# 16

# Knowledge-Intensive Collaborative Decision Support for Design Process

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In this chapter, we describe a hybrid decision model and a multi-agent framework for collaborative decision support in the design process. The proposed knowledge-based collaborative decision support model 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 multi-agent framework provides an efficient decision support environment involving distributed resources to shorten the realization of products with optimal life-cycle performance and competitiveness. 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 power supply product family design for mass customization.

## 16.1. Introduction

Engineering design is essentially a collaborative decision-making process that requires rigorous evaluation, comparison and selection of design alternatives as well as optimization from a global perspective on the basis of different classes of design criteria. Increasing design knowledge and supporting designers to make correct and 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.

This chapter aims to develop a knowledge supported decision support methodology for the smooth integration of stakeholders involved in collaborative product development and improved product performance. The goal is to develop a sound, robust, 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 focus in this chapter is to establish a knowledge-based decision model and framework for collaborative design.

The organization of this chapter is as follows. Section 16.2 reviews the previous research related to design decision support and current status. Section 16.3 discusses the design decision support process and decision-based design. Knowledge intensive decision support for design process is highlighted. Section 16.4 proposes a knowledge-based decision model. Section 16.5 discusses collaborative decision-making mechanisms. Section 16.6 proposes a multi-agent collaborative decision support framework. Section 16.7 provides the application of the proposed model in concept evaluation and selection. Section 16.8 provides a case study. Section 16.9 summarizes the chapter and points out opportunities for future work.

## 16.2. Literature Review

Design decision support problems necessitate the search for superior or satisficing design solutions (Simon 1976), 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), 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, 2) fuzzy set analysis, 3) probability analysis, 4) the hybrid approach, 5) design analytic methodology, and 6) the information content approach (Suh 1990).

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). Some recent techniques are intended to help designers collaborate or coordinate by sharing product information and manufacturing services through formal or 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: 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 the 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 by nature. They are only 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.

## 16.3. Design Decision Support Process

### 16.3.1 Decision Support Process

Generally speaking, decision is a choice, which is to realize a certain goal by analyzing subjective-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 Fig.16.1. It experiences the stages ranging from problem identification and classification, simplification of assumptions, data collection, model formulation, solution alternatives generation, evaluation, and selection, as well as model validation and verification and testing of the proposed solution to final plan implementation. The current research is focused on how knowledge support can aid the decision-maker to make a decision during the design process. Fig.16.2 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.

### 16.3.2 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 of design problems, and then optimize those solutions within the framework composed requirements and constraints set by physical, environmental and human-related considerations. 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, design equation can be expressed as follows (Mistree 1995): $\{K\} = T\ \{I\}$, where, K is knowledge output, I is information input, and T is 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 a competitive advantage in product development.

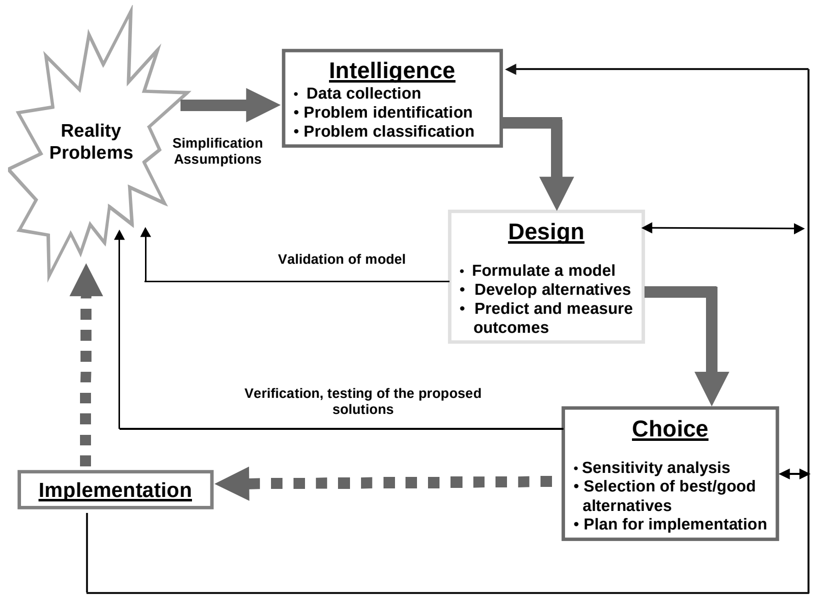


Fig.16.1: Decision support process (from Simon 1976)

