widetilde{r}_{ik}) \tag{5}$$

where, $\wedge^{\circ}$ is the minimum calculation operator. Through the mapping $g_i(z_i): R^{2n} \to R$, the fuzzy set $\widetilde{Z}_i$ induces a fuzzy rating set $\widetilde{R}_i$ with the membership function as

$$\mu_{\widetilde{R}_i}(\widetilde{r}_i) = \sup_{Z_i g(\widetilde{z}_i) = \widetilde{r}_i} \mu_{\widetilde{Z}_i}(\widetilde{z}_i), \bar{r}_i \in R \tag{6}$$

This membership function $\mu_{\tilde{R}_i}(\tilde{r}_i)$ characterizes the final fuzzy rating of design alternative a_i. It does not mean the alternative with the maximum $\mu_{\tilde{R}_i}(\tilde{r}_i)$ is the best. The following procedure must be employed to further characterize $\mu_{\tilde{R}_i}(\tilde{r}_i)$ with the following two fuzzy sets:

i) a conditional fuzzy set is defined with the membership function*:*

$$\mu_{I/R}(i \mid \widetilde{r}_1,...\widetilde{r}_m) = \begin{cases} 1 & \text{if} \quad \widetilde{r}_i > \widetilde{r}_k, \forall k \in (1,2,...,m) \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

ii) a fuzzy set is constructed with the membership function:

$$\mu_R(\widetilde{r}_1,...\widetilde{r}_m) = \overset{\circ}{\wedge}_{i=1,...,m}\mu_{\widetilde{R}_i}(\widetilde{r}_i) \tag{8}$$

A combination of these two fuzzy sets induces a fuzzy rating set in which the best design alternative can be determined with the highest final rating, i.e.,

$$\mu_I(i) = \sup_{\widetilde{r}_1,...\widetilde{r}_m} \mu_{I/R}(i \mid \widetilde{r}_1,...\widetilde{r}_m) \wedge^{\circ} \mu_R(\widetilde{r}_1,...\widetilde{r}_m) \tag{9}$$

Compared with Eq.(4), the fuzzy ranking for design alternatives is more flexible and presents uncertainty better. Based on this method, designers can effectively and consistently incorporate fuzzy linguistic weights and ratings such as "good," "fair," "important," and "rather important," in design alternative evaluation. The fuzzy comparison matrix *A* in the fuzzy AHP above (Section 4.2.1) can be used to determine the fuzzy linguistic weights for complex design evaluation. In some cases, a simplified model is employed to integrate linguistic terms and fuzzy numbers into the fuzzy preference model. The universe of discourse is a finite set of fuzzy numbers used to express an imprecise level of performance rating and weight of each criterion (Zha et al. 2004).

For a complex design problem, designers are often required to consider not only product functionality, but also other criteria including compactness and life-cycle issues, such as manufacturability, maintainability, reliability, and efficiency. Some of these criteria may contradict each other. Designers should analyze the trade-offs among various criteria and make the "best" selection from various criteria combinations and available alternatives for evaluation. Therefore, it is important to have a powerful search strategy that will lead to a near optimum solution in a reasonable amount of time. Here, the A* search algorithm (Sriram 1997) is employed for this purpose. The system calculates the weighted performance rating aggregation of each retrieved alternative by analyzing the trade-off among various criteria and their combinations as an evaluation index. Thus, the evaluation index is used as a heuristic evaluation function f_h by considering all the weighted performance ratings $\bar{r}_i$ (i=1,2, …, m) of its constituent members and the number k of its unsatisfied customer requirements, as follows:

$$f_h = \sum_{i=1}^{m} (1/\bar{r}_i) + k \tag{10}$$

where, $\bar{r}_i \in [0,1]$ is the numerical weighted performance rating of the design alternative a_i ; $1/\bar{r}_i = (1,+\infty)$ is defined as the performance cost of design alternative a_i. A higher weighted performance rating of a design alternative corresponds to a lower performance cost. $\sum_{i=1}^{m}(1/\bar{r}_i)$ represents the accumulated performance cost of the design alternative along the search path thus far. k is a heuristic estimate of the minimum remaining performance cost of the design alternative along all the possible succeeding search paths. f_h is the estimate of the total performance costs of the design alternative. In Eq.(10), a higher $\bar{r}_i$ translates to a better-aggregated performance of each retrieved design alternative a_i, and a lower m or k, i.e., a higher compactness of a design alternative, will result in a lower evaluation index f_h. Thus, at each step of the A* search process, the best design alternative, i.e., the one with the lowest value of the heuristic evaluation function is selected, by taking into account multiple factors, including design compactness and other life-cycle issues such as manufacturability, assemblability, maintainability, reliability, and efficiency.

4.2.3 Fuzzy Knowledge Base and Inference Mechanism

When evaluating and selecting design solution alternatives, fuzzy rules regarding the characteristics of the design solutions can be identified and used after analyzing various possible design solutions and discussing with marketing groups. The fuzzy knowledge base is composed by two components: the linguistic terms base and the fuzzy rule base. The former can be divided into two parts: the fuzzy premises (or inputs) and the fuzzy conclusions (or outputs). Both parts may contain more than one premise and one conclusion. The fuzzy synthetic design decision model would support fuzzy rules with n multiple inputs and m multiple outputs (MIMO). The fuzzy knowledge base expressed by k (k=1,2,…K) MIMO-type heuristic fuzzy rules may be written in the form:

$$R^k: \text{ If } x_1 \text{ is } X_1^k \text{ and } \ldots \text{ and } x_n \text{ is } X_n^k \text{ Then } y_1 \text{ is } Y_1^k \text{ and } \ldots\ y_m \text{ is } Y_m^k \tag{11}$$

where, $\{X_i^k\}_{i=1}^n$ denotes values of linguistic variables; $\{x_i^k\}_{i=1}^n$ is conditions defined in the universe of discourse $\{X_i^k\}_{i=1}^n$; $\{Y_j^k\}_{j=1}^m$ stands for the value of the dependent linguistic variable; and $\{y_j^k\}_{j=1}^m$ is conclusions (outputs) defined in the universe of discourse $\{Y_j^k\}_{j=1}^m$. The global relation aggregating all K rules is given as $R=\sum_{k=1}^{K}(R^k)$, where, $\sum$ denotes any t- or s- norm or average. For a given set k=l of fuzzy inputs or observations $\{X_i^l\}_{i=1}^n$, the fuzzy outputs (or conclusions) $\{Y_j^l\}_{j=1}^m$ may be expressed as: $\{Y_j^l\}_{j=1}^m=(X_1^l,\ldots,X_n^l)\circ R=X_n^l\circ\ldots\circ(X_2^l\circ(X_1^l\circ R))$, where, "$\circ$" denotes a compositional rule of inference which combines fuzzification and inference stages. Finally, determining the center of gravity is used as the defuzzification method for inference mechanism:

$$\{y_j^l\}_{j=1}^m=\frac{\sum\{Y_j^l\}_{j=1}^m(y_j)y_j}{\sum\{Y_j^l\}_{j=1}^m(y_j)} \tag{12}$$

4.3 Integration and Cooperation of cDSP and FSD Decision Models

The cDSP model is basically data and information centric and more appropriate for implementation in conjunction with tangible (quantitative) criteria rather than with intangible (qualitative) criteria. The FSD model is knowledge based and able to handle both intangible and tangible criteria (e.g., from fuzzy requirements to crisp design parameters). The synthesis of the cDSP and FSD models can generate a more powerful decision model. Figure 4 provides a schematic view of the hybrid decision model integrating the cDSP and FSD models and their cooperation.

The integration and cooperation could be either "loose" or "tight." In the "loose" mode, two or more models are combined with parallel or serial modeling and they work together but complement each other. Depending on the nature of the decision problem, a rule-based adaptor is employed in the model. This adaptor serves as a regulatory switch to adapt the decision problems by shifting the paradigms from one decision model (e.g., the cDSP) to another (e.g., the FSD). In the "tight" mode, two or more models co-exist and are integrated into a single unified hybrid model, for example, fuzzy cDSP mentioned above.

