Knowledge-Intensive Collaborative Decision Support for Design Process, Part I: A Hybrid Decision Model and Multi-agent Framework

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Abstract

Engineering design is essentially a collaborative decision-making process that requires rigorous evaluation, comparison and selection of design alternatives and optimization from a global perspective. Increasing design knowledge and supporting designers to make intelligent and correct decisions can result in higher quality designs. In this paper we present a hybrid decision support model and framework, focused on facilitating the integration of objective and subjective aspects of design, which can be extensively applied for engineering systems. The proposed system will facilitate the seamless/smooth integration of the stakeholder involved in collaborative product development and improve the likelihood of optimal product performance. The work focuses on the provision of methodologies/algorithms and a framework for knowledge-based intelligent design decision-making for improved product development and realization of business strategies. The reported hybrid decision model, which integrates the compromise Decision Support Problem (cDSP) and the fuzzy synthetic model (FSD), can quantitatively incorporate qualitative design knowledge and preferences for multiple, conflicting attributes stored in a knowledge repository so that a better understanding of the consequences of design decisions can be achieved from an overall perspective. The developed model and framework are generic and flexible enough to be used in a variety of design decision problems. The framework is illustrated with an application in concept evaluation and selection in product family design for mass customization.

Keywords: design decision support, hybrid, decision model, collaborative decision-making mechanism, autonomous decision agent, and multi-agent framework

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1. Introduction

Engineering design is essentially a collaborative decision-making process that requires rigorous evaluation, comparison and selection of design alternatives as well as eventual optimization from a systems 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 alternative designs. Increasing design knowledge and supporting designers to make correct, intelligent decisions can increase design efficiency. Thus, a design strategy must be devised to specifically address all aspects of design including process modeling, knowledge modeling, decision support, and the inherent complexity arising from representing physical design problems using idealized computer-based models. Such a strategy can, then, lead to the identification and development of knowledge decision support techniques that play a critical role in enabling designers to make intelligent decisions towards improving the overall quality of the products designed.

Contemporary design processes have become increasingly information-intensive and collaborative. Knowledge-based support is becoming more critical in the design process and has been recognized as a key solution for maintaining competitive advantages in future product development. A knowledge supported design system can help companies capture and archive their design knowledge and more effectively manage their design processes. It can also support communication and teamwork by sharing the most up-to-date design information. Designers, especially novices, can benefit from retrieval of knowledge about previous designs and applying it to new designs, or by gaining insight into the design of earlier, related products. By making use of design knowledge, companies are expected to improve the design process to facilitate the design of more innovative products and reduce product development cycle time. A design decision support system can aid design teams make better decisions and serve as a kernel of such a knowledge-supported design system.

In this paper we aim to develop a knowledge supported decision support methodology to serve as a basis for the smooth integration of stakeholders involved in collaborative product development and improving product performance. The goal is to develop a sound, practical trade-off based design decision model that can quantitatively incorporate qualitative knowledge and preferences for multiple, conflicting attributes stored in a knowledge repository. The research focus in this paper is to establish a hybrid decision model and framework which may integrate one or more techniques such as the cDSP, fuzzy systems, neural networks, intelligent agents, data mining and knowledge discovery (e.g. fuzzy clustering algorithm), etc. to solve both concurrent and sequential design decisions.

The work in this paper involves the development of a complex decision-making model and framework for a design process from the perspectives of knowledge management and decision support. Technologies, such as design process and knowledge modeling, decision theory, optimization, distributed agents and web-based collaboration support, are exploited to explore structured support for both single and distributed design teams. The hybrid decision model presented in this paper provides an effective interface for designers and a guideline for decision-making in knowledge intensive and distributed collaborative design processes. Specifically, several relevant technologies for the development of the decision support engine (as an autonomous agent) and integration with a web-based product design and realization system and framework will be addressed and developed:

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 process is highlighted. Section 4 proposes a hybrid decision model. Section 5 proposes 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. Section 7 provides two case studies. Section 8 summarizes the paper and points out opportunities for future work.

2. Current Research Status

Design Decision Support Problems necessitate a search for superior or satisficing (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 technologies to assist product designers to make decisions in the design process (Rosen et al. 2000, Mistree et al. 1995, Fernández et al. 2002a,b), where primary emphasis is on support for information management related to decision-making. Generally, the literature on design evaluation and selection decision support can be classified into six categories (Jiao and Tseng 1998): 1) multi-criteria utility analysis (Seepersad et al. 2002, Fernández et al. 2001), 2) fuzzy set analysis, 3) probability analysis, 4) the hybrid approach, 5) design analytic methodology, and 6) the information content approach (Suh 1990, 1998). The following review will focus on the first five approaches, due mostly to their current popularity.

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 multiple criteria. It has been widely applied 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 design criteria, *i.e.*, intangible criteria, are involved and difficult to quantify (Thurston and Carnahan, 1992, Fernández et al. 2001).

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," "medium," *etc.* It 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 most appropriate 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 with linguistic terms, it requires discreet deliberation in dealing with crisp information. A domain-specific method is needed to "fuzzify" each tangible criterion whose evaluation is naturally estimated as an ordinary real variable (Carnahan et al., 1994). Another challenge is the incomparability between 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. 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 at the preliminary stages of design (Carnahan, Thurston and Liu 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) presented 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) proposed to "fuzzify" the weights subsequent to their having been obtained via AHP.

There are also many other product feasibility and quality assessment tools that are useful for planning the design of products, such as quality function deployment (QFD) (Clausing 1994), concurrent function deployment (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 in the computer or network-centric design environment (Sriram 2002, Rosen et al. 2000, Panchal et al. 2002, Xiao et al. 2001, Gerhard et al.2000). Some techniques are intended to help designers collaborate or coordinate by sharing product information and manufacturing services through formal as well as informal interactions, while others are geared towards conflict management. Most decision support programs can only calculate satisfaction levels. 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 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 of the necessary knowledge and information (Forgionne, 1994). Mathematical programming, utility analysis and algorithm-rigorous optimization modeling approaches (e.g., compromise Decision Support Problem (cDSP) & goal programming techniques) 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). A knowledge-based decision support model, however, as proposed here, overcomes many of the shortcomings discussed earlier.

3. Design Decision Support Process: Decision-based Design

3.1 Decision Support Process

Generally speaking, decision-making 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, as shown in Figure 1. It involves several stages ranging from problem identification and classification, simplification of assumptions, data collection, model formulation, solution alternative generation, evaluation, selection, model validation, verification, and testing of the proposed solution to final implementation of the plan devised. Current research is focused predominantly on how knowledge support can aid the decision-maker during the design process. Figure 2 illustrates a scenario of implementing knowledge-based decision support (DDS) from the perspective of decision knowledge management (DKM), in which knowledge management technologies include knowledge generation and acquisition, knowledge codification, and knowledge processing and utilization (reasoning), etc.

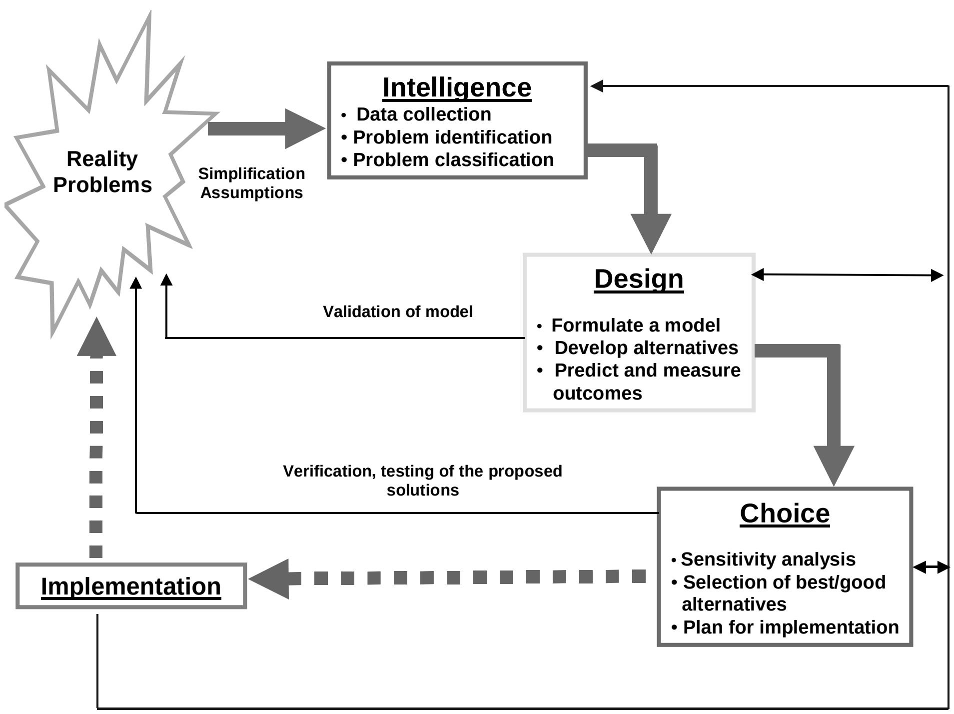


Figure 1: Decision support process (from Simon 1976)