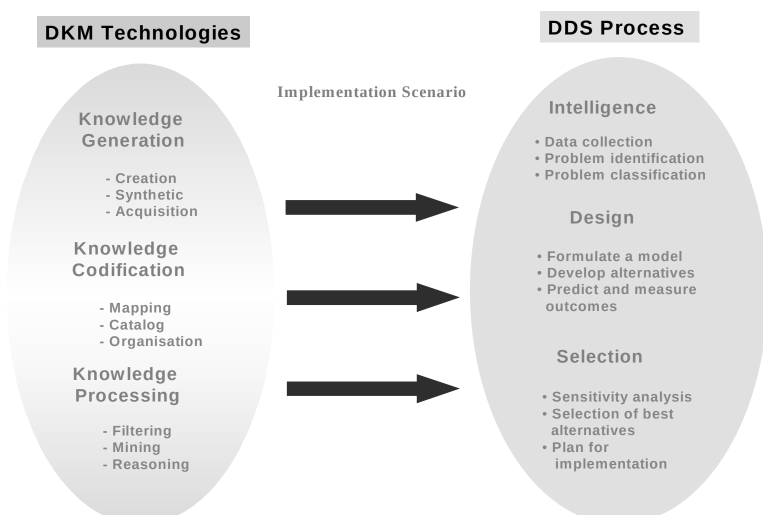


Fig.16.2: Decision support implementation scenario

In this chapter, we present the development of a knowledge intensive design decision support scheme, as depicted in Fig.16.3, in which design decision support is exploited from the synthesis of design process modeling (DPM), knowledge management (KM), and decision support (DS). From the motivations and an overview of the design decision- making support process, it can be seen that the decision theories for example game theory, utility theory, probability theory, fuzzy set theory and extension set theory, etc., play a key role during the process (see Hazelrigg 1996 for discussion of some of these techniques).

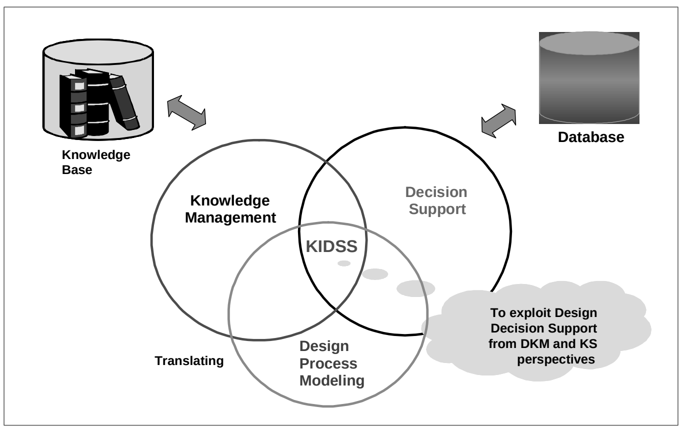


Fig.16.3: Knowledge intensive design support system (KIDSS)

## 16.4. Hybrid Robust Decision Model

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

### 16.4.1 Compromise Decision Support Model (cDSP)

Decision support problems (DSPs) are generally formulated using a combination of analysis-based hard 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, and along with several combinations of these. 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 is the improvement of a given alternative through modification. Another aspect of the DSP technique that is particularly relevant to distributed collaborative design is the facility of expressing 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). 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. For more details, please refer to (Mistree et al. 1993, 1995).

### 16.4.2 Fuzzy Synthetic Decision Model (FSD)

The problem of design evaluation and selection can be defined as: 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 based on fuzzy AHP, ranking algorithms and inference mechanisms for engineering design evaluation and selection.

#### 16.4.2.1 Fuzzy Analytic Hierarchy Process

The AHP mechanism proposed by Satty (1991) is widely recognized as a useful tool to support multi-attribute decision-making. 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:

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

Considering a pairwise comparison matrix $A = [a_{\mathrm{ij}}]$ 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, we should focus on the comparison matrix *A*. Currently, most of researchers compose AHP comparison matrix *A* according to user's individual and flexible preferences. In a flexible negotiation environment, however, most of 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*.