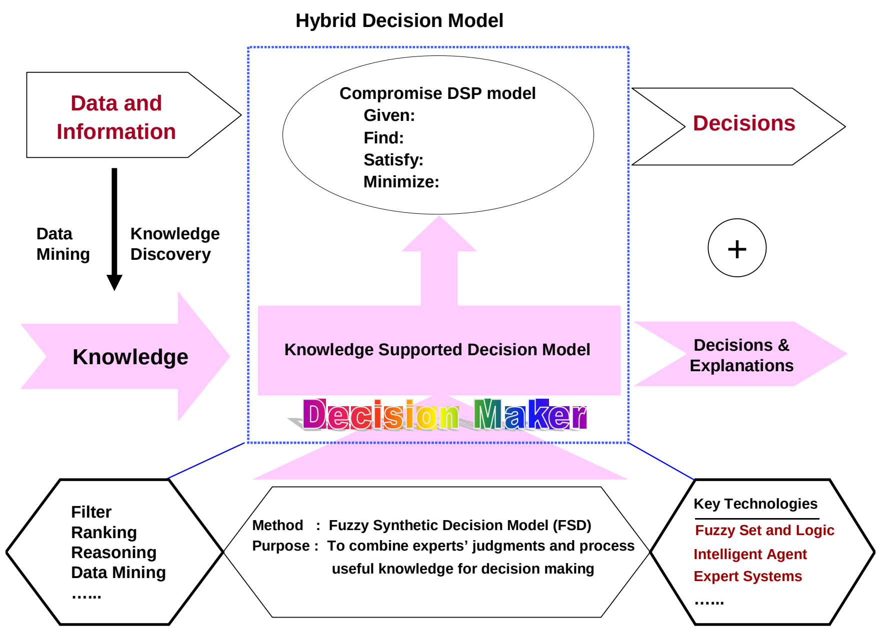


Figure 4: Hybrid decision support model

The decision of which models are to be used is not straight-forward, which it depends on many factors: degree of understanding of the design process, design process decomposition (stages), design complexity, quantitative (tangible) and qualitative (intangible) criteria, availability of expert knowledge about the design process under consideration, level of uncertainty, etc. Taking into account these factors, several structures of the hybrid decision model are illustrated in Figure 5. Figure 5(a) shows a rule-based selector incorporated in the scheme to switch on the most appropriate separate model for the current state of the process. Each of the separate models possesses its own input subspace and is tuned to be optimal for corresponding design specifications. For instance, two demonstrative heuristic rules for choosing the cDSP or the FSD models are given as: 1) If the problem is data or information centric and the criteria are tangible or quantitative then the cDSP model is used; 2) If the problem is knowledge-centric and the criteria are intangible or qualitative then the FSD model is used. Figure 5 (b) gives a serial structure of the hybrid model, in which two or more separate models (e.g., cDSP and FSD) are used to formulate hybrid models and model process behaviors and decisions at different design stages. Figure 5(c) is a parallel structure of the hybrid model, in which two separate models (e.g., cDSP and FSD) are used to formulate hybrid models in parallel. Figure 5(d) is a unified structure of the hybrid model, i.e., the fuzzy cDSP, in which two or more models (e.g., cDSP and FSD) co-exist and are integrated into a single unified model. Figure 5(e) and (f) are gain scheduling like structures, in which the above fuzzy ranking algorithm for some design parameters or variables is adopted, or the compromised results obtained by the cDSP model are used as references, respectively. Providing enough data for tuning multiple fuzzy models is a challenging problem when the quantity of special experiments must be restricted. A scenario of applications in conceptual design decision support is provided in Section 6.

The hybrid decision model is a kind of knowledge-supported model that can manage both qualitative and quantitative design decision knowledge and provide real-time or on-line support to designers during the decision-making process. More specifically, the benefits using the hybrid decision model are: 1) the lack of a formal means of incorporating qualitative information in the cDSP is addressed; 2) design solutions are suggested and explanations provided; 3) use in the early design stages becomes feasible; and 4) designers are stimulated in generating new design ideas (with learning, continuously taking place, being captured).

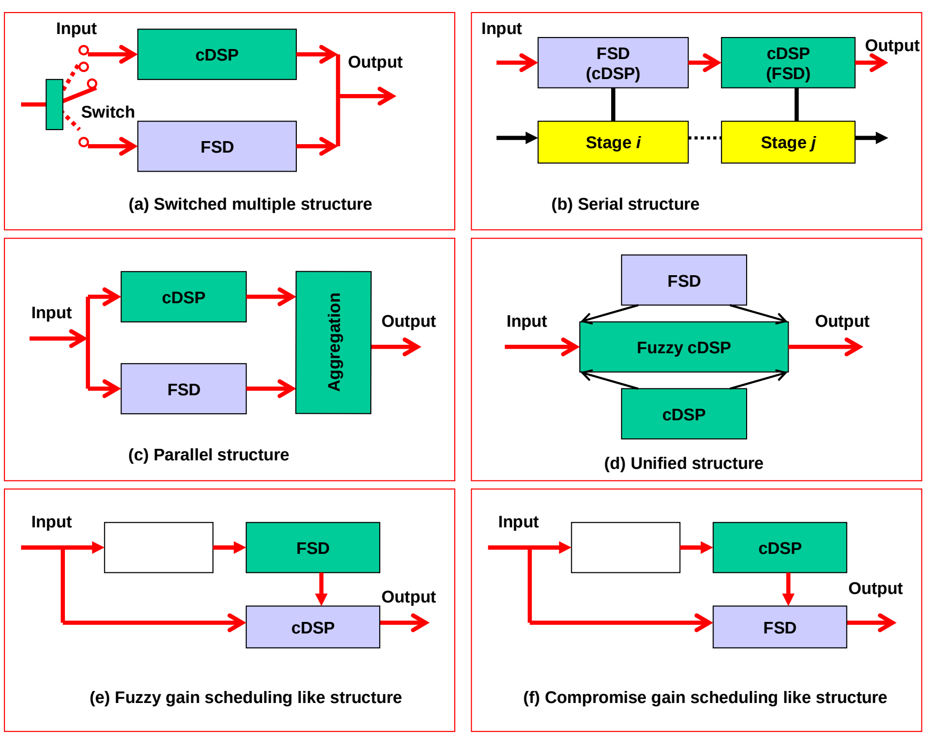


Figure 5: Structures of the hybrid decision models

4.4 Used as Collaborative Decision-Making Mechanisms

Coordination has been identified as the major problem with multi-agent systems as it is essential to any kinds of collaborations. In its definition, loosely integrated collaborative activities are coordinated by the protocol; tightly integrated collaborative activities need coordination mechanisms. The coordination problems discussed in this paper include cooperation and conflict resolution mechanisms for multi-agent collaborative decision support systems. The common ways to resolve the conflicts are arbitration and negotiation. Arbitration is based on the classic mathematical theory and reasoning rules according to the concept of the characteristic function "to be or not to be, {yes, no} or {0,1}." The negotiation is a form of decision-making with two or more actively involved agents who cannot make decisions independently but must make concessions to achieve a compromise.

The cDSP and FSD hybrid decision model proposed in Section 4 can be used for resolving decision conflicts in and between agents. As mentioned in Section 4.1, the cDSP model uses a hybrid of goal programming and mathematical programming to determine the values of design variables that satisfy a set of constraints and achieve as closely as possible a set of conflicting goals. Thus, the cDSP model is a well known approach for efficient conflict resolution and negotiation; it is already widely applied in decision constructs (Xiao et al. 2002, Fernández et al. 2002b, and Hernandez et al. 2002). These derived decision constructs are ideally suited for modeling networks of concurrent and sequential decisions that share information and knowledge in collaborative design. Due to the limitation of space, this section only focuses on the hybrid decision model for design decision conflict resolution and negotiation. The negotiation is based on fuzzy set theory and reasoning rules according to the concepts of membership functions and fuzzy comparison matrix. The fuzzy negotiation mechanism using the hybrid decision model is composed of the following six phases:

(1) Initial offering option settings for a design. The negotiation mechanism is started with the 'initial option settings for a design' of the agent or designer. In this phase, the negotiation agents offer their negotiation conditions reflecting their relative preferences for the design which is composed by quantitative conditions such as parameter values and cost. However, the fuzzy values for these conditions are changed by fuzzy membership functions reflecting qualitative conditions such as relative preferences.
(2) Fuzzy membership functions. After obtaining the initial design options of each agent or designer, 'fuzzy membership functions' are used to support the construction of the fuzzy pairwise comparison matrix *A*. With these fuzzy membership functions, designer's relative preferences are transformed into fuzzy membership values. During the transformation process, bell-shaped (or Z, λ, π, S-type) fuzzy membership functions can be adopted.
(3) Pairwise comparison matrix A. The 'pairwise comparison matrix A' is constructed. In this phase, the AHP comparison matrix is used to compute the relative importance of each alternative. Thus, design options of each agent are exclusively compared.
(4) Selection of preferred design options. Based on the result of comparison in Phase (3), the preferred design options are selected by one or several agents or designers. However, this is only the first step of dynamic negotiation process.
(5) Revision of design options and negotiation. In this phase, each agent or designer revises its 'initial design options for a design' and continues to negotiate with its counterpart. For this purpose, the 'goal-seeking' methodology (with cDSP or fuzzy cDSP) is used to revise the initial design options.
(6) Optimal design. The fuzzified pairwise comparison matrix *A* and the AHP inference mechanism are used to suggest the optimal design, and then go to the Phase (5) to lead towards a consensus with their counterparts. As a result, each designer or agent could be satisfied with the final design.

5. OVERVIEW OF KNOWLEDGE-INTENSIVE DECISION SUPPORT AGENT FOR COLLABORATIVE DESIGN DECISION

As design becomes increasingly knowledge-intensive and collaborative, the need for computational frameworks to support a collaborative product development environment becomes more critical (Shen 2001, Sriram 2002, Zha et al. 2003a). The overall knowledge-intensive collaborative design framework proposed in this paper is a multi-agent system framework that consists of a design process modeling and management agent, a knowledge capture agent, a knowledge repository, co-designers, a decision support agent, meta-system agent, etc. Designers are also agents.

The core of the scheme is the decision support agent and it is the focus of this paper. The knowledge repository is used to store, share, and reuse corporate design knowledge, including decision agent. The role of knowledge for next generation CAD systems is dicussed (Szykman 2001). The coordination, communication and execution mechanisms between these agents are modeled as FIPA contract net (FIPA 2001) based extension with knowledge-based Petri nets (Zha et al. 2003b) combined with other mechanisms supported by the hybrid decision model in Section 4.4.

