

KNOWLEDGE INTENSIVE DECISION SUPPORT FOR DESIGN PROCESS: A HYBRID ROBUST MODEL AND FRAMEWORK

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Abstract

This paper presents a hybrid robust decision support model and framework for the seamless integration of collaborative product development with optimal product performance. The developed hybrid robust design decision-support model quantitatively incorporates qualitative design knowledge and preferences of 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 work provides a framework for an efficient decision support environment involving distributed resources to shorten the realization of products with optimal life-cycle performance and competitiveness. The developed methodology and framework are generic and flexible enough to be used in a variety of decision problems. The application for the concept evaluation and selection in design for mass customization is provided.

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

1. Introduction

Engineering design is essentially a decision-making process that requires rigorous evaluation, comparison and selection of design alternatives and optimization from a global perspective on the basis of different classes of design criteria [1]. Increasing design knowledge and supporting designers to make right and intelligent decisions can achieve the improvement of the design efficiency. Thus, the design strategy must be devised to specifically address all aspects of design including process modeling, knowledge modeling, and 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 crucial role in enabling designers to make intelligent decisions towards improving the overall quality of the products designed.

This paper aims to develop a knowledge-based design decision support methodology and framework that can be extensively applied for engineering system design. The work involves the development of a complex decision-making model and framework for 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 knowledge-based approach presented in this paper will provide an

effective interface and design decision templates for a series of decisions in a knowledge intensive and distributed collaborative design environment.

The organization of this paper is as follows. Section 2 reviews the previous research related to design decision support and current status. Section 3 proposes a hybrid robust decision model. Section 4 develops a knowledge support framework. Section 5 provides a case application of the proposed model to concept evaluation and selection. Section 6 summarizes the paper and points out the future work.

2. Current Status of Research

Design decision support problems facilitate the search for superior or satisfying 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 researches in design decision support are working on enabling technologies to assist product designers to make decisions in the design process [1]. There are generally six categories of approaches on design evaluation and selection decision support [2]: multi-criteria utility analysis, fuzzy set analysis, probability analysis, design analytic methodology, and the information content approach. The first four approaches are prevalent.

Multi-criteria utility analysis 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. For example, Thurston [6] has applied this technique to the material selection problem that evaluates alternatives based on utility functions that reflect the designer's preferences for multiple criteria. Mistree *et al.* [8,9] modeled design evaluation and optimization as a compromise decision support problem (cDSP) and employed goal-programming techniques to make optimal selection 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 with a quantitative form. They are not appropriate for use in the early design stage, where some qualitative design criteria, *i.e.*, intangible criteria, are involved and difficult to quantify [7]. The main drawback of these evaluation methods is that they ignore the inconsistency issue on the part of the decision maker, which occurs when the solution does not match the decision maker's preference and results from the randomness of the decision maker's judgments [11].

Fuzzy analysis, based on fuzzy set theory [10], is capable of dealing with qualitative or imprecise inputs from designers by describing the performance of each criterion with some linguistic terms, such as "good," "poor," "medium," *etc.* It has proven to be quite useful in decision-making problems with multiple goals or criteria, especially rank alternatives at very early stages of the preliminary design process [12]. This approach is most appropriate when there are imprecise design descriptions, while probability analysis is most appropriate for dealing with stochastic uncertainty. It excels in capturing semantic uncertainty with linguistic terms. However, it requires discreet deliberation in dealing with crisp information, and a domain-specific method is needed to fuzzify each tangible criterion whose evaluation is naturally estimated as an ordinary real variable. Another challenge is the incomparability between various criteria, which necessitates some mechanisms to be capable of converting various types of performance evaluation with respect to different criteria to a common metric so as to specify

suitable membership functions for them. The design evaluation usually involves both tangible and intangible criteria, along with quantitative and qualitative performance measures. This motivates the hybrid approach of combining the quantitative, normative problem structuring capabilities of operations research techniques with the qualitative, descriptive problem-solving approach used in artificial intelligence techniques. For example, Maimon and Fisher [13] presented a robot selection model using integer programming and a rule-based expert system. A good number of efforts have been devoted to fuzzy goal programming to model mathematically the imprecise relationships using fuzzy goals and soft constraints. However, they mostly model a particular aspect of uncertainties in design evaluation, such as imprecise relationships, imprecise information, and uncertain information [14]. It is difficult for a fuzzy goal-programming model to consider all sources of uncertainty coherently at the preliminary design stage [15]. In addition, the computational complexity is a key issue, especially in case of a large number of design alternatives and criteria being involved [16,17].