### 16.4.2.2 Fuzzy Ranking for Evaluation

Using the design solution clustering techniques (e.g., cDSP model above) at the conceptual design stage, a reasonable number of possible design alternatives can be obtained. 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 analysis 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 (Zadeh 1965, Kickert 1978, Gui 1993). 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

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

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 one. 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:

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

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.,

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

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.

### 16.4.2.3 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 the 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). 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 $\bar{r}_i$ ($i$=1,2, …, $m$) of its constituent members and the number $k$ of its unsatisfied customer requirements, as follows:

$$f_h = \sum_{i=1}^{m} (1/\bar{r}_i) + k \tag{11}$$

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 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.(11), a higher $\bar{r}_i$, 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 multi-criteria factors including design compactness and other life-cycle issues, such as manufacturability, assemblability, maintainability, reliability, and efficiency.

### 16.4.3 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. 1996, Zha 2003). 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). The synthesis of the cDSP and FSD models can generate a more powerful robust decision model. 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, an adaptor is employed in the model and served 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). Together with a genetic algorithm (sGA), a systematic knowledge-based adjustment method for parameters is developed for the decision maker in the complex system design. The regulatory switch is implemented using sGA and the knowledge-based guidance (Lu et al. 2000). 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 above, etc.  Fig.16.4 provides a schematic view of the hybrid robust decision model integrating cDSP and FSD models. This kind of knowledge-based model can manage design decision knowledge and provide real-time or on-line support to designers in the decision-making process: 1) overcome shortcomings of cDSP; 2) suggest solutions and provide explanations to the designer; 3) may be used in the early design stage; and 4) stimulate the designer to generate new design ideas (with learning).

## 16.5. Collaborative Decision Making Mechanisms

Coordination is the central problem of multi-agent systems (MAS), which includes cooperation and conflict resolution problem. In fact, the conflict problem is non-cooperative problem, so the conflict resolution is the key technology for MAS. The common ways to solve the conflicts are arbitration and negotiation. The arbitration is based on the classic mathematic theory and reasoning rules according to the concept of characteristic function which means that "to be or not to be, (yes, no) or (0,1)," while the negotiation means is based on fuzzy set theory and reasoning rules according to the concept of membership function which means that the membership's degree of "to be or not to be, [yes, no] or [0,1]." Both ways result in the cost of sacrificing individual agents' interests with different degrees. In this section, two mechanisms, the transforming bridge and regulatory switch (Zha et al 2003), are used for solving conflict or incompatible problems and collaboration/negotiation between designers/ decision-makers in design.

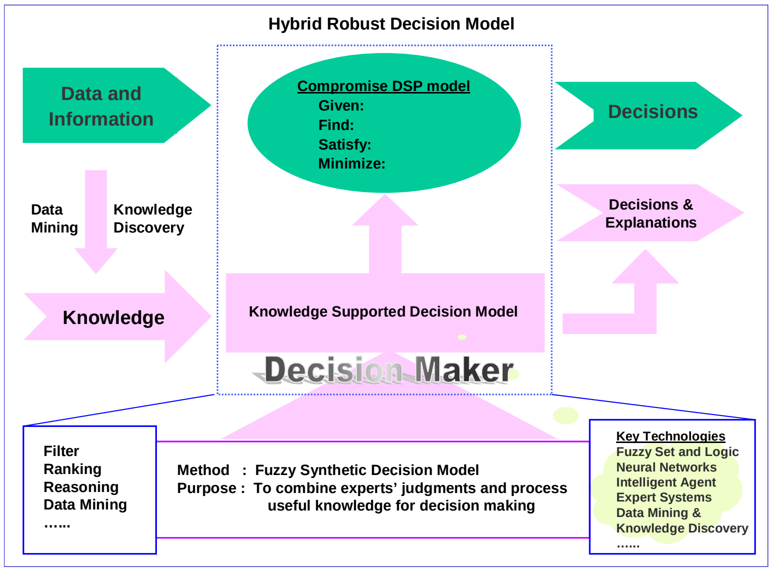


Fig.16.4: Hybrid robust decision support model

### 16.5.1 Transforming Bridge

The transforming bridge method is proposed to deal with conflict or incompatible decision problems. Two disputing factions require a bridge to span the river that separates them. The river is the neutral territory and therefore the bridge must physically transform to serve as a place for conflict resolution. When transformed, the "room" must no longer function as a bridge. The typical imaginary example for using this method is how people in Hong Kong solve the so-called "connections between right side drive and left side drive" problem. Thus, the concept of transforming bridge enables the two incompatible sides to prevail in maintaining their two own specific interests. It is neither a solution method based on competition nor the one that trade-off and balance are out their interests.