The decision support agent is a container specialized in providing decision making services. The comparative ranking of alternatives and selection/compromise decision-making is a fundamental component of the design decision agent. As reviewed in Section 2, several formal decision models exist. The proposed hybrid decision model of cDSP and FSD in Section 4 is used as the kernel of the decision support agent. The decision support agent contains criteria which pair design attributes (variable modules) with preference modules (a type of variable module used to define preference functions) and provides an overall multiple attribute evaluation and selection service while each criterion evaluates a single attribute. The criterion relations calculate the worth of the design attribute based upon the preference model, while the decision support agents automatically generate relations to aggregate single attribute evaluations for multiple attribute decisions. Thus, there are different types of decision agents based on the hybrid decision models and structures in Section 4.3. In the proof-of-concept implementation the decision agents have been developed by integrating the cDSP technique with the knowledge-based FSD model into the hybrid decision support model for criterion or argument analysis and fusion.

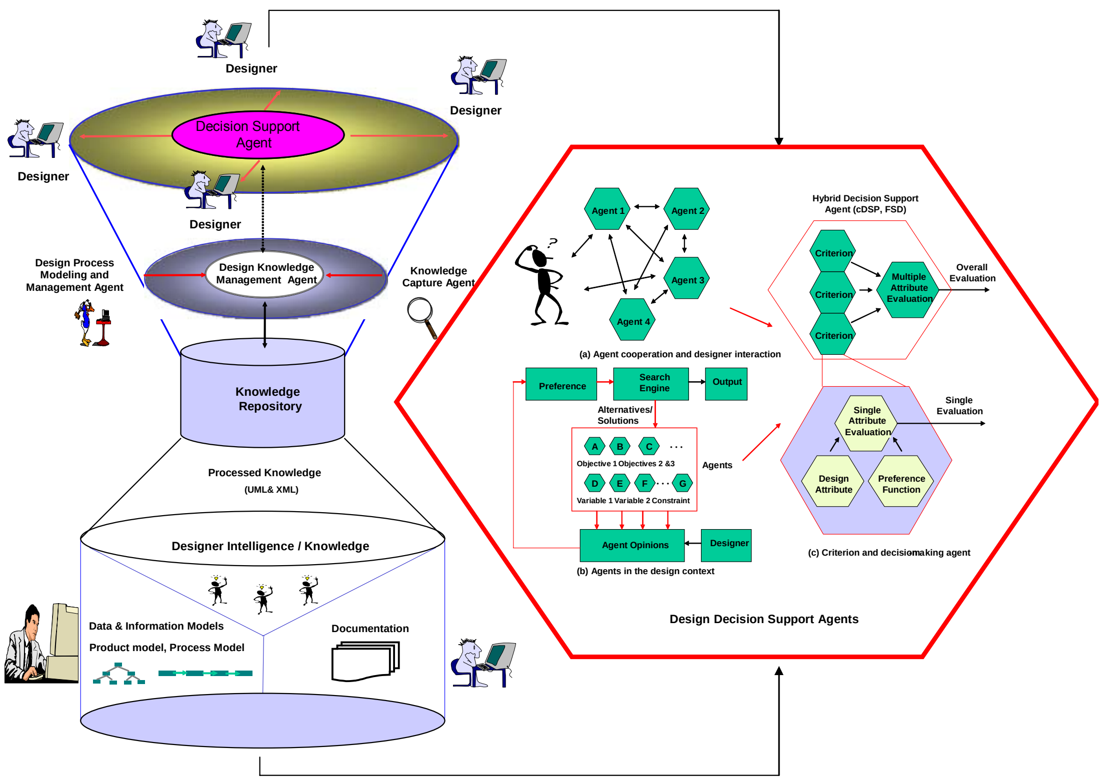


Figure 6: Knowledge-intensive decision support agent

Figure 6 gives an architecture framework and scenario for a knowledge-intensive decision support agent based on the proposed cDSP and FSD hybrid decision model. It shows that how the knowledge-intensive decision support agent can be applied for design decision, which instantiates and complies with the knowledge-intensive design decision support scheme shown in Figure 1. More specifically, the cDSP model is used to develop conceptual design alternatives or variants and determine similarity and commonality between modules and variants; while the FSD model is used to evaluate and select a design alternative that satisfies customer needs, meets design requirements and complies with the technical capabilities of the company. The final decision can be reached based on the knowledge resources retrieved through from the decision knowledge repository, including differentiating features and their membership functions, fuzzy rules, fuzzy rankings, etc. A web-based design decision support agent system prototype for proof-of-concept implementation has been developed to verify the proposed hybrid decision model and framework. Two case studies below are provided to illustrate the application of the knowledge supported decision for concept evaluation and selection in product family design for mass customization.

6. Application and Case Studies

Mass customization has been identified as a competitive strategy by an increasing number of companies. Family-based product design has been recognized as an efficient and effective means to realize sufficient product variety to satisfy a range of customer demands in support for mass customization. Various approaches and strategies for designing families of products and mass customized goods are reported in the literature. A product platform concept exploration method (PPCEM) was proposed to design a family of products (Simpson et al. 2001). The five steps of PPCEM are: 1) create market segmentation grid; 2) classify factors and ranges; 3) build and validate metamodels; 4) aggregate product platform specifications; and 5) develop product platform and family, in which formulating and exercising appropriate cDSP models are key procedures. To be in line with the general conceptual design stage, a family of product concepts (variants) can be explored and generated using the PPCEM and vary widely by selection and assembly of modules or pre-defined building blocks at different levels of abstraction so as to satisfy diverse customer requirements. A wrong or even a poor selection of either a building block or module can rarely be compensated for at a later design stage and can result in costly redesign. Concept evaluation and selection are crucial for product family design for mass customization (Zha et al. 2004).

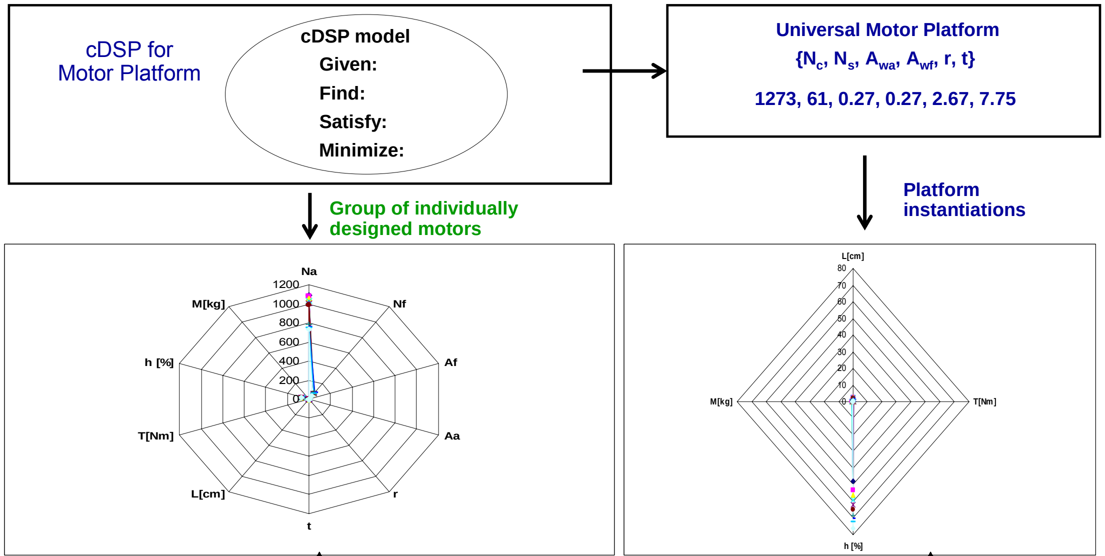
To illustrate and validate the hybrid decision model for product family design support, two examples are provided in this section: 1) a universal motor platform and family design selection, and 2) a power supply family design evaluation and selection.

6.1 Universal Motor Platform and Product Family Design Decision

Universal motors are the most common components in power tools. Black & Decker developed a family of universal motors for its power tools (Myer and Lehnerd 1997). They used different motors in each of their 122 basic tools with hundreds of variations. The challenging issue was to redesign the universal motor to fit into each of these 122 basic tools with hundreds of variations. Through redesign and standardization of the product line, they were able to produce all of their power tools using a line of motors that varied only in the stack length and the amount of copper wrapped within each motor. As a result, all the motors could be produced on a single product platform with stack lengths varying from 0.8in to 1.75in and power outputs ranging from 60 to 650W. Furthermore, new designs were developed using standardized components such as the redesigned motor, which allowed products to be introduced, exploited and retired with minimal expense related to product development.

We demonstrate in this example that the cDSP and FSD hybrid decision model (see Figure 5c) is used cooperatively in the decision support agent for universal motor platform and family design decision. Specifically, the decision support agent uses the hybrid decision model for universal motor platform and family design decision:

- The cDSP-based PPCEM is used to design a platform for a family of 10 universal motors, as given in Appendix B (Simpson et al. 2001). Figure 7 illustrates the cDSP model for the universal motor platform and shows the benchmark universal motor product family specifications and performance responses.
- The knowledge supported decision model, i.e., the FSD model, is used to evaluate and select an appropriate motor variant from the motor family obtained by the cDSP model.