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) [18], concurrent function deployment [19], conceptual selection matrix [20], Taguchi robust design method [21], etc. While these methodologies provide high-level guidelines for design evaluation, detailed supporting techniques are essential, 4Ms (models, methods, metrics and measures) are the core in integrated product development [19]. With the development of collaborative design, some researchers are working on enabling technologies or infrastructure to assist product designers in the computer or network-centric design environment [27,28]. Some are intended to help designers to collaborate or co-ordinate by sharing product information and manufacturing services through formal or informal interactions [28]. Others propose frameworks that manage conflicts between design constraints and assist designers in making decisions [27]. Most decision support programs can only calculate satisfaction levels. It is needed to add 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.

3. Hybrid Robust Decision Model

The research focus in this paper is on establishing a hybrid robust decision model which may integrate one or more techniques such as compromise decision support (cDSP), fuzzy systems, neural networks, intelligent agents, data mining (e.g. fuzzy clustering algorithm), and genetic algorithm to solve both compatible and no-non-compatible decision problems. Details are discussed below in this section.

3.1 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 [8,9]. 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 the evaluation and indication of preference based on multiple attributes for one among alternatives, while the

"compromise" type decision is the improvement of an 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) [22,27]. These derived decision constructs are ideally suited for modeling networks of concurrent and sequential decisions that share information and knowledge. In compromise decision support problem (cDSP) model, as shown in Figure 1, a hybrid of goal programming and math 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 [22].

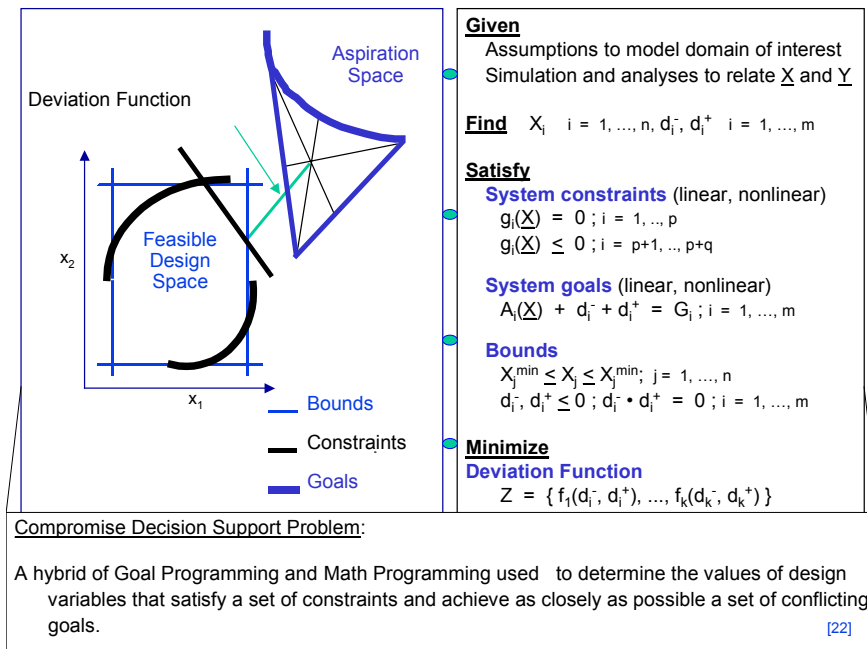


Figure 1 Compromise decision support model (cDSP)

3.2 Fuzzy Synthetic Decision Model (FSD)

A fuzzy synthetic decision model is developed based on a fuzzy ranking algorithm and a fuzzy inference mechanism for engineering design evaluation and selection. The problem of design evaluation and selection is 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.