We deal with the conflict problems as opposite (compatible and incompatible) problems. Transformation is based on the reasoning rules according to the concept of dependent (transfer) function, which means "to be or not to be can be interchanged". Based on the principles of "go the contrary way" and "disport frequency of multiple branches" a transforming bridge can be devised to solve multi-agent resource conflict problems and dynamic design conflict problems. Specifically, a design-transforming bridge, which can play a connected and transformable role, is designed between two players so that the conflict can be resolved and therefore two players can gain their satisfied solutions. By handling the incompatible problems, the searching range will be expanded step by step according to the degree of conflict of the to-be-solved problems. For example, the chess playing process could be analyzed using this bridge. When more than one piece of chess is in danger, by normal optimal algorithms the smallest loss will be calculated and the piece with the smallest loss will be abandoned. By means of an extension strategy, the already calculated smallest loss will be used to extend the set and search for a new chance among those pieces that are momentarily not in danger but have an opportunity to start a new attack. The price of this new attack must be even smaller than the calculated loss before.

### 16.5.2 Regulatory Switch

Traditionally, the designer usually depends on a human's knowledge and trial-and-error when determining a parameter value. However, these methods are not easy to apply when there are too many system parameters with potential relationships. A genetic algorithm has the advantage of searching optimum and avoids local values. Together with a genetic algorithm, a systematic adjustment method for parameters is developed for a decision maker in a complex system design. The sGA (Dasgupta and McGregor 1994) design representation uses regulatory genes that act as a switch to turn genes on (active) and off (passive). Each gene in higher levels acts as a switchable pointer that has two possible targets: when the gene is active (on) it points to its lower-level target (gene), and when passive (off) it points to the same-level target. At the evaluation stage only the expressed genes of an individual are translated into the phenotypic functionality, which means that only the genes that are currently active contribute to the fitness of the decision. The passive genes do not influence fitness and are carried along as redundant genetic material during the evolutionary decision making process. Therefore, the utilization of the sGA approach to collaborative design decision can be summarized as follows. First, genes represent decision modules or subsystems that are either active or passive, depending on whether or not they contribute to the decision problem. Then, a family of decision solutions relied on the addition or subtraction of decision modules could be evaluated by alternating different "active" and "passive" modules or subsystems. A family of solutions would thus correspond to decision model variants that have different active and passive combinations of modules or subsystems.

### 16.5.3 Negotiation Support

During the decision-making between multiple designers, it is crucial to negotiate on multiple attributes of a design deal such as material, manufacturing method, parameters values, cost, quantity, quality, and relative preference. The negotiation is a form of decision-making with two or more actively involved agents who could not make decisions independently, and therefore must make concessions to achieve a compromise. Therefore, negotiations for an enormous volume of transaction on the

Internet became a fundamental mechanism to automating collaborative design. Furthermore, the flexibility and adaptability of the negotiation mechanism may be used as a plausible source of motivation and framework for the design of intelligent and autonomous agent systems (Kim et al. 2003). In this work, the negotiation mechanism using the FSD model is composed of the following six phases:

(1) The negotiation mechanism is started with the 'initial offers for a design deal' of agent (designer). In this phase, each negotiation agent offers their negotiation conditions reflecting their relative preference for a deal. The design deal is composed of quantitative conditions such as parameters values and cost. However, the fuzzy values for these conditions are changed by fuzzy membership functions reflecting qualitative conditions such as relative preference.

(2) After the initial offers of agent, 'fuzzy membership functions' are used to support the construction of fuzzy pairwise comparison matrix *A*. Using this fuzzy membership function, designer's relative preferences are transformed into fuzzy membership values. During the transformation process, bell-shaped (or Z, $\lambda$, $\pi$ and S-type) fuzzy membership functions can be adopted.

(3) The 'pairwise comparison matrix A' is constructed. In this phase, the AHP comparison matrix is used to compute the relative importance about each alternative (deal). As a result, each agent's offers are fully compared.