	Na	Nf	Af	Aa	r	t	L[cm]	T[Nm]	η [%]	M[kg]
1	1087	72	0.28	0.25	2.71	7.15	3.16	0.5	55.3	0.99
2	1082	72	0.27	0.24	2.58	6.67	2.87	0.4	57.7	0.84
3	1056	73	0.26	0.24	2.51	6.46	2.81	0.35	59.8	0.78
4	1030	73	0.25	0.23	2.44	6.35	2.74	0.3	62.2	0.71
5	1007	73	0.25	0.22	2.35	6.17	2.61	0.25	64.9	0.64
6	988	74	0.24	0.22	2.26	5.75	2.38	0.2	67.9	0.56
7	785	95	0.21	0.21	2.82	8.88	1.63	0.15	70.5	0.5
8	760	89	0.19	0.2	3.12	11.2	1.41	0.13	70	0.5
9	750	76	0.19	0.2	3.31	11.77	1.28	0.1	70.6	0.5
10	730	45	0.2	0.21	3.62	9.69	0.998	0.05	71.4	0.5

	L[cm]	T[Nm]	η [%]	M[kg]
1	2.44	0.5	47.9	0.83
2	2.4	0.4	53.1	0.82
3	2.33	0.35	55.9	0.8
4	2.21	0.3	58.8	0.78
5	2.04	0.25	61.8	0.73
6	1.81	0.2	65.1	0.68
7	1.5	0.15	68.5	0.61
8	1.32	0.13	70.3	0.56
9	1.11	0.1	72.2	0.51
10	0.62	0.05	76	0.4

.

Figure 7: Benchmark universal motor family specifications and performance responses

Table 1: Weights and partial performance ratings, evaluation results (12 criteria)

Criterion No.	Criterion Item	Criterion Weight			Partial Performance Rating		
		Linguistic Term	Fuzzy Number	Weight Value	Linguistic Term	Fuzzy Number	Rating Crisp Value
1	Nc	High	(0.7,0.8,0.8,0.9)	W_1=0.80	Very Low	(0.0, 0.0,0.1,0.2)	r_{11}=0.500
2	Ns	High	(0.7,0.8,0.8,0.9)	W_2=0.80	Very Low	(0.0, 0.0,0.1,0.2)	r_{12}=0.800
3	Awf(mm^2)	Fairly Low	(0.2,0.3,0.4,0.5)	W_3=0.35	Very Low	(0.0, 0.0,0.1,0.2)	r_{13}=0.075
4	Awa(mm^2)	Fairly Low	(0.2,0.3,0.4,0.5)	W_4=0.35	Very Low	(0.0, 0.0,0.1,0.2)	r_{14}=0.500
5	I(Amp)	Fairly Low	(0.2,0.3,0.4,0.5)	W_5=0.35	Very Low	(0.0, 0.0,0.1,0.2)	r_{15}=0.500
6	r(cm)	Medium	(0.4,0.5,0.5,0.6)	W_6=0.50	Very High	(0.8,0.9,1.0,1.0)	r_{16}=0.950
7	t(mm)	Fairly High	(0.5,0.6,0.7,0.8)	W_7=0.65	High	(0.7,0.8,0.8,0.9)	r_{17}=0.800
8	T(Nm)	High	(0.7,0.8,0.8,0.9)	W_8=0.80	Very Low	(0.0, 0.0,0.1,0.2)	r_{18}=0.075
9	P(W)	High	(0.7,0.8,0.8,0.9)	W_9=0.00	Very Low	(0.0, 0.0,0.1,0.2)	r_{19}=0.075
10	M(kg)	Very High	(0.8,0.9,1.0,1.0)	W_{10}=0.95	Very Low	(0.0, 0.0,0.1,0.2)	r_{110}=0.075
11	L(cm)	High	(0.7,0.8,0.8,0.9)	W_{11}=0.80	Very Low	(0.0, 0.0,0.1,0.2)	r_{111}=0.075
12	η (%)	Very High	(0.8,0.9,1.0,1.0)	W_{12}=0.95	Very High	(0.8,0.9,1.0,1.0)	r_{112}=0.950

Evaluation Results:

Family (Variants)	Evaluation Index	Rankings
Motor 1	2.108	5
Motor 2	2.920	10
Motor 3	2.478	8
Motor 4	2.594	9
Motor 5	2.175	6
Motor 6	2.319	7
Motor 7	1.825	2
Motor 8	1.928	3
Motor 9	2.049	4
Motor 10	1.655	1

The decision support agent is required to select the best motor for a customer out of 10 motor variants in the family obtained above. If 12 performance features, i.e., Nc, Ns, Awf(mm^2), Awa(mm^2), I(Amp), r(cm), t(mm), L(cm), T(Nm), P(W), η(%), and M(kg) are considered as criteria, Motor 10 in the family will be selected. Table 1 gives weights and partial performance ratings for each criterion (for motor No.1) alongside evaluation results. If the last 5 performance features above, i.e., L(cm), T(Nm), P(W), η(%), and M(kg) are considered as evaluation criteria, Motor 8 will be selected. Figures 8 and 9 show a comparison of the obtained results using the cDSP and FSD models: (a) Comparison of the benchmark group and cDSP for mass-efficiency relations (Simpson et al. 2001), and (b) Evaluation with the FSD model for 5 and 12 criteria cases.

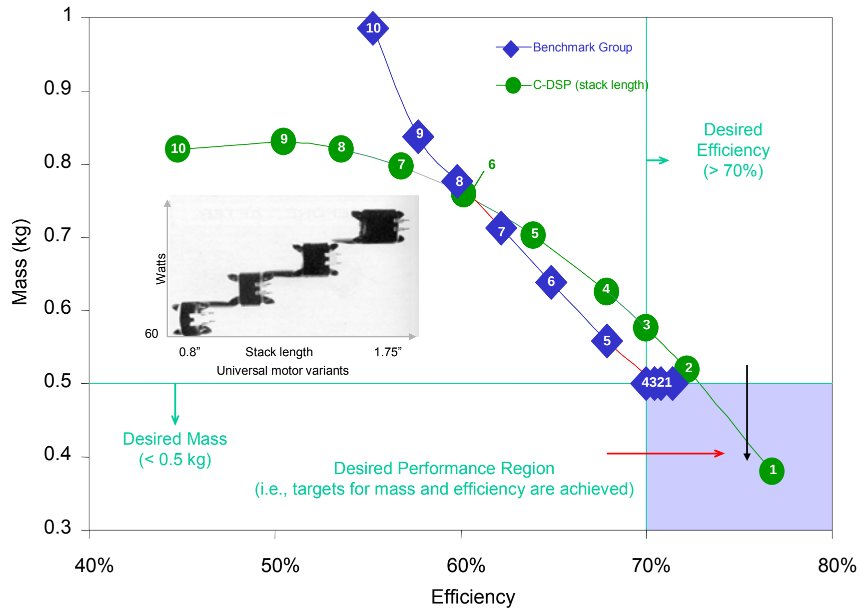


Figure 8: Comparison of the benchmark group and cDSP for mass-efficiency relations

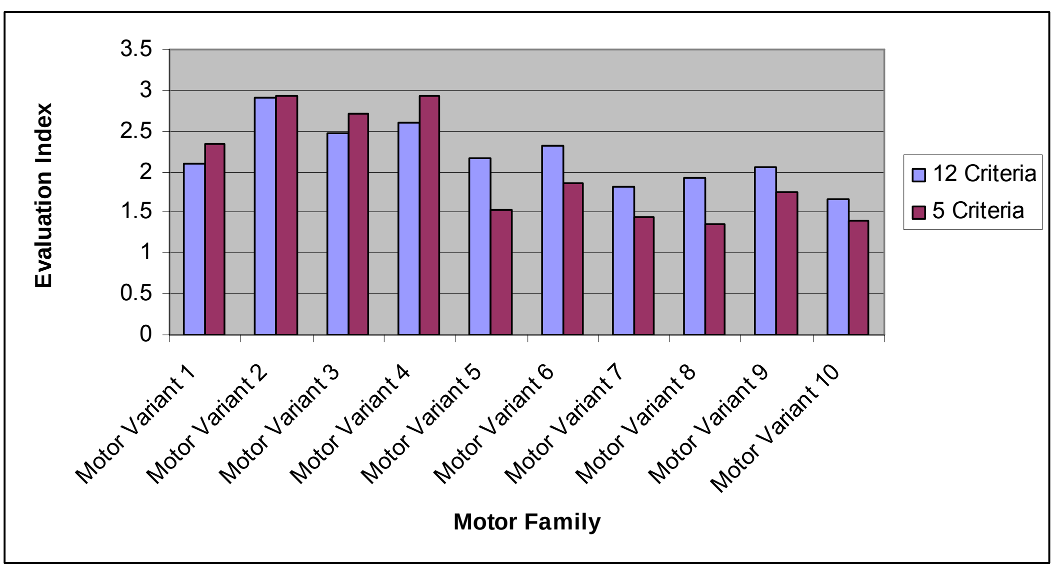


Figure 9: Evaluation with the FSD model for 5 and 12 criteria cases

6.2 Collaborative Design Evaluation and Selection for Power Supply Family

Power supplies are necessary components of all electronic products. Power supply products are often customized because their requirements are diverse. The proposed hybrid decision model is used for decision making in power supply family designs for mass customization. The design of power supply products is based on the modular design approach (Tseng and Jiao 1998, Zha et al. 2004). In this example, the fuzzy cDSP model is used to generate power supply design alternatives or variants and determine similarity and commonality between modules and product variants, while the FSD model is used for evaluating and selecting a power supply design alternative. In addition, the FSD model is used for conflict resolution and negotiation in collaborative family evaluation and selection.