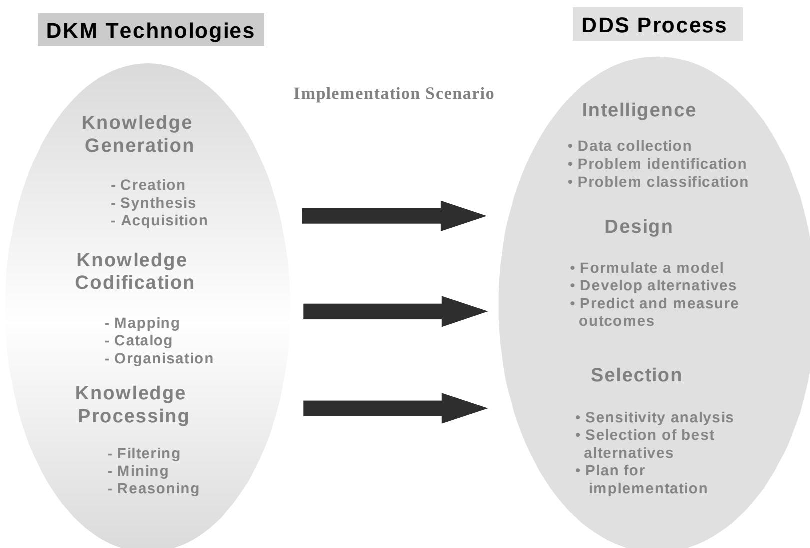


Figure 2: Decision support implementation scenario

3.2 Decision-Based 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, as shown in Figure 3. We view design as the process of converting information that characterizes the needs and requirements for a product into knowledge about a product. 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.

In this paper, we present the development of a knowledge intensive design decision support scheme, as depicted in Figure 4, in which design decision support is exploited from the perspective of synthesis of design process modeling (DPM), knowledge management (KM), and decision support (DS). Game theory, utility theory, probability theory, fuzzy set theory and extension set theory, among others, play a key role for implementing our framework (see Hazelrigg 1996 and Fernández et al. 2002b for discussion of some of these techniques).

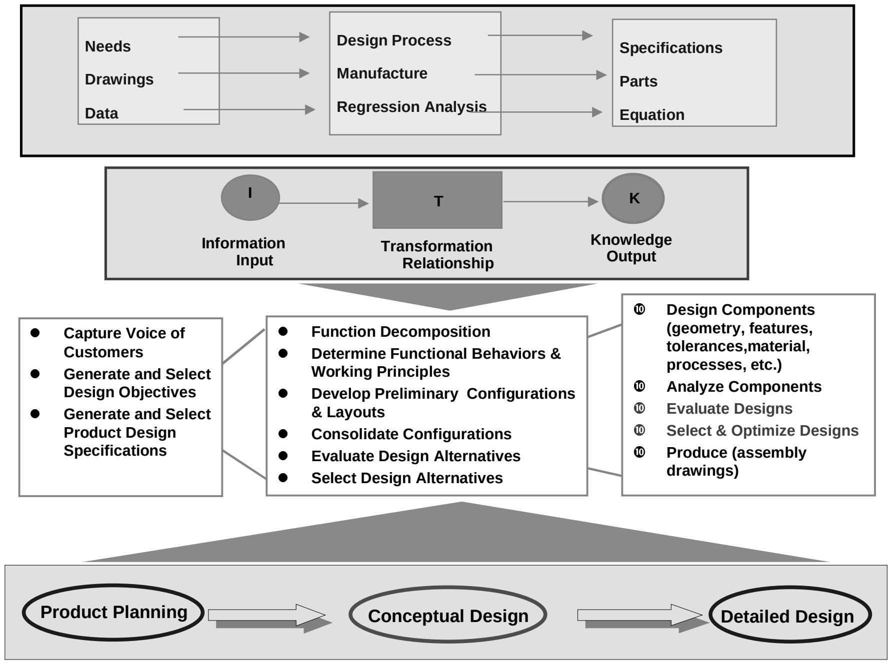


Figure 3: Design process task and decision-based design

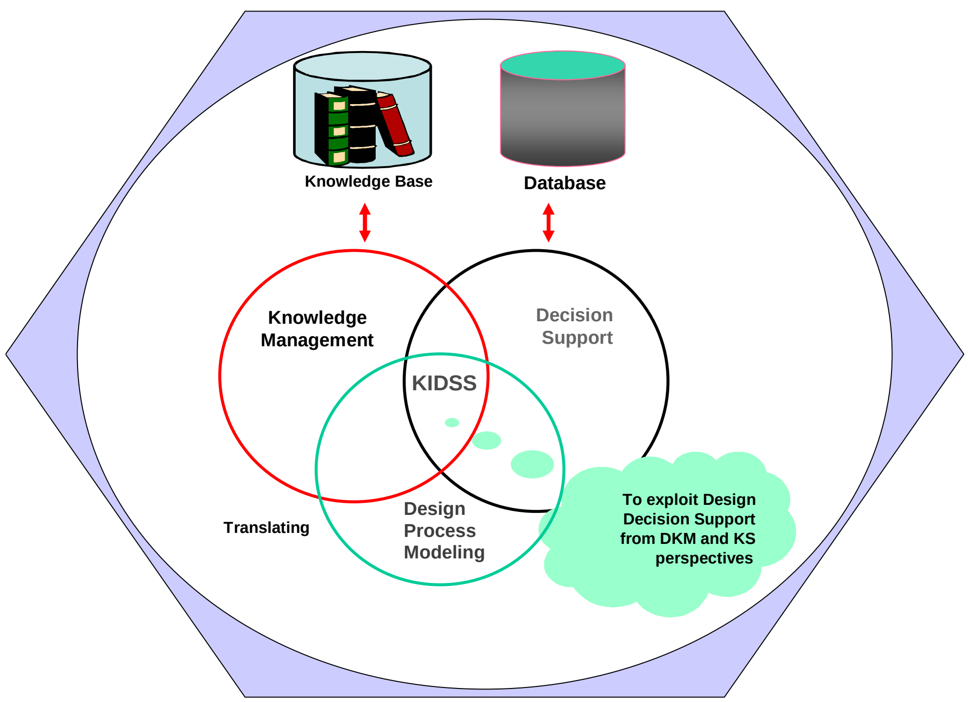


Figure 4: Knowledge intensive design support system (KIDDS)

4. Hybrid Decision Model: Technical Description

In this section, we present a hybrid decision model which may integrate one or more techniques such as the cDSP, fuzzy systems, neural networks, intelligent agents, data mining and knowledge discovery (e.g. fuzzy clustering algorithm), extension theory and genetic algorithms, etc., to solve both compatible and incompatible decision problems. Details of these techniques are provided below.

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,

$g_i(\boldsymbol{X})$: system constraint functions ,

$f_k(d_i)$: function of deviation variables to be minimized at priority level k for the preemptive case.

Find

System Design Variables**,** X_i, $i = 1,\ldots, n$

Deviation Variables, d_i^-, d_i^+, $i = 1,\ldots, m$

Satisfy

System constraints (linear, nonlinear)

$g_i(\boldsymbol{X}) = 0$; $i = 1, .., p$

$g_i(\boldsymbol{X}) \geq 0$; $i = p+1, .., p+q$

System goals (linear, nonlinear)

$A_i(\boldsymbol{X}) + d_i^- - d_i^+ = G_i$; $i = 1, \ldots, m$

Bounds

$X_i^{\min} \leq X_i \leq X_i^{\max}$; $i = 1, \ldots, n$

$d_i^-, d_i^+ \geq 0$, $d_i^- \cdot d_i^+ = 0$; $i = 1, \ldots, m$

Minimize: deviation function

$\boldsymbol{f} = [\, f_1(d_i^-, d_i^+), \ldots, f_k(d_i^-, d_i^+)\,]$

Figure 5: Mathematical form of a cDSP (Mistree et al. 1993)

4.1 The compromise Decision Support Problem (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 (Mistree et al. 1993, 1995). Two primary types of decisions are supported within the DSP technique: *selection* and *compromise*. Complex decisions are supported though 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) (Xiao et al. 2002, Fernández et al. 2002b). 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 (cDSP) model, 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 (Figure 5).

4.2 Fuzzy Synthetic Decision Model (FSD)

The problem of design evaluation and selection can be defined as follows: given a set of design alternatives, evaluate and select a design alternative that can satisfy customer needs, meet design requirements and fit the technical capabilities of a company. To combine expert judgment and process-useful knowledge for decision-making, a fuzzy synthetic decision model is developed in this section, based on fuzzy AHP, ranking algorithms and inference mechanisms for engineering design evaluation and selection.