Fuzzy Ranking for Design Evaluation

Using the design solution clustering techniques [26], a reasonable number of possible design alternatives can be obtained in conceptual design stage. The remaining procedure is to examine the design alternatives against marketing and econo-technical and even ergonomic criteria as well as aesthetic criteria. This is actually a multi-criteria decision-making problem. The traditional procedure for calculating a weighted average rating by use of the cost-benefit analysis [3] is not applicable for the situations where uncertainty exists and the information available is

incomplete, for example, the terms "very important," "good," or "not good," themselves are a fuzzy set. Let a set of m alternatives $A=\{a_1, a_2, \dots, a_m\}$ be a fuzzy set on a set of n criteria $C=\{C_1, C_2, \dots, C_n\}$ to be evaluated. Suppose that the fuzzy rating r_{ij} to certain C_j of alternative a_i be characterized by a membership function $\mu_{R_{ij}}(r_{ij})$, where, $r_{ij} \in R$, and a set of weights $W=\{w_1, w_2, \dots, w_n\}$ is fuzzy linguistic variables characterized by $\mu_{W_j}(w_j), w_j \in R^+$. Consider the mapping function $g_i(z_i): R^{2n} \rightarrow R$ defined by:

$$g_i(z_i) = \frac{\sum_{j=1}^n (w_j r_{ij})}{\sum_{j=1}^n w_j} \quad (1)$$

where, $z_i = (w_1 w_2 \dots w_n, r_{i1} r_{i2} \dots r_{in})$. Define the membership function $\mu(z_i)$ by

$$\mu_{Z_i}(z_i) = \bigwedge_{j=1, \dots, n}^{\circ} \mu_{W_j}(w_j) \bigwedge_{k=1, \dots, n}^{\circ} \mu_{R_{ik}}(r_{ik}) \quad (2)$$

Therefore, through the mapping $g_i(z_i): R^{2n} \rightarrow R$, the fuzzy set Z_i induces a fuzzy rating set R_i with a membership function

$$\mu_{R_i}(r_i) = \sup_{Z_i, g(z_i)=r_i} \mu_{Z_i}(z_i), r_i \in R \quad (3)$$

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 $\mu_{R_i}(r_i)$ is the best one. The procedure needs to further evaluate the following two fuzzy sets as [4]:

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

$$\mu_{I/R}(i | r_1, \dots, r_m) = \begin{cases} 1 & \text{if } r_i > r_k, \forall k \in (1, 2, \dots, m) \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

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

$$\mu_R(r_1, \dots, r_m) = \bigwedge_{i=1, \dots, m}^{\circ} \mu_{R_i}(r_i) \quad (5)$$

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

$$\mu_I(i) = \sup_{r_1, \dots, r_m} \mu_{I/R}(i | r_1, \dots, r_m) \bigwedge^{\circ} \mu_R(r_1, \dots, r_m) \quad (6)$$

The fuzzy ranking is more flexible and presents uncertainty better. With this method the designer can use linguistic rating and weights such as "good," "fair," "important," and "rather important," for design alternatives evaluation.

Neural Network Adjustment for Membership Functions

Due to the complexity and uncertainty of design problems, it is required to further improve the above fuzzy synthetic decision model and evaluation method. One of aspects in improvement is learning ability. In a fuzzy set, a variable v can belong to more than one set, according to a given membership function $\mu_X(v)$. Standard membership function types as Z, λ , π and S-type can be mathematically represented as piecewise linear functions, which can be easily implemented and adjusted by using neural networks. The neuro-fuzzy hybrid approach uses neural networks (e.g. back propagation) to optimize certain parameters of an ordinary fuzzy system, or to preprocess data and extract fuzzy rules from data [25]. The fuzzy system is reflected in three basic elements: fuzzification, fuzzy inference and defuzzification. The fuzzification in the input interfaces translates analog inputs into fuzzy values. The fuzzy inference takes place in rule blocks that

contain the linguistic control rules. The output of these rule blocks is linguistic variables. The defuzzification in the output interfaces translates them back into analog variables. Each of the fuzzy rules can be interpreted as a training pattern for a multi-layer neural network, where the antecedent part of the rule is the input and the consequent part of the rule is the desired output of the neural network.

There are two main approaches commonly used to implement fuzzy if-then rule blocks above by standard error back propagation network. One is to represent a fuzzy set by a finite number of its membership values (normally by linear functions). The other is to represent fuzzy numbers by a finite number of α -level sets. The fuzzy neural network turns into n inputs and m outputs crisp network, which can be trained by the generalized delta rule. For more complex fuzzy systems, however, there are other more suitable approaches such as ANFIS (adaptive-network-based fuzzy inference system) to be used for implementing the fuzzy system [23].