First, different clusters can be obtained for families by using the fuzzy cDSP model and the fuzzy clustering model (Zha et al. 2004). Figure 10(a)-(c) illustrates the process of clustering design variations and instances. From a customer's point of view, a power supply product is defined based on the following required features (RFs): power, output voltage (OutV), output current (OutC), size, regulation, mean time between failure (MTBF). From an engineer's point of view, the power supply product is designed by determining values for these variables (parameters) (DPs): core of transformer (Core), coil of transformer (Coil), switch frequency (SwitchF), rectifier, heat sink type (TypeHS), heat sink size (SizeHS), control loop (Control). Figure 10(d) shows the relationships between RFs, DPs, configurations (a hierarchy of building block) and clusters. Three power supply product families I, II and III are generated based on three different clusters, which have 4, 5 and 3 base products (BPs) respectively. Each cluster has its own ranges or limitations with regard to the particular product features and/or design parameters. When the product is configured the design requirements and constraints are satisfied in terms of product functions or functional features. From an assembly or disassembly or maintenance point of view, it is advantageous for those parts with low exchange rates to be placed inside of the product. The locations of some parts, however, are fixed in advance due to design constraints.

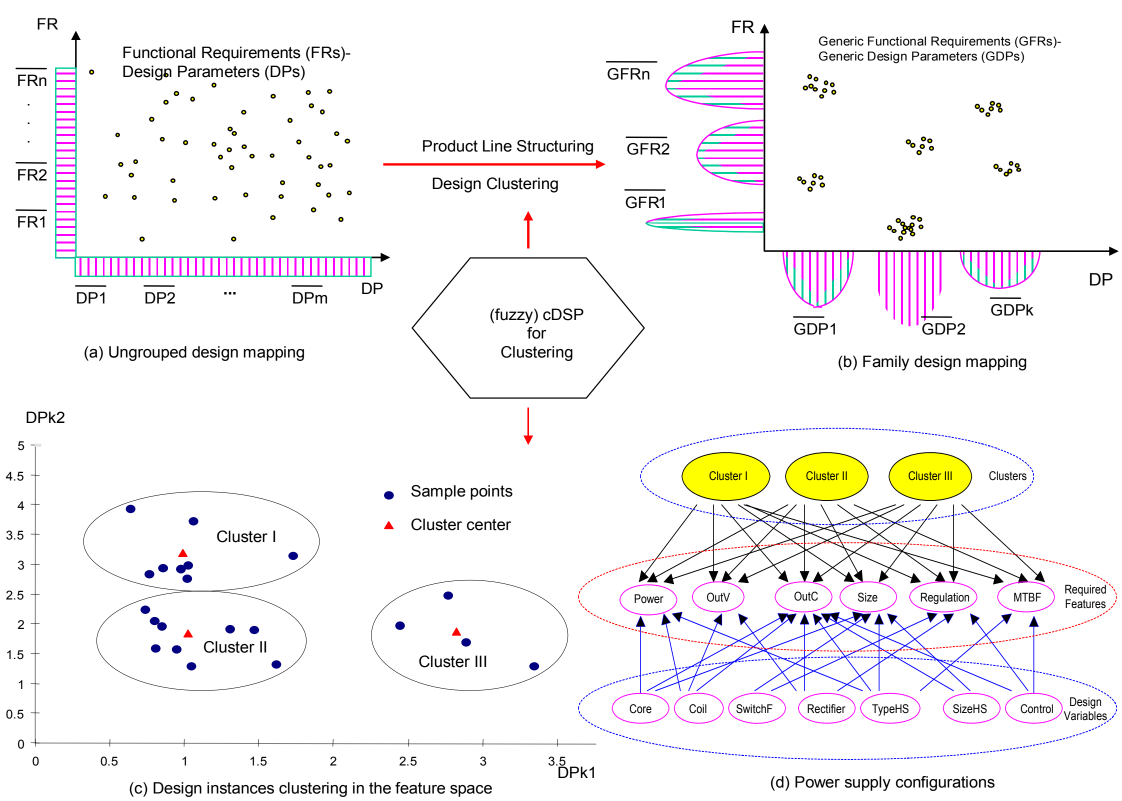


Figure 10: Clustering design variations and instances, power supply configurations

The customers' requirements for Family-I power supplies include AC/DC, 45W, 5V & ±15V, 150khrs, $20-50, with or without auto-start function or feature. The knowledge decision support system (design advisor) first eliminates unacceptable alternatives and determines four acceptable alternatives: NLP40-7610, NFS40-7610, NFS40-7910, and NFS 42-7610. The final design decision is reached based on the knowledge resources (1)-(4) in Figure 11, including differentiating features (MTBF, price, and special offer) and their utility/membership functions, fuzzy rules, fuzzy rankings, etc. The final design decision made by the design decision agent in the system is NFS42-7610 as it has maximum MTBF, medium price and special offer of auto-start function furthermore it is acceptable based on the rules. Table 2 gives weights and partial performance ratings for each criterion (for NLP40-7610) and evaluation results.

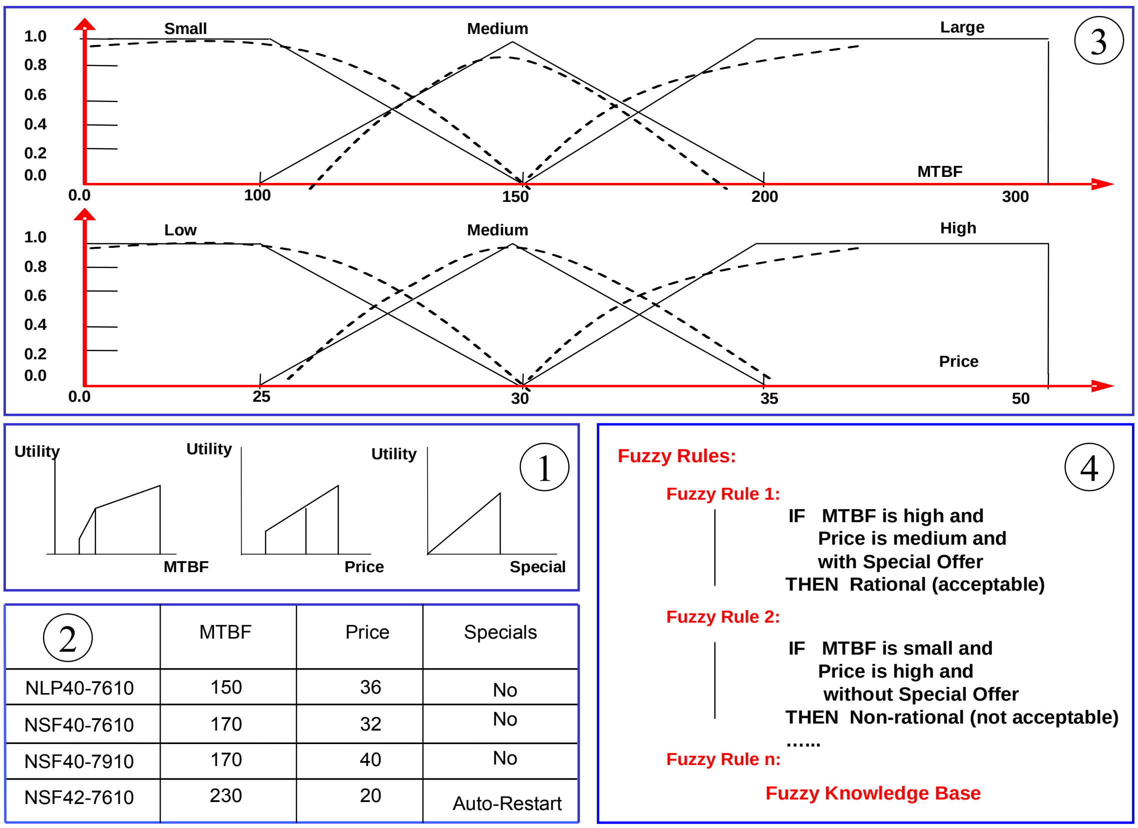


Figure 11: Knowledge instances used in power supply evaluation and selection

Table 2: Weights and partial performance ratings

Criterion No.	Criterion Item	Criterion Weight			Partial Performance Rating		
		Linguistic Term	Fuzzy Number	Weight Value	Linguistic Term	Fuzzy Number	Rating Crisp Value
1	MTBF	High	(0.7,0.8,0.8,0.9)	w_1=0.80	Medium	(0.4,0.5,0.5,0.6)	r_{11}=0.500
2	Price	Fairly High	(0.5,0.6,0.7,0.8)	w_2=0.65	High	(0.7,0.8,0.8,0.9)	r_{12}=0.800
3	Special Offer	Medium	(0.4,0.5,0.5,0.6)	w_3=0.50	Very Low	(0.0, 0.0,0.1,0.2)	r_{13}=0.075

Evaluation Results:

Family I	Evaluation Index (h)	Rankings
NLP40-7610	2.128	3
NFS40-7610	2.041	2
NFS40-7910	2.222	4
NFS42-7610	1.449	1

Second, the proposed FSD-based negotiation mechanism is used for design conflict resolution in collaborative power supply family selection for customization. Suppose that three designers and one customer may exchange and revise their suggestions or option settings by using the FSD model during the collaboration. Detailed conditions for the negotiation in collaborative selection are composed by MTBF, price, and special offer. In the first phase, three designers suggest their initial options (represented by options 1, 2, and 3 respectively) and the customer changes option (option 4) settings with his/her own conditions. The initial options shown in Table 3(a) are transformed into fuzzy membership values by using the fuzzy membership functions (Table 3(b)). In this phase, the bell-shaped fuzzy membership functions are adopted to transform the value of each condition. However, the customer or designer could set the limits of each factor used in fuzzy membership functions, which are the range of data, center value, and others. The fuzzy AHP-based 'goal-seeking' methodology are then used to compute the relative importance among variables (negotiation conditions: MTBF, price and special offer) and obtain the pair-wise comparison matrix for negotiation. Table 4 (a)(b) show the paired comparisons among variables as negotiation conditions and the normalized comparison matrix. The consistency value of AHP is 0.01 (CR=0.01), which means that the comparison matrix shown in Table 4 could be used to make a meaningful decision or serve as the basis for next round negotiation.