4.2.1 Fuzzy Analytic Hierarchy Process

The AHP mechanism proposed by Saaty (1991) is widely recognized as a useful tool to support multi-attribute decision-making. Its versatility in dealing with qualitative factors, multiple objectives, and decision makers has resulted in an impressive array of applications such as energy planning, conflict resolution, finance and banking (Kim et al. 2003). It is a compositional approach where a multi-attribute problem 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 ration matrix of pairwise comparisons. Using AHP, a designer is capable of choosing weights by comparing the importance of two criteria subjectively. The pairwise comparison ratio which is comparison of 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. In this study, each agent has its own matrix A, and exchanges the matrix between agents to cooperatively adapt to changes in the design process. In AHP, the pairwise comparison matrix should be examined for reliability of consistency. 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, the matrix should be reset by comparing importance again. Therefore, the focus should be on the comparison matrix A. Currently, most researchers compose AHP comparison matrix A according to user's individual and flexible preferences. In a flexible negotiation environment, however, most agents may change their offers according to counter offers. Hence, there is a need to build the comparison matrix A dynamically. In this work, we combine fuzzy membership functions with the AHP to pursue the preference of agents dynamically, and as a result, we propose the fuzzy comparison matrix A.

4.2.2 Fuzzy Ranking for Evaluation

Using the design solution techniques at the conceptual design stage a reasonable number of possible design alternatives can be obtained (Pahl and Beitz 1996, Suh 1990). Once this is achieved, one needs to examine the design alternatives against marketing and econo-technical as well as ergonomic criteria and aesthetic criteria. This is actually a multi-criteria decision-making problem. One of the well-known methods for multi-criteria decision-making is the traditional procedure for calculating a weighted average rating $\bar{r}_i$ by use of value or cost-benefit analysis (Pahl and Beitz 1996):

$$\bar{r}_i = \sum_{j=1}^{n} (w_j r_{ij}) / \sum_{j=1}^{n} w_j \tag{4}$$

where, i=1,2,…,m, j=1,2,3,…, n , r_{ij} denotes the merit of alternative a_i according to the criterion C_j; w_j denotes the importance of criterion C_j in the evaluation of alternatives. The higher $\bar{r}_i$ is, the better is its aggregated performance.

However, the above traditional procedure is not applicable for situations where uncertainty exists and the available information is incomplete. For example, the terms "very important," "good," or "not good" themselves constitute a fuzzy set. Here, we give an example of the problem of fuzzy ranking in terms of evaluating a set of alternatives against a set of criteria. Let a set of m alternatives A={a_1, a_2,...,a_m} be a fuzzy set on a set of n criteria C={C_1,C_2,...,C_n } to be evaluated. Suppose that the fuzzy rating $\tilde{r}_{ij}$ to certain C_j of alternative a_i is characterized by a membership function $\mu_{\tilde{R}_{ij}}(\tilde{r}_{ij})$, where, $\tilde{r}_{ij} \in R$, and a set of weights $\tilde{W} = \{\tilde{w}_1, \tilde{w}_2, ..., \tilde{w}_n\}$ is fuzzy linguistic variables characterized by $\mu_{\tilde{W}_j}(\tilde{w}_j)$, $\tilde{w}_j \in R^+$. Consider the mapping function $g_i(\tilde{z}_i) : R^{2n} \to R$ defined by:

$$g_i(\tilde{z}_i) = \sum_{j=1}^{n} (\tilde{w}_j \tilde{r}_{ij}) / \sum_{j=1}^{n} \tilde{w}_j \tag{5}$$

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 $\mu_{\tilde{Z}_i}(\tilde{z}_i)$ by

$$\mu_{\tilde{Z}_i}(\tilde{z}_i) = \overset{\circ}{\wedge}_{j=1,...,n} \mu_{\tilde{W}_j}(\tilde{w}_j) \overset{\circ}{\wedge}_{k=1,...,n} \mu_{\tilde{R}_{ik}}(\tilde{r}_{ik}) \tag{6}$$

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

$$\mu_{\tilde{R}_i}(\tilde{r}_i) = \sup_{Z_i g(\tilde{z}_i) = \tilde{r}_i} \mu_{\tilde{Z}_i}(\tilde{z}_i), \bar{r}_i \in R \tag{7}$$

The final fuzzy rating of design alternative a_i can be characterized by this membership function. But it does not mean the alternative with the maximal $\mu_{\tilde{R}}(\tilde{r}_i)$ is the best. The following procedure can be employed to further characterize the two fuzzy sets as (Gui 1993):

(1) a conditional fuzzy set is defined with the membership function:

$$\mu_{I/R}(i \mid \tilde{r}_1, ... \tilde{r}_m) = \begin{cases} 1 & \text{if} \quad \tilde{r}_i > \tilde{r}_k, \forall k \in (1,2,...,m) \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

(2) a fuzzy set is constructed with membership function:

$$\mu_R(\tilde{r}_1, ... \tilde{r}_m) = \overset{\circ}{\wedge}_{i=1,...,m} \mu_{\tilde{R}_i}(\tilde{r}_i) \tag{9}$$

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

$$\mu_I(i) = \sup_{\tilde{r}_1, ... \tilde{r}_m} \mu_{I/R}(i \mid \tilde{r}_1, ... \tilde{r}_m) \overset{\circ}{\wedge} \mu_R(\tilde{r}_1, ... \tilde{r}_m) \tag{10}$$

Comparing with Eq.(4), the fuzzy ranking for design alternatives is more flexible and presents uncertainty better. Based on this method, a designer can now effectively and consistently incorporate linguistic rating and weights such as “good,” “fair,” “important,” “rather important,” etc., in design alternatives evaluation.

4.2.3 Evaluation Function and Index for Selection

The design space for a complex system is very large. The designer is often required to consider not only product functionality, but also other criteria including compactness and other 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 available alternatives. As such, it is important to have a powerful search strategy that will lead to a near optimum solution in a reasonable amount of time. The A* search algorithm constitutes such a method (Sriram 1997, Zhang et al. 2002).

In the proposed approach, the system first calculates the weighted performance rating aggregation of each retrieved alternative by analyzing the trade-off among various criteria. Then, it calculates the evaluation index of each design alternative by considering all the weighted performance ratings. After calculating the numerical weighted performance ratings of all design alternatives, the evaluation index is used as a heuristic evaluation function f_h, by considering all the weighted performance ratings $\overline{r}_i$ (i=1,2, …, m) of its constituent members and the number k of its unsatisfied customer requirements, as follows:

$$f_h = \sum_{i=1}^{m} (1/\overline{r}_i) + k \tag{8}$$

where, $\overline{r}_i \in [0,1]$ is the numerical weighted performance rating of the design alternative a_i ; $1/\overline{r}_i = (1,+\infty)$ 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. $\sum_{i=1}^{m} (1/\overline{r}_i)$ represents the accumulated performance cost of a design alternative along the search path thus far. k is a heuristic estimate of the minimal remaining performance cost of a design alternative along all the possible succeeding search paths. f_h is the estimate of the total performance costs of a design alternative. f_h is also called the evaluation index or the heuristic evaluation function. In Eq.(8), a higher $\overline{r}_i$, i.e., 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 of a design alternative 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.

4.3 Integration and Cooperation of Decision Models

All available algorithms for optimization and constraint satisfaction have weaknesses; more rigorous algorithms tend to be too slow, heuristics, too unreliable. 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 2003).

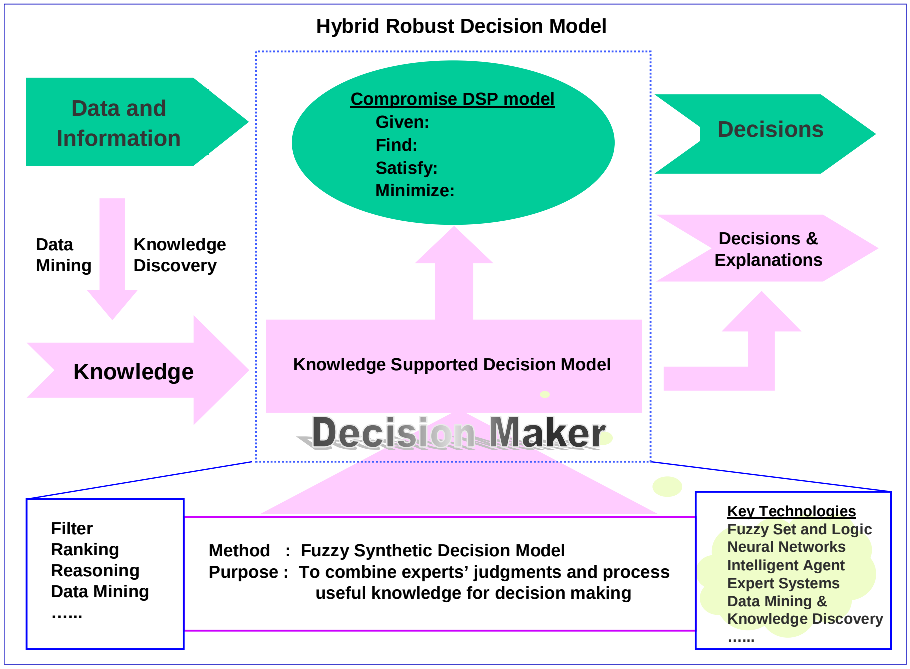


Figure 6: Hybrid decision support model

As stated above, the cDSP model is basically data and information centric and more appropriate for implementation in conjunction with tangible (quantitative) criteria rather than for 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 6 provides a schematic view of the hybrid decision model integrating the cDSP and FSD models. The scheme or mode of integration and coordination could be either "loose," or "tight." In the loose mode, two or more models are combined and they work together but complement each other. Depending on the nature of the decision problem, a rule-based adaptor (selector) is employed in the model. This adaptor serves as a regulatory switch to adapt the decision problems by shifting the paradigms from one decision method (e.g., cDSP) to another (e.g., FSD). In the tight mode, two or more models co-exist and are integrated into a single hybrid model, for example, fuzzy cDSP, fuzzy neural networks or the neuro-fuzzy system, etc. This kind of knowledge supported model can manage design decision knowledge and provide real-time or on-line support to designers in the decision-making process. Specifically, 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) designer are stimulated in generating new design ideas (with learning continuously taking place being captured).