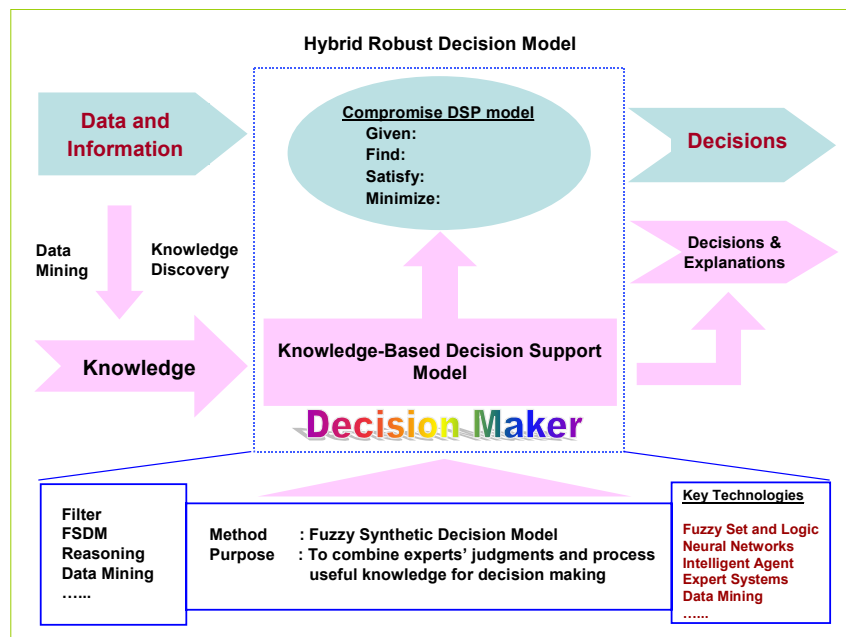


Figure 2. The hybrid robust decision support agent model

3.3 Integration of FSD Model and cDSP Model

As stated above, the cDSP model is data and information based, and is therefore only effective for the tangible (quantitative) criteria but not for the intangible (qualitative) criteria. The FSD model is knowledge based, and is able to handle both the tangible and the intangible criteria. The integration of the cDSP model and the FSD model generates a hybrid robust decision model. The mode of integration could be either “loose” or “tight.” In the loose mode, two or more models are combined and 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). In the tight mode, however, two or more models are co-existent and integrated into a single hybrid model, for example, fuzzy cDSP, fuzzy neural networks or the neuro-fuzzy system above [25]. Figure 2 illustrates the scheme of the hybrid robust decision support model. Therefore, 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.

4. Multi-Agent Design Decision Support Framework

Based on the distributed autonomous agent technology, the knowledge-based decision templates are developed based on the hybrid robust decision model to provide effective digital interfaces for a series of decisions during the design process. A knowledge-intensive multi-agent framework with the client-knowledge server architecture is developed for distributed design decision-making in the early design stages, including concept evaluation and selection. Thus, an efficient decision support environment involving distributed resources could be built up to shorten the realization of products having an optimal life-cycle performance and competitiveness [27,28].

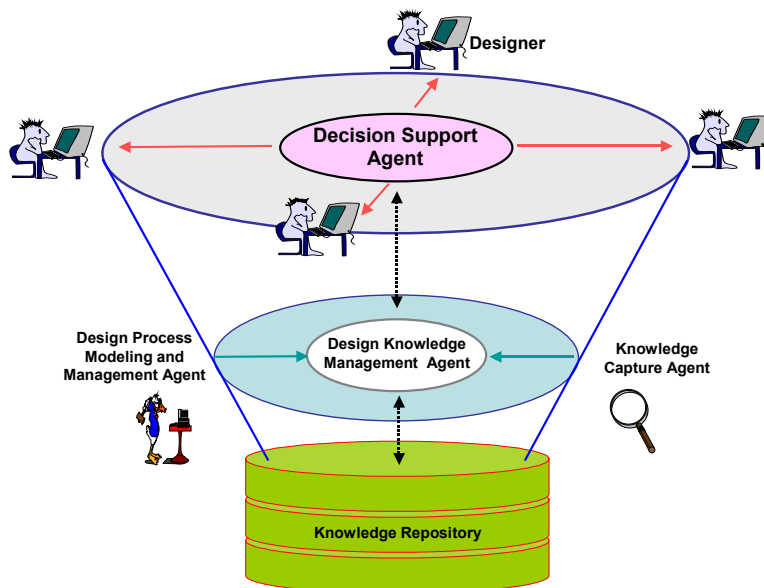


Figure 3. The overall multi-agent knowledge intensive design decision support framework