(4) This phase is for 'selection of preferred offer' of the negotiation agent. Based on the result of comparison in phase (3), the preferred offers are selected by one or some designers. However, this is the first step of dynamic negotiation process.

(5) The fifth phase is for 'revision of offers and negotiation'. In this phase, each agent revises their 'initial offer' and continues to negotiate with their counterpart. For this purpose, the 'goal-seeking' methodology is used to revise the initial offers.

(6) The final phase is to suggest the 'optimal offer'. The fuzzified pairwise comparison matrix *A* and the AHP inference mechanism are used to suggest the optimal offer, and then go to the phase (5) to lead a consensus with their counterpart. As a result, each designer could satisfy with the final offers.

## 16.6. Multi-Agent Collaborative Design Decision Support Framework

The overall knowledge-intensive multi-agent design decision support scheme proposed in (Zha 2003) is shown in Fig.16.5. This secheme consists of a design process modeling and management agent, a knowledge capture agent, a knowledge repository, co-designers, a decision support agent, etc. The communication, negotiation and execution mechanisms between these agents are modeled with contract nets. The core of the scheme is the decision support agent which is the focus of discussion. The knowledge repository is used to store, share, and reuse the corporate design knowledge (Szykman 2001). A prototype web-based design decision support system has been developed to verify and demonstrate the developed methodologies (algorithms) and 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.

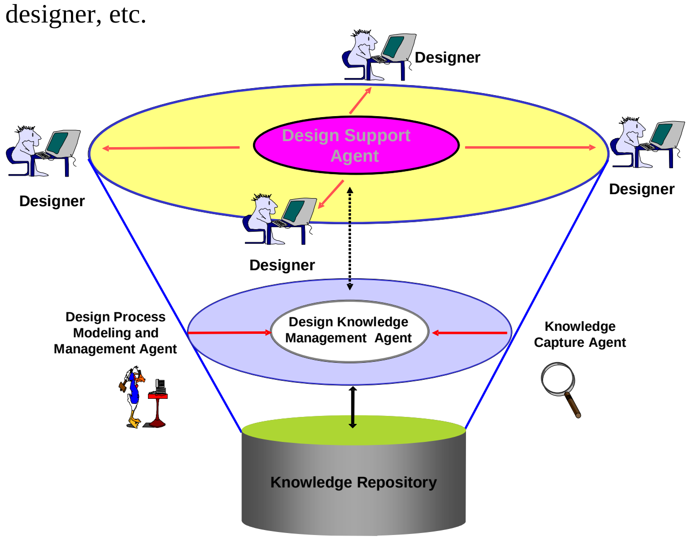


Fig.16.5: The overall multi-agent knowledge intensive decision support framework

The comparative ranking of alternatives and decision-making discussed in section 16.4.2 is a fundamental component of the design decision agent. As stated previously several formal decision models exist (Section 16.2). Utility theory (Keeney and Raiffa 1976) and AHP (Saaty 1991) are well known examples. The decision agent, illustrated in Fig.16.6, 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). 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 for each decision theory. In the prototype implementation the decision agent has been developed by integrating the cDSP technique with an expert/knowledge model into a hybrid robust decision support model for criterion/argument analysis and fusion

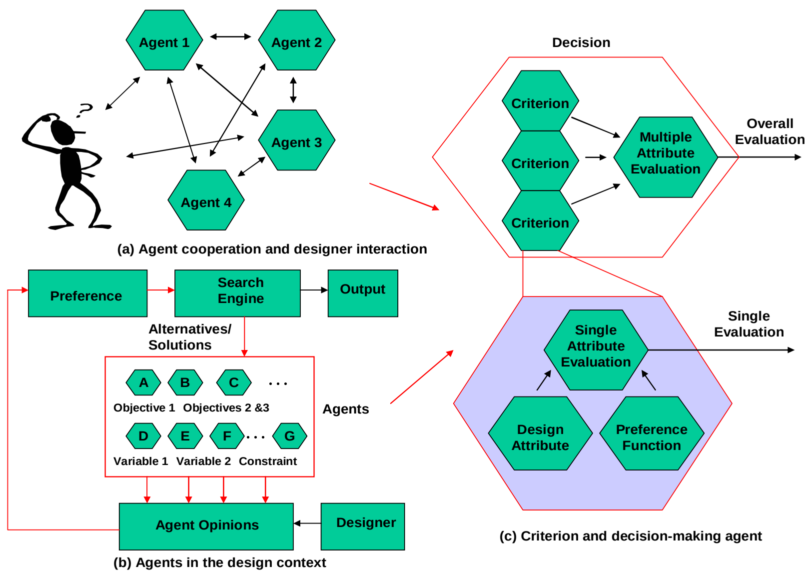


Fig.16.6: Decision support agent.