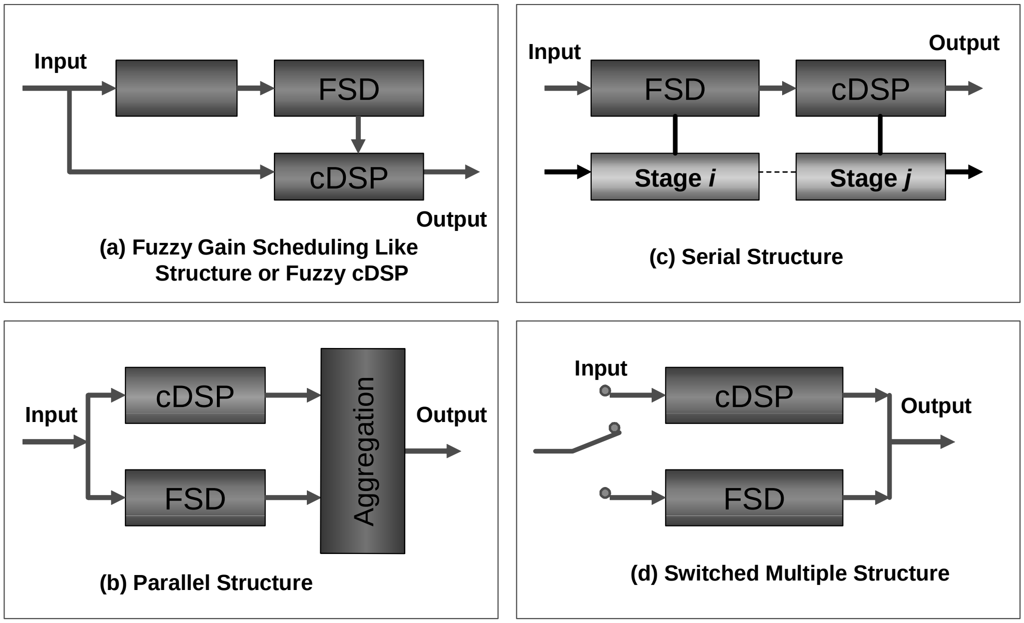


Figure 7: Structure of the hybrid models

The decision of which models are to be used 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 hybrid models are illustrated in Figure 7. Figure 7(a) is a gain scheduling like structure. The above fuzzy ranking algorithm for some design parameters or variables is adopted in this hybrid structure. Figure 7(b) is a parallel structure of the hybrid model. Figure 7(c) gives a serial modeling structure of the hybrid model. It is proposed that a set of separate models be used to formulate hybrid models and model process behavior at different design stages. Figure 7(d) shows a rule-based selector incorporated in the scheme, which switches 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. To provide 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 will be provided in Section 6. A more detailed discussion regarding the integration and cooperation of decision models is required. This discussion, however, is deferred to a separate paper.

5. Multi-Agent Collaborative Design Decision Support Framework

The overall knowledge-intensive multi-agent design decision support scheme, proposed, is shown in Figure 8. This scheme consists of a design process modeling and management agent, a knowledge capture agent, a knowledge repository, co-designers, a decision support agent, etc. The core of the scheme is the decision support agent and will be the focus of our discussion. The knowledge repository is used to store, share, and reuse the corporate design knowledge, as shown in Figure 9 (for discussion on the role of knowledge in next generation CAD systems, see Szykman 2001). The communication, negotiation and execution mechanisms between these agents can be modeled with contract nets. A prototype web-based design decision support system has been developed to verify the developed methodologies (algorithms) and framework.

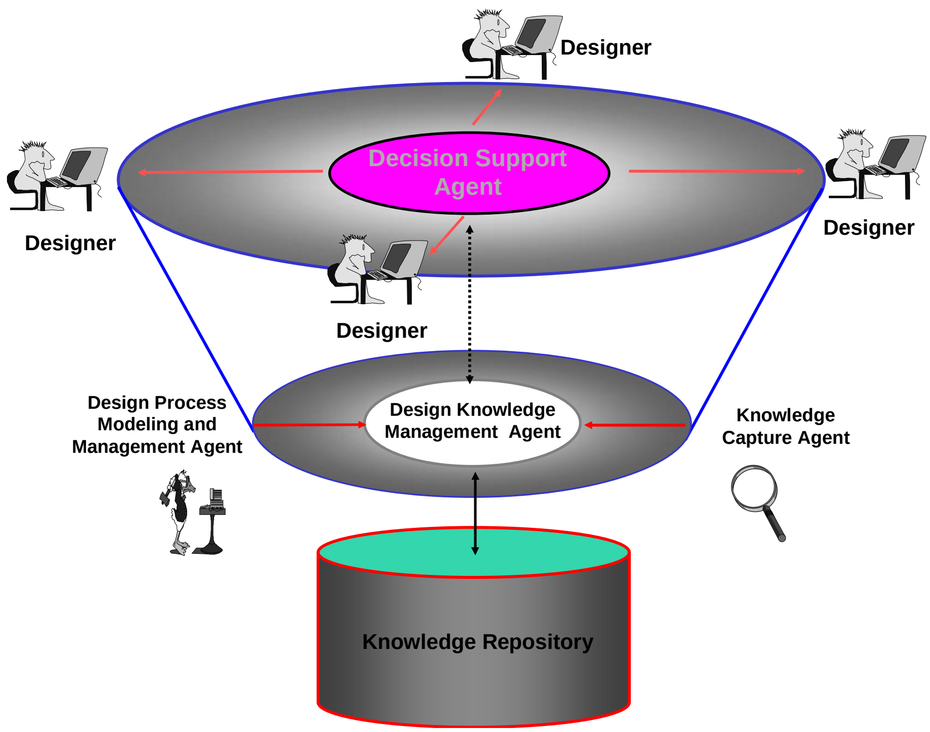


Figure 8: The overall multi-agent knowledge intensive decision support framework

The decision support agent could be used as an autonomous agent to be finally integrated into a web-based product design and realization framework to support collaborative decision-making in the product development process (design chain). The decision support agent should be able to make autonomous decisions concerning: 1) spawning an agent to search in a given direction, 2) killing an agent that is not very successful, 3) negotiation between agents (unless they need to consult the designer), 4) recognition of novelty of a solution (eventually consulting the knowledge repository or database of existing solutions) and turning designer's attention towards it, 5) when to consult the designer, etc.

The comparative ranking of alternatives and decision-making discussed in Section 4.2 is a fundamental component of the design decision agent. As stated previously, several formal decision models exist (see Section 2). Utility theory (Keeney and Raiffa 1976) and AHP (Saaty 1991) are well known examples. The decision support agent, illustrated in Figure 10, is a container specialized in providing evaluation services. It contains criteria which pair design attributes (variable modules) with preference modules (a type of variable module used to define preference functions).