Table 3: Initial option settings of designers and fuzzy membership values for each option setting

(a) Initial option settings s of designers and customer				
	Designer 1 (Option 1)	Designer 2 (Option 2)	Designer 3 (Option 3)	Customer (Option 4)
MTBF	170	170	190	100-250
Price	32	40	26	15-50
Special Offer	0	0	1	0,1

(b) Fuzzy membership values for each selection setting			
	Designer 1	Designer 2	Designer 3
MTBF	0.44	0.44	0.90
Price	0.85	0.79	0.90
Special Offer	0.00	0.00	1.00
Averaged satisfaction	0.43	0.41	0.93

Table 4: Pairwise comparison matrix for negotiation

(a) Initial comparison matrix			
	MTBF	Price	Special Offer
MTBF	1	3	5
Price	1/3	1	1/2
Special Offer	1/5	2	1

(b) Normalized comparison matrix			
	MTBF	Price	Special Offer
MTBF	0.65	0.50	0.77
Price	0.22	0.17	0.08
Special Offer	0.13	0.33	0.15

To get a meaningful relative comparison matrix for all conditions, the computation example is shown for all optional settings using 'MTBF' condition only. First, the third option (option 3, Table 3(b)) is selected as the most preferred option (average satisfaction score = 0.93). In contrast with this result, a change is made and the relative importance of all options is computed with all negotiation conditions, and thus could decide that the second option (option 2) as the most preferred option (the total score = 0.44), whereas the third option (option 3) is now ranked the second. Consequently, the customer may select the second option (option 2) as the best option. The negotiation process will be continued between the customer and designer 2, and the customer may want to improve the satisfaction level from 0.51 to 0.7~0.9. To get an optimal solution, the fuzzy cDSP is used, and the goal-seeking algorithm based on the random number generation and an iterative simulation (a hybrid of goal programming and mathematical programming) is used. The objective function and subject constraints used during this process are summarized as below:

Objective: Satisfaction level =0.9
Subject to:

Fuzzy value of each condition >= current fuzzy value of each condition
Fuzzy value of each condition <=1.0

In addition, the fuzzy value of each condition is related to the fuzzy membership functions and the real value directly. Therefore, the fuzzy values are transformed into real values such as quantity, price, quality, etc.. Table 5 shows the results of computations (real value transformed) that improve customer's satisfaction level from 0.51 to 0.9. The revision and negotiation processes will continue to find an optimal solution or consensus among designers and the customer. Eventually, each negotiation condition of designers and customer will be agreed upon. Table 6 shows the final consensus among designers and customer and the summarized final design option (MTBF=196, price=36, special offer=auto-start). Figure 13 gives a screen snapshot of the proof-of-concept multi-agent design decision system for collaborative power supply product evaluation and selection for customization.

Table 5: Customer's new design option setting after the first round negotiation

	Before Revision (Designer)		After Revision (Customer)	
	Design Option	Fuzzy Value	Revised Design Option	Fuzzy Value
MTBF	170	0.86	190	0.86
Price	32	0.04	30	0.74
Special Offer	0	0.84	1	1.00
Averaged Satisfaction	-	0.58	-	0.87

Table 6: Designer and customer's final design option setting

Final Design Option	
MTBF	196
Price	36
Special Offer	Auto-start

Figure 12 gives a screen snapshot of the proof-of-concept multi-agent design decision system for collaborative power supply product evaluation and selection for customization.

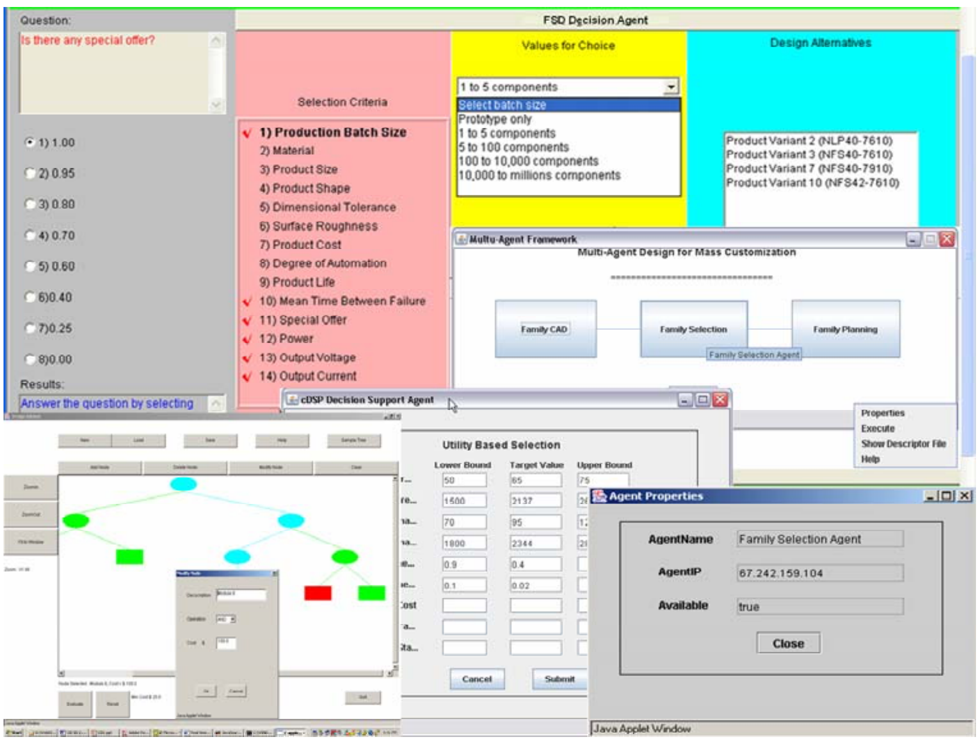


Figure 12: Screen snapshot for collaborative power supply evaluation and selection

7. SUMMARY, CONCLUSIONS AND FUTURE WORK

This paper presented a hybrid decision model and a multi-agent framework for collaborative design decision support. Decision theories and technologies, such as design process and knowledge modeling, optimization, distributed agents and web-based collaboration support, are exploited to explore structured support for both single and distributed design teams. The contribution of the work is the description of a knowledge intensive decision support approach, which rests on an interrelated set of algorithms and methods: cDSP, fuzzy cDSP, and FSD. Compared with existing models and methods, the proposed hybrid decision model can provide an effective means of integrating both subjective and objective elements in the design process, making it particularly suitable for supporting collaborative design decisions in knowledge-intensive intelligent and distributed environments. As such, the design decision knowledge can be managed and real-time or on-line knowledge support can be provided for designers. Typical technical barriers including incomplete and evolving information, uncertain evaluations, inconsistency of team members' inputs, etc. could be overcome for the decision-making process. Designers, especially novices, can benefit from retrieval of knowledge evolving from previous design decisions by gaining insight into how an earlier decision was made or by abstracting information and applying it to a new design. By making use of the design knowledge, the design decision support system (agent) can help design teams make better confident decisions so that companies are expected to improve the design process for more innovative products and reducing the product development cycle time. The developed model and framework are flexible enough to be used in a variety of decision problems. The applications in concept evaluation and selection in design for mass customization validate the feasibility of the developed decision support methodology and framework.

Although substantial efforts have been made in this work to develop a knowledge- intensive support model and framework for collaborative design decision-making, there are still some practical and theoretical issues to be addressed in some detailed topics and models and applications such as structured models and design knowledge acquisition and repositories, the expert judgment and process-useful knowledge for decision-making, and the decision of which models to be used. There are several ways in which the model and framework could be expanded and refined, including decision process models, alternative generation models, and other agents in the framework. The system itself is a prototype for proof-of-concept; it therefore requires further development. Future work is expected on the development of the decision support agent and integrating it with a web-based product design and realization system and framework. It may also include applying the approaches of this paper to the wide product lifecycle decision support.

ACKNOWLEDGEMENTS AND DISCLAIMER

The authors thank Janet Allen for her inputs to the earlier version of this paper. This work was partly supported by the U.S. Department of Commerce System Integration for Manufacturing Automation (SIMA) program, National Institute of Standards and Technology.

Commercial equipment and software, many of which are either registered or trademarked, are identified in order to adequately specify certain procedures. In no case does such identification imply recommendation or endorsement by the US National Institute of Standards and Technology, nor does it imply that the materials or equipment identified are necessarily the best available for the purpose.

APPENDIX A

Mathematical form of a fuzzy cDSP

Given

An alternative to be improved, domain dependent assumptions

The system parameters:

n: number of system variables,

q: inequality constraints,

$p + q$: number of system constraints,

m: number of system goals,

$\tilde{g}_i(\tilde{X})$: fuzzy system constraint functions ,

$\tilde{f}_k(\tilde{d}_i)$: fuzzy function of deviation variables to be minimized at priority level k for the preemptive case.