The overall multi-agent design support framework is shown in Figure 3. The core of the framework is the hybrid robust decision support agent developed by integrating the cDSP model, the FSD model, the design process model, and the knowledge capture and management model. Knowledge repository is used to store, share and reuse the corporate design knowledge. It contains a more comprehensive representation of an artifact. The artifact representation in a traditional design database generally consists of geometry (drawings and CAD models), version information, and the related documents, while the knowledge repository may also include the characterization of functions, behaviors, working principles, design rationales, simulation models, qualitative design knowledge and preferences of multiple and conflicting attributes, etc. The knowledge capture agent is used to acquire and discover new design knowledge. A prototype web-based design decision support engine that provides support for design evaluation and selection has been developed to verify and demonstrate the developed methodologies (algorithms) and framework. The engine could be used as an autonomous agent to be finally

integrated into a web-based product design and realization framework to support decision-making in the collaborative product development process (design chain).

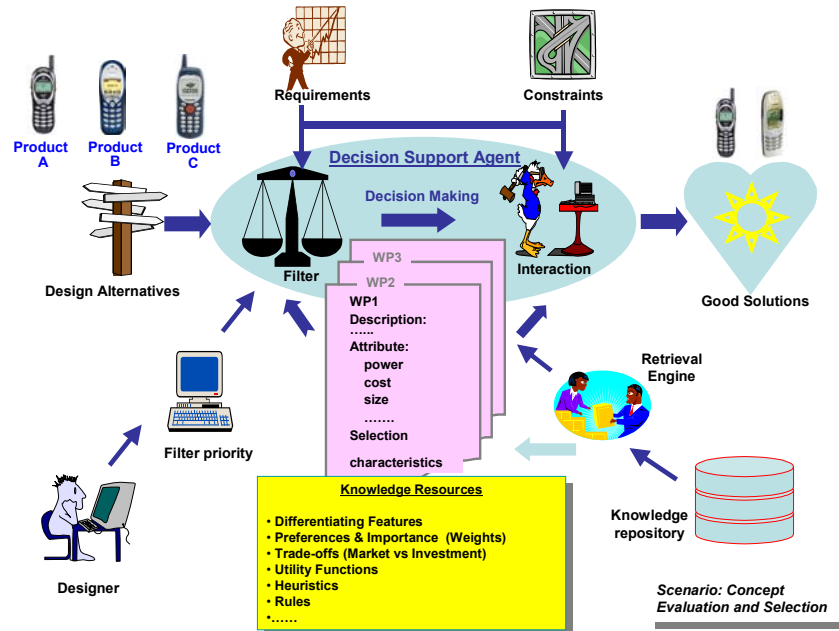


Figure 4 Knowledge decision support for concept evaluation and selection in design

5. Application for Concept Evaluation and Selection in Design

During the process of design for mass customization (DFMC) [24, 26], a family of products can widely variegate the selection and assembly of modules or pre-defined building blocks at different levels of abstraction so as to satisfy diverse customization requirements. The essence of DFMC is to synthesize product structures by determining what modules or building blocks are in the product and how they are configured to satisfy a set of requirements and constraints. A wrong or even a poor selection of either a building block or module can rarely be compensated at later design stages and give rise to a great expense of redesign costs [3]. Thus, the concept evaluation and selection is crucial for DFMC. While a number of methods have been investigated, there is still much to be desired due to the hindrance inherent in the concept evaluation and selection process [2]. With respect to the traditional approaches [2,3], the hybrid robust model is tailored for concept evaluation and selection for product customization. The knowledge resource utilized during this process extensively includes differentiating features, customers' requirements, desirabilities, preferences and importance (weights), trade-offs (e.g. market vs investment), and utilities functions, and heuristic knowledge, rules, *etc.* Figure 4 shows a knowledge decision support scheme for product evaluation and customization process. The kernel of the knowledge decision support scheme is the fuzzy synthetic model with fuzzy ranking algorithms for design evaluation and selection discussed above. To illustrate and validate the knowledge support scheme, a scenario of the knowledge support for the product customization in power supply family design is provided in [26].