## 16.7. Application in Conceptual Design Decision Support

During the conceptual design stage (Fig.16.7), a family of product concepts (or product concept variants) can vary widely by the selection and assembly of modules or pre-defined building blocks at different levels of abstraction so as to satisfy diverse customers' requirements. A wrong or even a poor selection of either a building block or module can rarely be compensated for at later design stages and can give rise to a great expense of redesign costs (Pahl and Beitz, 1996). Thus, concept evaluation and selection is crucial in this stage. We propose a knowledge decision support approach to concept evaluation and selection, as shown in Fig.16.8. The kernel of the knowledge decision support scheme is the hybrid decision support model discussed above. This model is used for design concept evaluation and selection, in which the cDSP model is used to cluster/classify design alternatives or variants and determine similarity and commonality between modules, product variants and product families; 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 a company. The knowledge resource utilized in the process extensively includes differentiating features, customers' requirements, desires, preferences and importance (weights), tradeoffs (e.g., market vs investment), and utility functions, and heuristic knowledge, rules, etc.

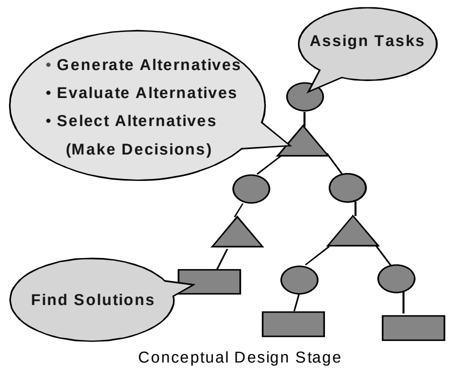


Fig.16.7: Concept evaluation and selection in design

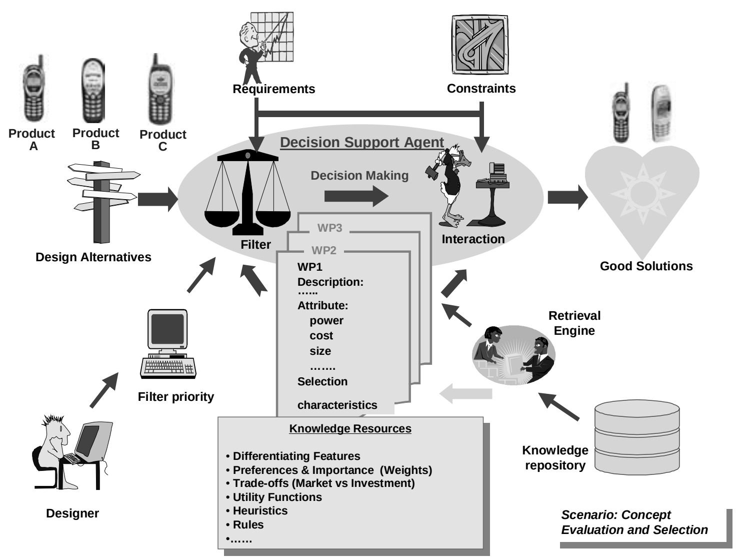


Fig.16.8: Knowledge decision support for concept evaluation and selection

## 16.8. Case Study

The above proposed knowledge support scheme has been used for decision making in a power supply family design for customization. Specifically, the cDSP model is used to cluster/classify power supply family product design alternatives or variants and determine similarity and commonality between modules and product variants. The FSD model is used to evaluate and select the power supply design alternatives that satisfy customer needs, meet design requirements and comply with the technical capabilities, in which the negotiation is involved.

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. Using the cDSP model and fuzzy clustering, three different clusters are obtained. 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 configuration is carried out, the design requirements and constraints are satisfied especially in terms of product functions or functional features.