Find

Fuzzy system design variables**,** $\tilde{X}_i$, i = 1,…, n

Fuzzy deviation variables, $\tilde{d}_i^-$, $\tilde{d}_i^+$, i= 1,…, m

Satisfy

Fuzzy system constraints (linear, nonlinear)

$\tilde{g}_i(\tilde{X}) = 0$; i = 1, .., p

$\tilde{g}_i(\tilde{X}) \gtrsim 0$; i = p+1, .., p+q

Fuzzy system goals (linear, nonlinear)

$\tilde{A}_i(\tilde{X}) + \tilde{d}_i^- - \tilde{d}_i^+ = \tilde{G}_i$; i = 1, …, m

Fuzzy bounds

$\tilde{X}_i^{\min} \lesssim \tilde{X}_i \lesssim \tilde{X}_i^{\max}$; i = 1, …, n

$\tilde{d}_i^-$, $\tilde{d}_i^+ \gtrsim 0$, $\tilde{d}_i^- \cdot \tilde{d}_i^+ = 0$; i = 1, …, m

Minimize

Minimize the deviation function

$$\tilde{f} = [\,\tilde{f}_1(\tilde{d}_i^-, \tilde{d}_i^+), \ldots, \tilde{f}_k(\tilde{d}_i^-, \tilde{d}_i^+)]$$

APPENDIX B

cDSP for designing a group of individual universal motors

(Simpson et al 2001)

Given

Universal motor equations

Find

The system variables:

$N_{c,j}$: Number of wire turns on the armature;

r_j: Radius of the motor

$N_{s,j}$: Number of wire turns on each pole on the field

t_j: Thickness of the stator

$A_{wa,j}$: Cross-sectional area of the wire on the armature

I_j: Current drawn by the motor

$A_{wf,j}$: Cross-sectional area of the wire on the field

$L_{i,j}$: Stack length

Satisfy

The system constraints (linear, nonlinear)

Magnetizing intensity: $H_j \leq 5000$ Amp.turns/m

Feasible geometry: $t_j < r_j$

Torque: T_j={0.05, 0.1, 0.125, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.5} Nm

Power: P_j =300 Watts

Efficiency: $\eta_j \geq 0.15$

Mass: $M_j \leq 2.0$ kg

The system goals (linear, nonlinear):

Efficiency: $\eta_j/0.70 + d_{1,j}^- - d_{1,j}^+ = 1.0$

Mass: $M_j/0.50 + d_{2,j}^- - d_{2,j}^+ = 1.0$

The bounds on the system variables:

$100 \leq N_{c,j} \leq 1500$ turns, $0.5 \leq t_j \leq 10.0$mm

$1 \leq N_{s,j} \leq 500$ turns, $0.1 \leq I_j \leq 6.0$ Amp
$0.01 \leq A_{wa,j} \leq 1.0$ mm^2, $1.0 \leq r_j \leq 10.0$ cm
$0.01 \leq A_{wf,j} \leq 1.0$ mm^2, $0.0566 \leq L_j \leq 5.18$ cm

The bounds on the derivation variables:

$d_{i,j}^-$, $d_{i,j}^+ \geq 0$, $d_{i,j}^- \cdot d_{i,j}^+ = 0$ $i = 1,2$

Minimize:

The deviation function

$Z_i = [0.5(d_{1,j}^-)+0.5(d_{2,j}^+)]$ All, j=1,..., 10

REFERENCES

Allen, J.K., Krishnamachari, R.S., Masetta, J., Pearce, D., Rigby, D., and Mistree, F. (1992), Fuzzy Compromise: an Effective Way to Solve Hierarchical Design Problems, Structural Optimization, 4:115-120, 1992

Altshuller, G. (1999), The Innovation Algorithm, Technical Innovation Center, Inc.,Worcester, MA

Bahrami, A., and Dagli C.H. (1993), From Fuzzy Input Requirements to Crisp Design, International Journal of Advanced Manufacturing Technology, 8: 52-60

Bock, C., and Zha, X.F. (2007), Ontological Product Modeling for Collaborative Design, U.S. National Institute of Standards and Technology, Interagency Report, July, 2007

Boender, C. G., de Graan, J. G. and Lootsma, F.A. (1989), Multicriteria Decision Analysis with Fuzzy Pairwise Comparisons, Fuzzy Sets and Systems, 29: 133-143

Carnahan, J. V., Thurston, D. L. and Liu, T. (1994), Fuzzy Rating for Multi-attribute Design Decision-Making, ASME Journal of Mechanical Design, 116(2): 511-521

Chen, S.J., Hwang, C.L. and Hwang, F.P. (1992), Fuzzy Multiple Attribute Decision Making: Methods and Applications, Berlin; Hong Kong: Springer-Verlag

Chiu, D.K.W., Cheung, S. C., Hung, P.C.K., and Leung, H.-F. (2005), Facilitating e-Negotiation Processes with Semantic Web Technologies, Proceedings of the 38th Annual Hawaii International Conference on System Sciences (HICSS'05) - Track 1, p.36a, 2005

Clausing, D. (1994), Total Quality Development: A Step-by-Step Guide to World Class Concurrent Engineering, New York: ASME Press

FIPA 2001, http://www.fipa.org/specs/fipa00029/

Forgionne, G. (1994), Decision Technology System to Deliver Effective Concurrent Engineering, Concurrent Engineering: Research and Applications, 2(2): 67-76.

Frazell, E. (1985), Suggested Techniques Enable Multi-criteria Evaluation of Material Handling Alternatives, Industrial Engineering, 17(2)

Fernández, M.G., Rosen, D.W., Allen, J.K., and Mistree F. (2002), Digital Interfaces: The Key to Effective Decision-Making in Distributed Collaborative Design and Manufacture, ASME Design Engineering Technical Conferences, Montreal, Canada: ASME. Paper Number: ASME DETC2002/CIE-34466.

Fernández, M.G., Rosen, D.W., Allen, J.K., and Mistree, F. (2002), On a Decision Support Framework for Distributed Collaborative Design and Manufacture, 9th AIAA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, Atlanta, GA, USA: AIAA. Paper Number: AIAA-2002-5496.

Fernández, M.G., Seepersad, C.C., Rosen, D.W., Allen, J.K. and Mistree, F. (2001), Utility-Based Decision Support for Selection in Engineering Design, ASME Design Engineering Technical Conferences, Pittsburg, PA, USA: ASME. Paper Number: ASME DETC/DAC-21106.

Gero, J.(1990), Knowledge-Based Design Systems, Addison-Wesley, 1990.

Gerhard, J.F., Allen, J.K. Rosen, D.W. and Mistree F. (2000), A Distributed Product Realization Environment for Design and Manufacturing, Proceedings of ASME DETC, Paper Number: DETC2000/CIE-14624.

Gui, J.K. (1993), Methodology for Modeling Complete Product Assemblies, PhD Dissertation, Helsinki University of Technology, Finland

Hazelrigg, G. (1996), System Engineering: An Approach to Information-based Design, Prentice-Hall International Series in Industrial and System Engineering

Hadjiski, M.B., Christova, N.G., and Groumpos, P.P. (1999), Design of Hybrid Models for Complex Systems, European Symposium on Intelligent Techniques, Orthodox Academy of Crete, Greece, June 3-4, 1999

Hernandez, G., C.C. Seepersad, J.K. Allen and F. Mistree (2002), A Method for Interactive Decision-making in Collaborative, Distributed Engineering Design, International Journal of Agile Manufacturing Systems, 5(2):47-65

Hsing, J., et al. (2001), Conflict Resolution Using TRIZ and Design of Experiment (DOE), Proceedings of TRIZCON2001, The Altshuller Institute, March 2001

Hwang, C.L. and Yoon, K. (1981), Multiple Attribute Decision Making: Methods and Applications, Berlin: Springer

Jiao, J.X., and Tseng, M.M. (1998), Fuzzy Ranking for Concept Evaluation in Configuration Design for Mass Customization, Concurrent Engineering: Research and Application, 6(3): 189-206

Keeney R.L. and Raiffa, H. (1993), Decisions with Multiple Objectives: Preferences and Value Tradeoffs, Cambridge University Press

Knosala, R. and Pedrycz, W. (1992), Evaluation of Design Alternatives in Mechanical Engineering, Fuzzy Sets and Systems, 47(3): 269-280

Kim, J.S. (2003), Negotiation Support In Electronic Commerce using Fuzzy Membership Functions and AHP, Proceedings of the 6th Pacific Rim International Workshop on Multi-Agents (PRIMA) 2003, Seoul (Korea), pp.93-104

Lambright, J.P. and Ume, C. (1996) A Flat Composite Panel Design Advisory System Using Knowledge Based and Case Based Reasoning, *Journal of Mechanical Design*, 118**,** December, pp. 461-475.

Li, W.D., Ong, S.K., Nee, A.Y.C., Ding, L., and McMahon, C.A., Intelligent Process Planning Optimization for Product Cost Estimation, Integrated Intelligent Systems for Engineering Design, Vol. 149, Frontiers in Artificial Intelligence and Applications, IOS Press, 2006

Lu, J., Quaddus, M.A., and Williams, R. (2000), Developing a Knowledge–based Multi-Objective Decision Support System, Proceedings of the 33rd Hawaii International Conference on System Sciences, pp. 1-10

Maimon, O., and Fisher, E. (1985), Analysis of Robotic Technology Alternatives, Proceedings of the 1985 Annual Industrial Engineering Conference, pp. 227–236

Mascle, C. (2003), Decision Support System in a Design for Assembly and Disassembly Methodology, Proceedings of the 5th IEEE International Symposium on Assembly and Task Planning, Besancon, France, July 10-11, 2003

Meyer, M.H. and Lehnerd, A.P. (1997), The Power of Product Platforms, New York: The Free Press.