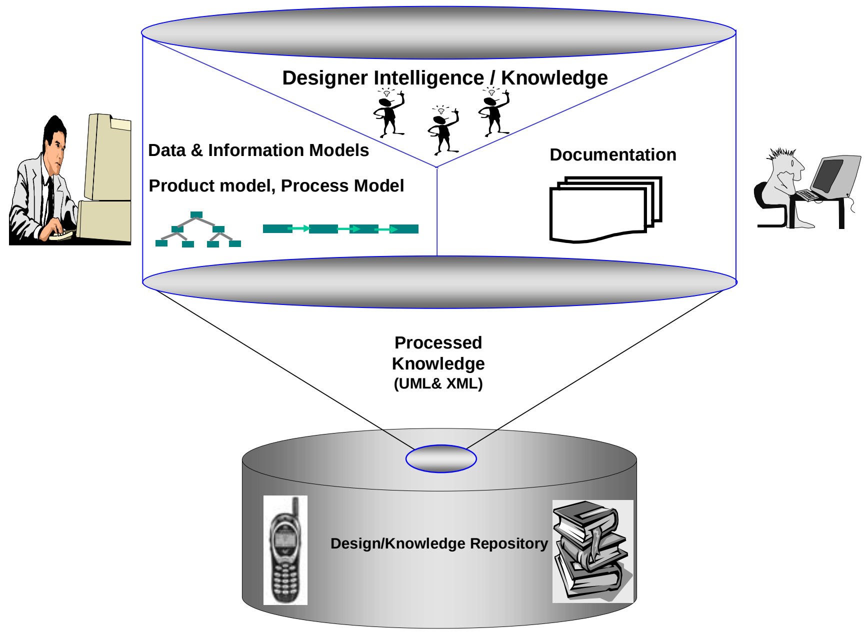


Figure 9: Knowledge repository for the design process

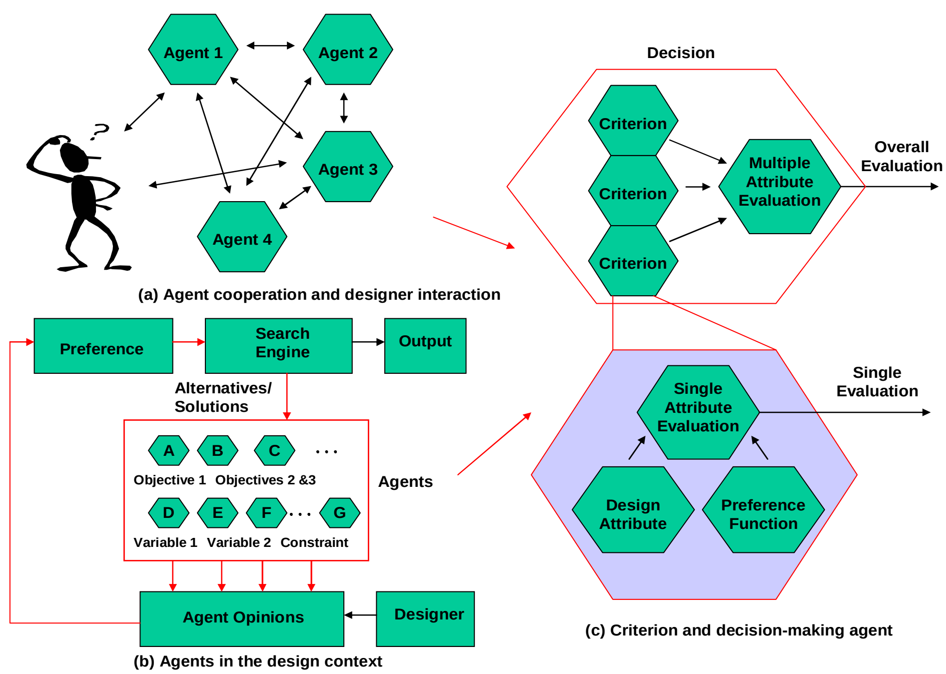


Figure 10: Decision support agent.

The decision agent provides an overall multiple attribute evaluation service while each criterion evaluates a single attribute. The relations of the criterion and decision agent are not user defined. The criterion relations calculate the worth of the design attribute based upon the preference model, while decision agents automatically generate relations to aggregate single attribute evaluations for multiple attribute decision. Thus, there are different types of decision agents. In the prototype implementation the decision agent has been developed by integrating the cDSP technique with an expert/knowledge model into a hybrid decision support model for criterion/argument analysis and fusion.

6. Application in Conceptual Platform-based Family Design Decision Support

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. 1998, 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 compromise Decision Support Problem (cDSP) models are key procedures. This means that the cDSP models play a key role in the platform and family design process. Our goal in this research is to use the knowledge supported decision model (i.e., FSD model) for family design evaluation and selection. In general, we intend to demonstrate a typical application of the hybrid decision model for product platform and family design evaluation and selection. More specifically, the cDSP model is used to develop 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 (see Figure 7). In what follows, we provide more details on knowledge decision support for family design evaluation and selection.

To be in line with the general conceptual design stage (Figure 11), a family of product concepts (variants) can be explored and generated using the PPCEM and vary widely by the 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 stages and can result in costly redesign. Thus, concept evaluation and selection are crucial for product family design and mass customization. While a number of methods have been investigated (see Section 2), there is still much work to be done due to the difficulty inherent in the conceptual evaluation and selection process. In line with more traditional approaches (e.g., Pahl and Beitz

1996), we use a knowledge decision support approach for concept evaluation and selection, as shown in Figure 12.

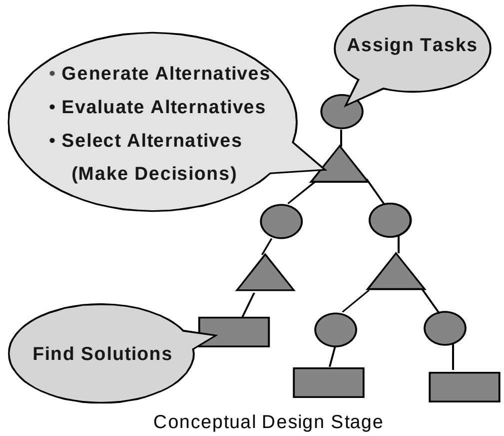


Figure 11: Concept evaluation and selection in design

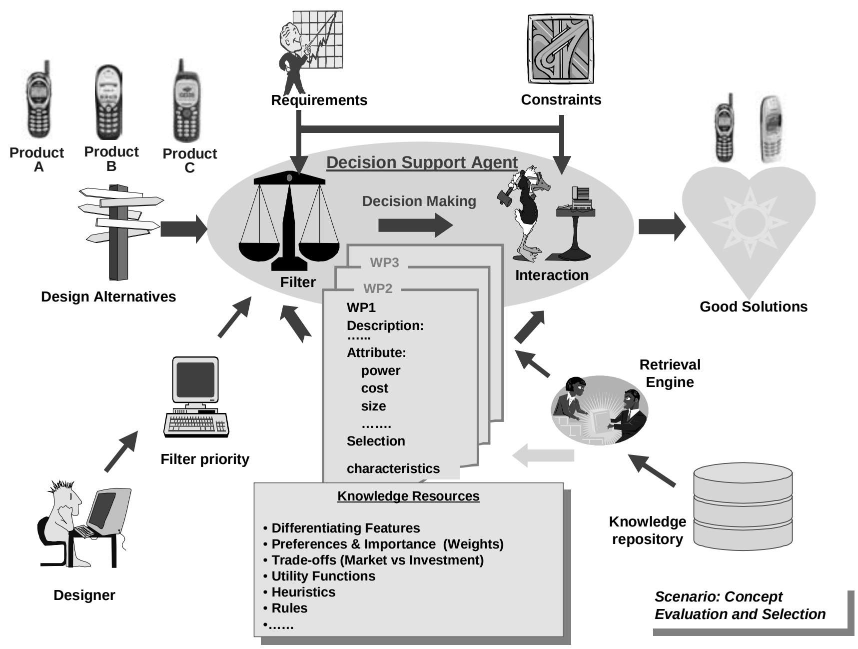


Figure 12: Knowledge decision support for concept evaluation and selection

Typically, the stage of family evaluation and selection characterizes a feasible set of product variants generated from a product platform as an input and the final customized product as an output, experiencing the elimination of unacceptable alternatives, the evaluation of candidates for customization, and the final decision under the various customers' requirements and design constraints. The designer is required to consider not only product functionality, but also some other criteria including compactness and life-cycle issues such as assemblability, manufacturability, maintainability, reliability, and efficiency. Of course, some criteria may conflict with one another. Designers should analyze the inherent trade-offs among various criteria and make the "best" selection from among the design alternatives considered. Due to the fuzziness of voice of customers (VoCs) or customer requirements/preferences, it is even more difficult to model and assess the performance of a product platform/family and product variants when handling fuzzy knowledge. The kernel of the knowledge decision support scheme is the fuzzy ranking algorithm for design evaluation and selection discussed above. The knowledge resource utilized in the process includes extensive features, customers' requirements, desires, preferences and importance (weights), trade-offs (e.g., market vs investment), and utility functions, and heuristic knowledge, rules, etc.

7. Case Studies

To illustrate and validate the hybrid decision model, 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.

7.1 Universal Motor Platform and Product Family Design Decision

Universal motors are the most common component in power tools. According to Myer and Lehnerd (1997), in the 1970s Black & Decker developed a family of universal motors for its power tools in response to a new safety regulation: double insulation. Prior to that, Black & Decker 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 machine 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. Figure 13 shows the universal motor platform and family design. Simpson et al. (2001) reported the use of the cDSP-based Product Platform Concept Exploration Method (PPCEM) to design a universal motor platform and a family of universal motors in a similar manner. The cDSP model used for this case is given in Appendix A. Figure 14 illustrates the cDSP model for the universal motor platform and shows the benchmark universal motor product family specifications and performance responses. For more details, please refer to Simpson et al. (2001).