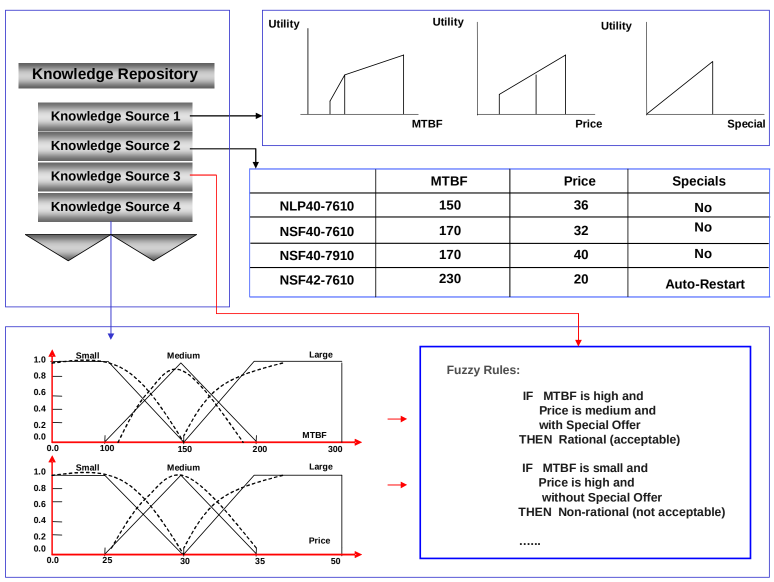


Fig.16.9: Knowledge used in power supply product design for customization decision

With reference to the knowledge decision support scheme for product evaluation, a scenario of knowledge support for power supply product evaluation for customization in Family I is shown in. The customers' requirements for Family-I power supplies include AC/DC, 45W, 5V & ±15V, 150khrs, \$20-50, 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 can be reached based on the knowledge resources given in Fig.16.9, including differentiating features (MTBF, price, and special offer) and their utility/membership functions, fuzzy rules, 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 16.1 gives weights and partial performance ratings for each criterion (for NLP40-7610) and evaluation results. Fig.16.10 shows a screen snapshot for the power supply product evaluation and selection for customization.

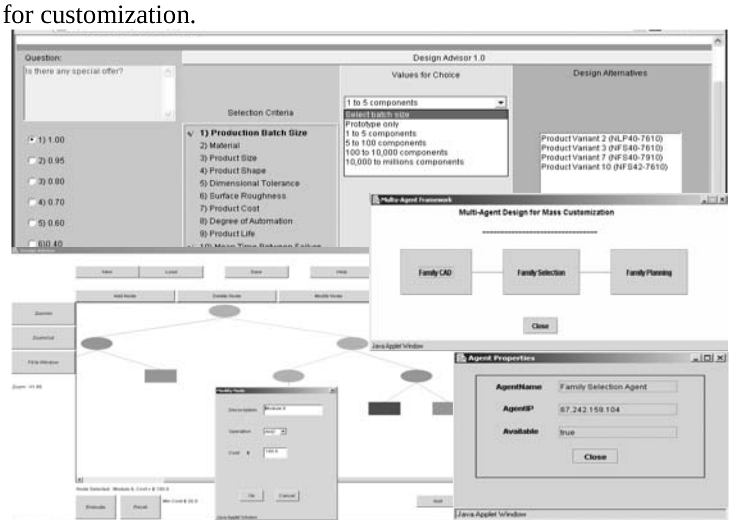


Fig.16.10: Screen snapshot for power supply product evaluation and selection for customization

Table 16.1: 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:

| No. | Family I | Evaluation Index (h) | Rankings |
|---|---|---|---|
| 1 | NLP40-7610 | 2.128 | 3 |
| 2 | NFS40-7610 | 2.041 | 2 |
| 3 | NFS40-7910 | 2.222 | 4 |
| 4 | NFS42-7610 | 1.449 | 1 |

## 16.9. Conclusions and Future Work

In this chapter we presented a hybrid decision model and a multi-agent framework for collaborative decision support in the design process. The hybrid decision model presented in this chapter provides a clean and effective digital interface and design decision templates for a series of decisions in design process in the knowledge intensive and distributed collaborative environment. 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 robust decision assessment process can be used and refined for the product development process mapping, 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 designs by abstracting information and applying it to a new design or by gaining insight into how an earlier related product was designed. 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 application in concept evaluation and selection in design for mass customization illustrates the feasibility and potentials of the developed methodology and framework. The developed methodology is flexible enough to be used in a variety of decision problems.

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