Mistree, F., Hughes, O.F. and Bras, B.A. (1993), The Compromise Decision Support Problem and the Adaptive Linear Programming Algorithm, Structural Optimization: Status and Promise, M.P. Kamatt (ed.), AIAA, Washington D. C., Paper 11, pp.247-286

Mistree, F., Bras, B., Smith, W.F., and Allen, J.K. (1995), Modeling Design Processes: A Conceptual Decision-Based Perspective, Engineering Design & Automation, 1(4): 209-321

Mocko, G.M. (2006), A Knowledge Framework for Integrating Multiple Perspectives in Decision-Centric Design, PhD Thesis, Georgia Institute of Technology, 2006

Nielsen, E.H., Dixon, J.R. and Simmons, M.K. (1986), GERES: A Knowledge Based Material Selection Program for Injection Molded Resins, Proceedings of the ASME 1986 Computers in Engineering Conference, Chicago, IL, pp.255-262.

Pahl, G. and Beitz, W. (1996), Engineering Design - A Systematic Approach, New York: Springer.

Panchal, J.H., Chamberlain, M.K., Rosen, D.W., and Mistree F. (2002), A Service Based Architecture for Information and Asset Utilization in Distributed Product Realization, 9th AIAA/ISSMO Symposium on Multidisciplinary Analysis and Optimization, Atlanta, GA: AIAA-2002-5617.

Prasad, B. (1996), Concurrent Engineering Fundamentals, Volume 1-2, NJ.: Prentice Hall PTR

Pugh, S. (1991), Total Design: Integrating Methods for Successful Product Engineering, Addition- Wesley Publishing Co. Inc.

Rosen, D. W., Chen, Y., Gerhard, J., Allen, J. K., and Mistree F. (2000), Design Decision Templates and Their Implementation for Distributed Design and Solid Freeform Fabrication, Proceedings of ASME DETC00, Paper No. DETC00/DAC-14293, Baltimore, Maryland, September 10-13

Saaty, T.L. (1991), The Analytic Hierarchy Process, McGraw-Hill, New York, NY

Schoop, M., Becks, A., Quix, C., Burwick, T., Engels, C., Jarke, M. (2002), Enhancing Decision and Negotiation Support in Enterprise Networks Through Semantic Web Technologies, www.sewasie.org/documents/ xsw2002.pdf

Seepersad, C.C., Mistree, F. and Allen. J.K. (2002), A Quantitative Approach for Designing Multiple Product Platforms for an Evolving Portfolio of Products, ASME Design Engineering Technical Conferences, Advances in Design Automation. Montreal, Canada: ASME, DETC2002/DAC-34096.

Simon, H. A. (1976), Administrative Behavior, Free Press, New York

Simon, H.A. (1996), The Sciences of the Artificial, Cambridge, Mass.: The MIT Press.

Simpson, T.W., Maier, J.R., and Mistree, F. (2001), Product Platform Design: Method and Application, Research in Engineering Design, 13(1): 2-22

Siskos, J., Lochard, J. and Lombard, J. (1984), A Multicriteria Decision-Making Methodology under Fuzziness: Application to the Evaluation of Radiological Protection Nuclear Power Plants, TIMS/Studies in Management Sciences, H.J. Zimmermann (ed.), Amsterdam: North-Holland, pp.261-283

Shen, W.M., Norrie, D.H., and Barthes, J.P. (2001), Multi-Agent Systems for Concurrent Intelligent Design and Manufacturing, Taylor & Francis**,** 2001

Sriram, R.D. (1997), Intelligent Systems for Engineering: A Knowledge-based Approach, London: Springer Verlag, UK

Sriram, R.D. (2002), Distributed and Integrated Collaborative Engineering Design, Sarven Publishers, Glenwood, MD, USA

Sriram, R.D., Szykman, S., and Durham, D. (2006), Special Issue on Collaborative Engineering, Guest Editorial, Journal of Computing and Information Science in Engineering, 6:2, pp.93-95, June 2006

Suh, N. P. (1990), The Principles of Design, Oxford University Press, New York, NY

Szykman, S., Sriram, R.D., and Regli, W. (2001), The Role of Knowledge in Next-Generation Product Development System, ASME Journal of Computing and Information Science in Engineering, 1(1): 3-11

Taguchi, G. (1986), Introduction to Quality Engineering, Tokyo, Japan: Asian Productivity Organization

Talukdar, S., Baerentzen, L., Gove, A., and de Souza, P. (1998), Asynchronous Teams: Cooperation Schemes for Autonomous Agents, Journal of Heuristics, 4, 295–321

Tanino, T. (1988), Fuzzy Preference Relations in Group Decision Making, Non-Conventional Preference Relations in Decision Making, J. Kacprzyk and M. Roubens (eds.), Berlin: Springer, pp.54-71

Tien, J.M. (2003), Toward a Decision Informatics Paradigm: A Real-Time, Information-Based Approach to Decision Making, IEEE Transactions on Systems, Man and Cybernetics, 33(1):102-113

Tong, C. and Sriram, R.D. (1992), Artificial Intelligence in Engineering Design, Academic Press, 1992

Thurston, D.L. (1991), A Formal Method for Subjective Design Evaluation with Multiple Attributes, Research in Engineering Design, 3(2): 105-122

Thurston, D.L., and Carnahan, J.V. (1992), Fuzzy Rating and Utility Analysis in Preliminary Design Evaluation of Multiple Attributes, ASME Journal on Mechanical Design, 114(4): 648-658

Thurston, D.L. and Locascio, A. (1994), Decision Theory for Design Economics, Special Issue, Engineering Economist, 40(1): 41-72

Thurston, D.L. and Crawford, C.A. (1994), A Method for Integrating End-User Preferences for Design Evaluation in Rule-Based Systems, ASME Journal of Mechanical Design, 116(2): 522-530

Tseng, T.Y. and Klein, C.M. (1989), New Algorithm for the Ranking Procedure in Fuzzy Decision-Making, IEEE Transactions on Systems, Man and Cybernetics, 19(5): 1289-96

Tseng, M.M. and Jiao, J.X. (1998), Product Family Modeling for Mass Customization, Computers in Industry, Vol. 35(3-4): pp 495-498.

Turban, E. and Aronson, R. (1998), Decision Support Systems and Expert Systems (Management Support Systems), Englewood Cliffs, NJ: Prentice-Hal, Chapter 2.

Vadde, S., Allen, J.K., and Mistree, F. (1994), Compromise Decision Support Problems for Hierarchical Design Involving Uncertainty, Computers and Structure, 52(4):645-658, 1994

von Neumann, J. and Morgenstern, O. (1947), Theory of Games and Economic Behavior, Princeton University Press

Wang, J. (1997), A Fuzzy Outranking Method for Conceptual Design Evaluation, International Journal of Production Research, 35(4): 995-1010

Wood, K.L., E.K. Antonsson and Beck, J.L. (1989), Representing Imprecision in Engineering: Comparing Fuzzy and Probability Calculus, Research in Engineering Design, 1(3-4): 187-203

Wood, K.L. and Antonsson, E.K. (1989), Computations with Imprecise Parameters in Engineering Design: Background and Theory, ASME Journal of Mechanism, Transmissions, and Automation in Design, 11(1): 616-625

Xiao,A., Choi, H., Allen, J.K., Rosen, D.W., and Mistree, F. (2002), Collaborative Decision Making Across Digital Interfaces, Proceedings of ASME DETC 2002, Paper No.: DETC2002/ DAC-34073, Montreal, Canada

Xiao, A., Choi, H., Kulkarni, R., Allen, J., Rosen, D., Mistree, F., and Feng, S.C. (2001), A Web-Based Distributed Product Realization Environment, Proceedings of ASME DETC 2001, Paper No.: DETC2001/CIE-21766, Pittsburgh, Pennsylvania.

Zimmermann, H.J. (1987), Fuzzy Sets, Decision Making, and Expert Systems, Boston: Kluwer Academic Publishers

Zadeh, L.A. (1965), Fuzzy Sets, Information and Control, 8: 338-353

Zha, X.F., Sriram, R.D., and Lu, W.F. (2003a), Knowledge-Intensive Collaborative Decision Support for Design Processes, Proceedings of ASME DETC 2003, Paper No: DETC2003/DAC-48747, Chicago

Zha, X.F., Lim, Y.E., Lu, W.F. (2003b), A Knowledge Intensive Multi-agent System for Cooperative/ Collaborative Assembly Modeling and Process Planning, Transaction of the SDPS, Journal of Integrated Design and Process Science, March 2003, Vol. 7, No. 1, pp.99-122.

Zha, X.F., Sriram, R.D., and Lu, W.F. (2004), Evaluation and Selection in Product Design for Mass Customization: A Knowledge Decision Approach, Artificial Intelligence for Engineering Design, Analysis and Manufacturing (AIEDAM), 18(1): pp. 87-109

Zha, X.F., Sriram, R.D. (2006), Knowledge-intensive Collaborative Decision Support for Design Process, Intelligent Decision-making Support Systems, J.N.D. Gupta, G.A. Forgionne and M. Mora (eds), Chapter 16, Springer, 2006

Zhang W.Y., Tor, S.B., and Britton, G.A. (2002), A Heuristic State-space Approach to the Functional Design of Mechanical Systems, International Journal of Advanced Manufacturing Technology, Vol.19, pp. 235-244