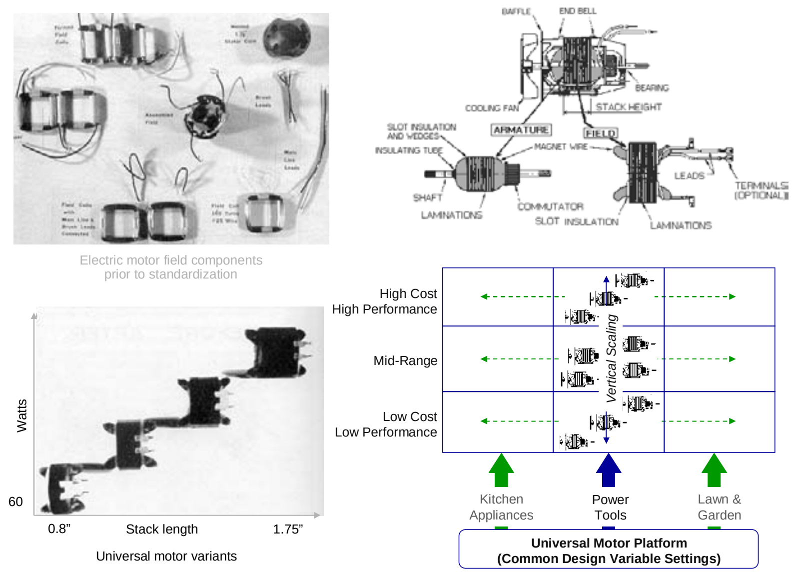


Figure 13: Universal motor product platform and family design (Myer and Lehnerd 1997)

Platform instantiations:

	L [cm]	T [Nm]	μ	M [kg]	
High	2.44	0.50	47.9	0.83	10
	2.40	0.40	53.1	0.82	9
	2.33	0.35	55.9	0.80	8
Mid	2.21	0.30	58.8	0.78	7
	2.04	0.25	61.8	0.73	6
	1.81	0.20	65.1	0.68	5
	1.50	0.15	68.5	0.61	4
Low	1.32	0.13	70.3	0.56	3
	1.11	0.10	72.2	0.51	2
	0.62	0.05	76.0	0.40	1

Group of individually designed motors:

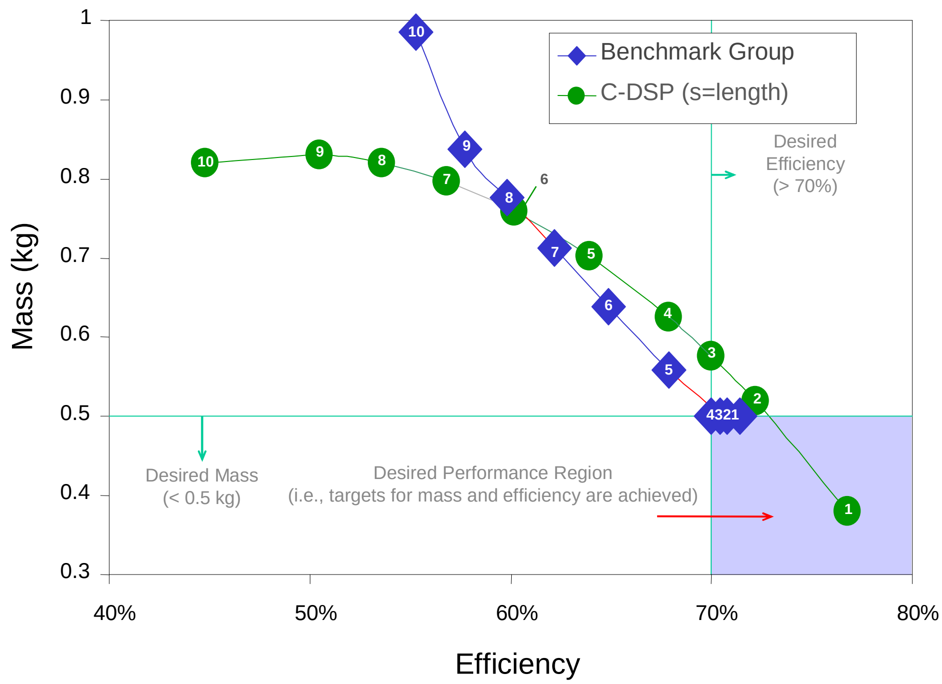
	N_a, N_f, A_f, A_a, r, t	L [cm]	T [Nm]	η [%]	M [kg]
10	1087, 72, 0.28, 0.25, 2.71, 7.15	3.16	0.50	55.3	0.99
9	1082, 72, 0.27, 0.24, 2.58, 6.67	2.87	0.40	57.7	0.84
8	1056, 73, 0.26, 0.24, 2.51, 6.46	2.81	0.35	59.8	0.78
7	1030, 73, 0.25, 0.23, 2.44, 6.35	2.74	0.30	62.2	0.71
6	1007, 73, 0.25, 0.22, 2.35, 6.17	2.61	0.25	64.9	0.64
5	988, 74, 0.24, 0.22, 2.26, 5.75	2.38	0.20	67.9	0.56
4	785, 95, 0.21, 0.21, 2.82, 8.88	1.63	0.15	70.5	0.50
3	760, 89, 0.19, 0.20, 3.12, 11.20	1.41	0.13	70.0	0.50
2	750, 76, 0.19, 0.20, 3.31, 11.77	1.28	0.10	70.6	0.50
1	730, 45, 0.20, 0.21, 3.62, 9.69	0.998	0.05	71.4	0.50

Universal Motor Platform
{N_c, N_s, A_{wa}, A_{wf}, r, t}
1273, 61, 0.27, 0.27, 2.67, 7.75

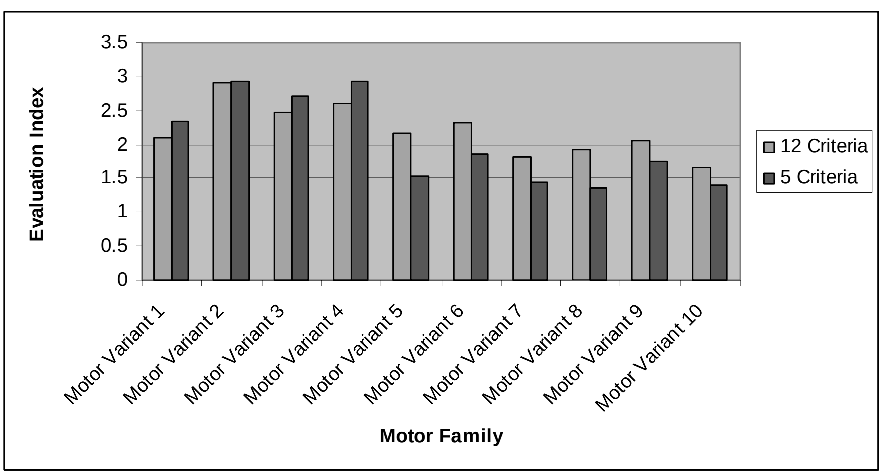
cDSP for Product Platform

Figure 14: Benchmark universal motor product family specifications and performance responses

As stated above, our goal in this case is to use the knowledge supported decision model (i.e., FSD model) to evaluate and select an appropriate motor family. Suppose that we need to select the best motor for a customer from 10 motor variants in the family obtained above. We first consider 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). The final decision can be reached based on knowledge resources, including differentiating features and their membership functions, fuzzy rules, fuzzy rankings, etc. The final design decision made by the decision support agent is Motor 10 in the family. Table 1 gives weights and partial performance ratings for each criterion (for No.1 motor) alongside evaluation results. Only the last 5 performance features (above) are considered as criteria for evaluation and selection (i.e., L(cm), T(Nm), P(W), η(%), and M(kg)). As such, the final design decision made by the decision support agent is Motor 8. Table 2 shows weights and partial performance ratings for each criterion (for No.1 motor) and evaluation results. Figure 15 shows a comparison of the obtained results using the cDSP and FSD models.



(a) Comparison of the benchmark group and cDSP for mass-efficiency relations (based on Simpson et al. 2001)



(b) Evaluation with the FSD model for 5 and 12 criteria cases

Figure 15: Comparison of the obtained motor family design results using the cDSP and FSD models

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:

No.	Family (Variants)	Evaluation Index	Rankings
1	Motor 1	2.108	5
2	Motor 2	2.920	10
3	Motor 3	2.478	8
4	Motor 4	2.594	9
5	Motor 5	2.175	6
6	Motor 6	2.319	7
7	Motor 7	1.825	2
8	Motor 8	1.928	3
9	Motor 9	2.049	4
10	Motor 10	1.655	1

Table 2: Weights and partial performance ratings, evaluation results (5 criteria)

Criterion No.	Criterion Item	Criterion Weight			Partial Performance Rating		
		Linguistic Term	Fuzzy Number	Weight Value	Linguistic Term	Fuzzy Number	Rating Crisp Value
1	T(Nm)	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}=0.075
2	P(W)	High	(0.7,0.8,0.8,0.9)	W_2=0.00	Very Low	(0.0, 0.0,0.1,0.2)	r_{12}=0.075
3	M(kg)	Very High	(0.8,0.9,1.0,1.0)	W_3=0.95	Very Low	(0.0, 0.0,0.1,0.2)	r_{13}=0.075
4	L(cm)	High	(0.7,0.8,0.8,0.9)	W_4=0.80	Very Low	(0.0, 0.0,0.1,0.2)	r_{14}=0.075
5	η (%)	Very High	(0.8,0.9,1.0,1.0)	W_5=0.95	Very High	(0.8,0.9,1.0,1.0)	r_{15}=0.950

Evaluation Results:

No.	Family (Variants)	Evaluation Index	Rankings
1	Motor 1	2.331	7
2	Motor 2	2.932	9
3	Motor 3	2.705	8
4	Motor 4	2.933	10
5	Motor 5	1.538	4
6	Motor 6	1.849	6
7	Motor 7	1.434	2
8	Motor 8	1.367	1
9	Motor 9	1.759	5
10	Motor 10	1.403	3

7.2 Power Supply Family Design Selection

Power supplies are necessary components of all electronic products. Because of diverse requirements, power supply products are often customized. The proposed hybrid decision model is used for decision making in power supply family design for mass customization. The 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 to evaluate and select a power supply design alternative. Using the cDSP model, three different clusters (families) are obtained. The modular design of power supply products is based on the work presented in (Tseng and Jiao 1998, Zha and Lu 2002, Zha et al. 2004). Figure 16 illustrates the process of clustering design variations and instances.

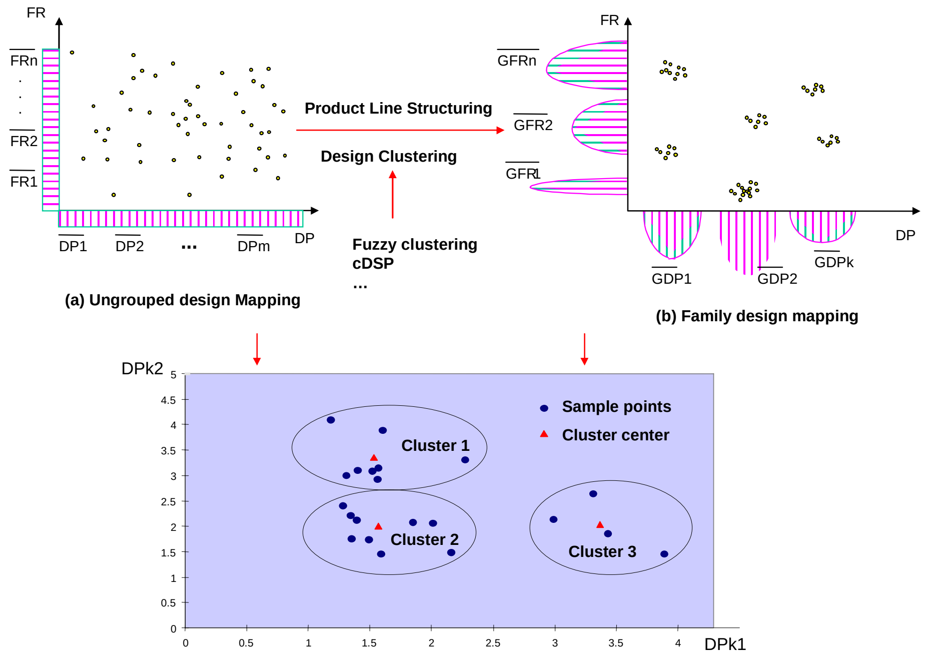
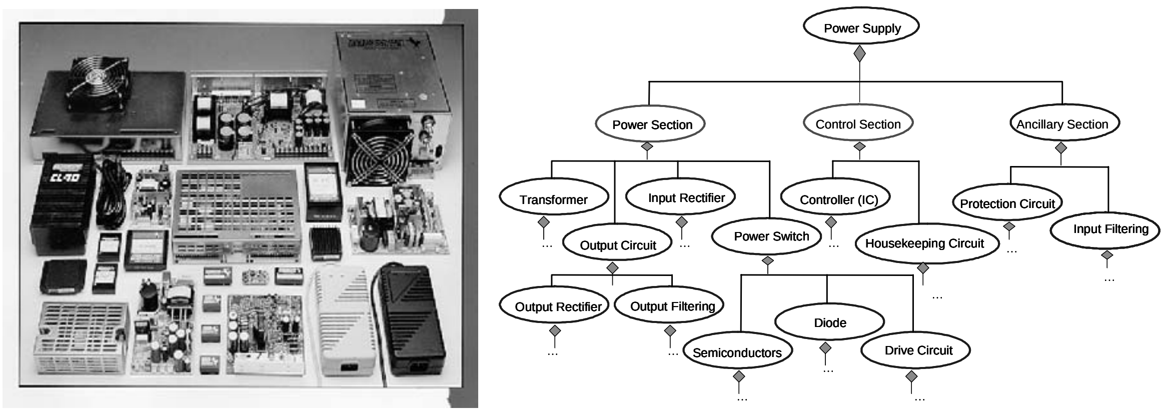
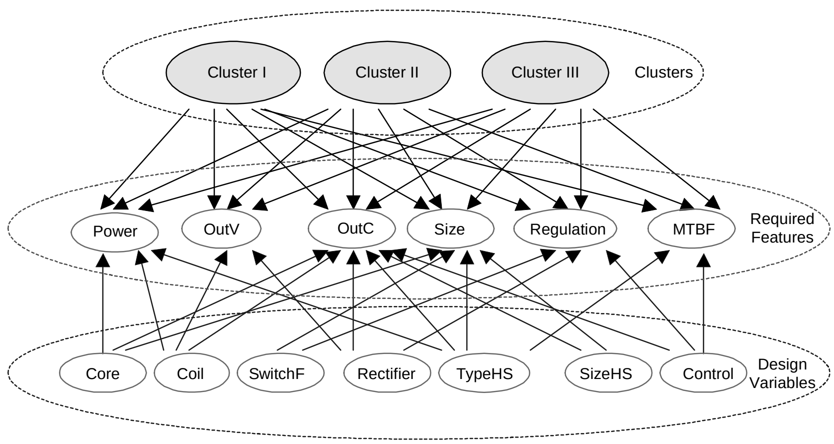


Figure 16: Clustering design variations and instances

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), etc. From an engineers' point of view, the power supply product is designed by determining 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), etc. Figure 17 shows the relationships between RFs, DPs, configurations (hierarchy of building block) and clusters. Three 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 range/limitation with regard to 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/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.



(a) Configuration



(b) Clusters

Figure 17: Configurations and clusters of power supply products

With respect to the knowledge decision support scheme for product evaluation (see Figure 12), a scenario of knowledge support for Family I selection is shown in Figure 18. The customers' requirements for Family-I power supplies include AC/DC, 45W, 5V & ±15V, 150khrs, \$20-50, with or without auto-start function, etc. The knowledge decision support system 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 given in Figure 19, 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 system is NFS42-7610 as it has maximum MTBF, medium price and special offer of auto-start function, and it is acceptable based on the rules. Table 3 gives weights and partial performance ratings for each criterion (for NLP40-7610) and evaluation results. Figure 20 gives a screen snapshot for power supply product evaluation and selection for customization.

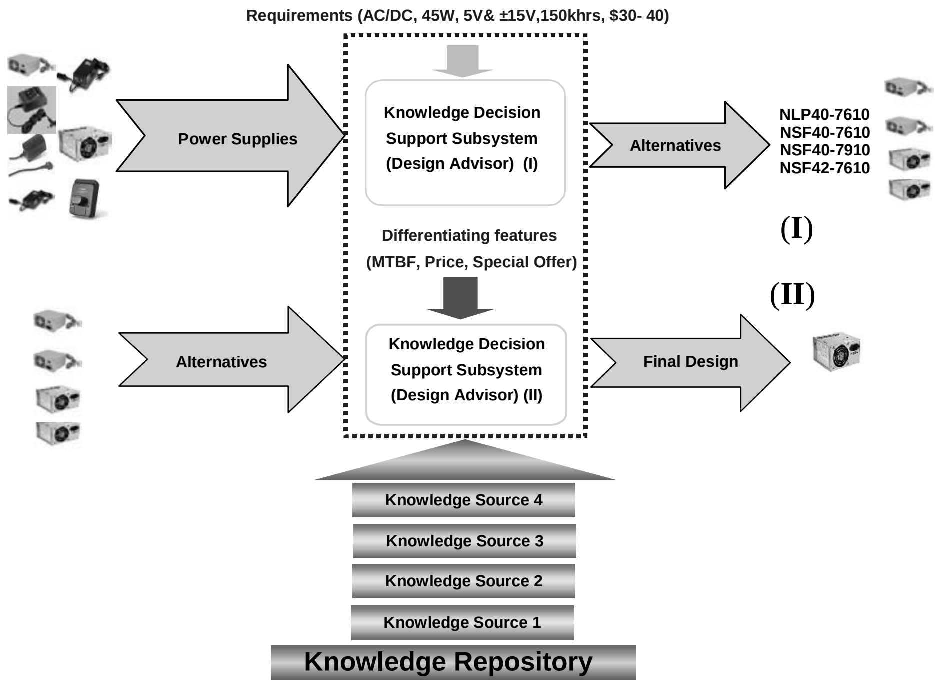


Figure 18: Scenario of knowledge support for product evaluation and selection for customization

Table 3: Weights and partial performance ratings

<table>
<tr><th>Criterion No.</th><th>Criterion Item</th><th colspan="3">Criterion Weight</th><th colspan="3">Partial Performance Rating</th></tr>
<tr><td colspan="2"></td><td>Linguistic Term</td><td>Fuzzy Number</td><td>Weight Value</td><td>Linguistic Term</td><td>Fuzzy Number</td><td>Rating Crisp Value</td></tr>
<tr><td>1</td><td>MTBF</td><td>High</td><td>(0.7,0.8,0.8,0.9)</td><td>w_1=0.80</td><td>Medium</td><td>(0.4,0.5,0.5,0.6)</td><td>r_{11}=0.500</td></tr>
<tr><td>2</td><td>Price</td><td>Fairly High</td><td>(0.5,0.6,0.7,0.8)</td><td>w_2=0.65</td><td>High</td><td>(0.7,0.8,0.8,0.9)</td><td>r_{12}=0.800</td></tr>
<tr><td>3</td><td>Special Offer</td><td>Medium</td><td>(0.4,0.5,0.5,0.6)</td><td>w_3=0.50</td><td>Very Low</td><td>(0.0, 0.0,0.1,0.2)</td><td>r_{13}=0.075</td></tr>
<tr><td colspan="8">Evaluation Results:</td></tr>
<tr><td colspan="2">No.</td><td colspan="2">Family I</td><td colspan="2">Evaluation Index (h)</td><td colspan="2">Rankings</td></tr>
<tr><td colspan="2">1</td><td colspan="2">NLP40-7610</td><td colspan="2">2.128</td><td colspan="2">3</td></tr>
<tr><td colspan="2">2</td><td colspan="2">NFS40-7610</td><td colspan="2">2.041</td><td colspan="2">2</td></tr>
<tr><td colspan="2">3</td><td colspan="2">NFS40-7910</td><td colspan="2">2.222</td><td colspan="2">4</td></tr>
<tr><td colspan="2">4</td><td colspan="2">NFS42-7610</td><td colspan="2">1.449</td><td colspan="2">1</td></tr>
</table>

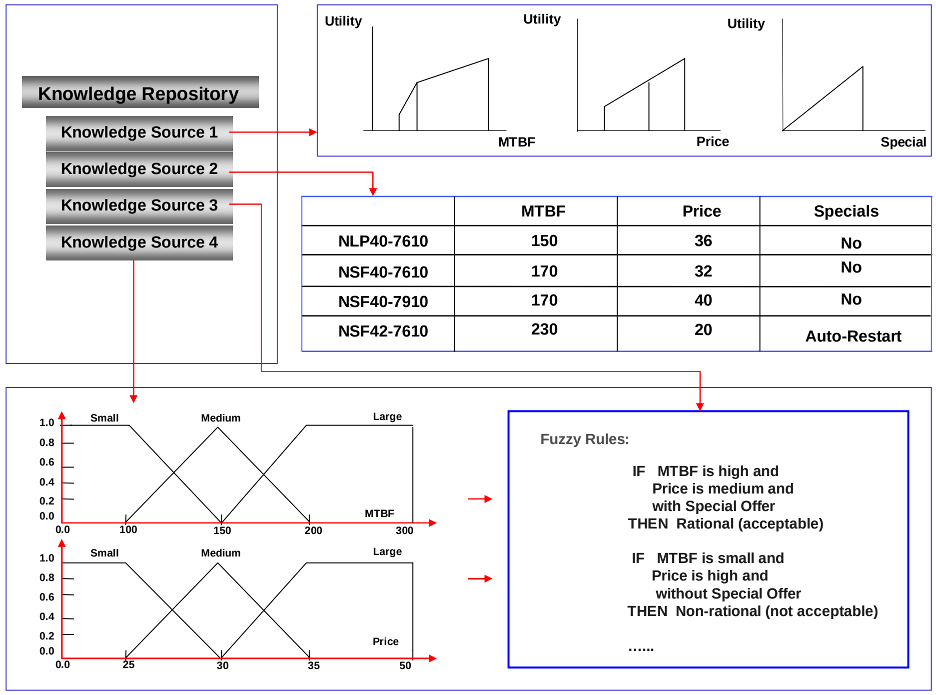


Figure 19: Knowledge used in power supply product evaluation and selection for customization

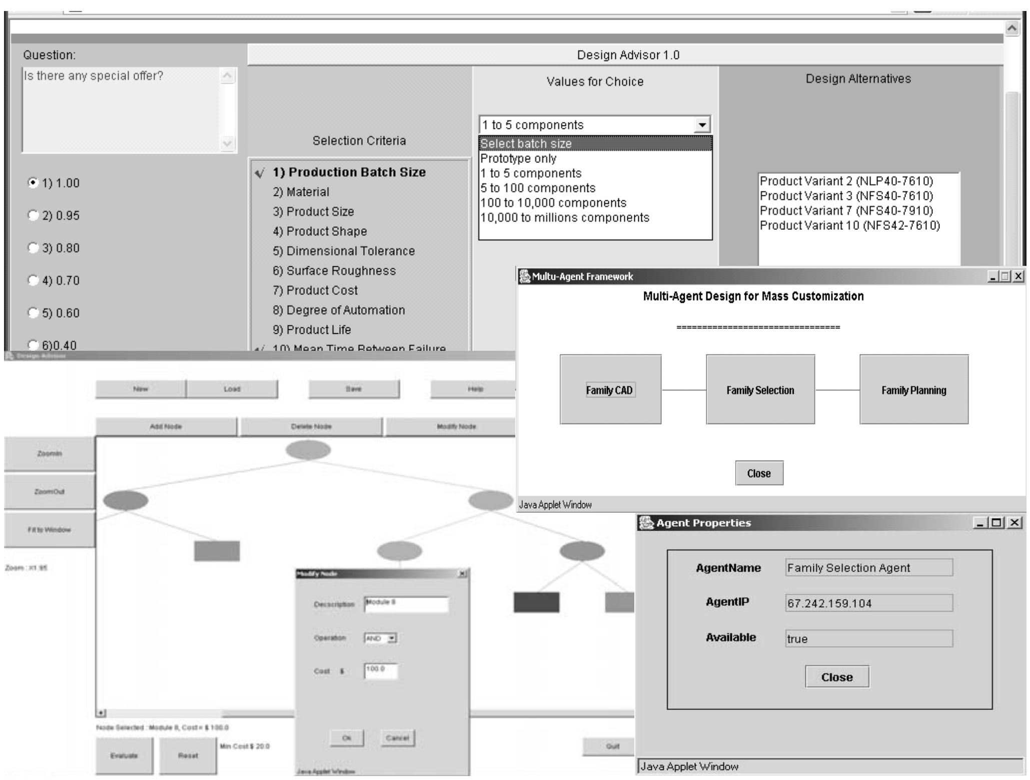


Figure 20: Screen snapshot for power supply product evaluation and selection for customization

8. Conclusions and Future Work

In this paper we presented a hybrid decision model and a multi-agent framework for collaborative decision support in the design process. The hybrid decision model presents an effective means of integrating both subjective and objective elements of design, making it particularly suitable for supporting design decisions in knowledge intensive and distributed collaborative environments. The knowledge-based decision support model can manage design decision knowledge and provide real-time or on-line knowledge support to designers in the decision-making process. It can compensate for typical barriers to the decision-making process, including incomplete and evolving information, uncertain evaluations, inconsistency of team members' inputs, etc. The decision assessment process can be used and refined for the product development process mapping, assessment /optimization constraint and gap identification, tracking the information development and flow, and measuring the effectiveness of current processes. Designers, especially novices, can benefit from retrieval of knowledge about previous design decisions by abstracting information and applying it to a new design or by gaining insight into how an earlier decision was made. By making use of the design knowledge, companies are expected to improve the design process for more innovative products and reducing product development cycle time. As a kernel of the knowledge supported design system, the design decision support system (agent) can help design teams make better decisions. The developed methodology is flexible enough to be used in a variety of decision problems. The applications in concept evaluation and selection in design for mass customization illustrate and validate the feasibility and potential of the developed decision support methodology and framework. Future work is desired to develop collaborative decision-making mechanisms based on the hybrid decision model, and to incorporate the decision agent into the web-based product design and realization framework.

Nomenclature

DDS: Design decision support
QFD: Quality function deployment
CFD: Concurrent function deployment
DKM: Decision knowledge management

DPM: Design process modeling

KM: Knowledge management (KM)

DS: Decision support

4Ms: Models, methods, metrics and measures

K: Knowledge output

I: Information input

T: Transformation relationship

FSD: fuzzy synthetic model

cDSP: Compromise Decision Support Problem

AHP: Analytic Hierarchy Process

FMCDM: fuzzy multi-criteria decision-making

a_i: Design alternative (DA)

r_{ij}: The merit of alternative a_i according to the criterion C_j

$\mu_{\tilde{R}_{ij}}(\tilde{r}_{ij})$: Membership function of r_{ij}

$\bar{r}_i$: Weighted average rating

$\mu_{\tilde{R}}(\tilde{r}_i)$: Fuzzy rating membership function

f_h : Heuristic evaluation function

FR: Functional requirement

GFR: General functional requirement

DP: Design parameter

GDP: General design parameter

DC: Design constraints

DS: Design solutions

MTBF: Mean time between failure

Appendix A: cDSP for designing a group of individual universal motors

Given

Universal motor equations (Simpson et al. 2001)

Find

The system variables:

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

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

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

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

r_j: Radius of the motor

t_j: Thickness of the stator

I_j: Current drawn by the motor

$L_{i,j}$: 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:

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

Minimize: deviation function

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

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