6. Conclusions and Future Work

This paper presented the effort on the hybrid robust decision support model and framework for engineering design process. The work focused on the provision of methodologies/algorithms and framework for intelligent design decision-making in improved product development and business strategies. It can help bring products to market faster, and with more certainty of success. The proposed hybrid robust decision model was based on the processes of product information development and decision-making, in particular, assessment and selection. 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 product development process mapping, constraint and gap identification, tracking information development and flow, and measuring effectiveness of current processes. The application in concept evaluation and selection in design for mass customization illustrates the feasibility and potentials of the developed methodology and framework. The future work is desired to develop a knowledge-intensive collaborative decision support model for design process based on the hybrid robust decision support model, and incorporate it into the web-based product design and realization framework.

References

- [1] Rosen, D. W., Chen, Y., Gerhard, J., Allen, J. K., and Mistree F., 2000, "Design Decision Templates and Their Implementation for Distributed Design and Solid Freeform Fabrication," Proceedings of ASME DETC00, Paper No. DETC00/DAC-14293, Baltimore, Maryland, September 10-13
- [2] Jiao, J.X., Tseng, M.M., 1998, "Fuzzy Ranking for Concept Evaluation in Configuration Design for Mass Customization," Concurrent Engineering: Research and Application, Vol.6, No.3, pp. 189-206
- [3] Pahl, G. and W. Beitz, 1996, Engineering Design - A Systematic Approach, New York: Springer.
- [4] Gui, J.K., 1993, Methodology for Modeling Complete Product Assemblies, PhD Dissertation, Helsinki University of Technology
- [5] Hwang, C.L. and K. Yoon, 1981. Multiple Attribute Decision Making: Methods and Applications, Berlin: Springer.
- [6] Thurston, D.L., 1991. "A Formal Method for Subjective Design Evaluation with Multiple Attributes," Research in Engineering Design, Vol.3, No.2, pp.105-122.
- [7] Thurston, D.L. and J.V. Carnahan, 1992. "Fuzzy Rating and Utility Analysis in Preliminary Design Evaluation of Multiple Attributes," ASME Journal on Mechanical Design, Vol.114, No.4, pp.648-658.
- [8] Mistree, F., O.F. Hughes and B.A. Bras, 1992. "The Compromise Decision Support Problem and the Adaptive Linear Programming Algorithm," Structural Optimization: Status and Promise, M.P. Kamatt (ed.), AIAA, Washington D. C., Chapter 11, pp.247-286.
- [9] Mistree, F., B. Bras, W.F. Smith, J.K. Allen, 1995. "Modeling Design Processes: A Conceptual, Decision-Based Perspective," Engineering Design & Automation, Vol.1, No.4, pp.209-321.
- [10] Zadeh, L.A., 1965. "Fuzzy Sets," Information and Control, Vol.8, pp.338-353.
- [11] Saaty, T.L., 1991. The Analytic Hierarchy Process, McGraw-Hill, New York.

- [12] Zimmermann, H.J., 1996, Fuzzy Set Theory and Its Applications, 3rd ed., Boston: Kluwer Academic Publishers
- [13] Maimon, O. and E. Fisher, 1985, "Analysis of Robotic Technology Alternatives," Proceedings of the 1985 Annual Industrial Engineering Conference, pp.227-236.
- [14] Knosala, R. and W. Pedrycz, 1992, "Evaluation of Design Alternatives in Mechanical Engineering," Fuzzy Sets and Systems, Vol.47, No.3, pp.269-280.
- [15] Carnahan, J. V., D. L. Thurston and T. Liu, 1994, "Fuzzy Rating for Multi-attribute Design Decision-Making," ASME Journal of Mechanical Design, Vol.116, No.2, pp.511-521.
- [16] Wang, J., 1997, "A Fuzzy Outranking Method for Conceptual Design Evaluation," International Journal of Production Research, Vol.35, No.4, pp.995-1010.
- [17] Boender, C. G., J. G. de Graan and F. A. Lootsma, 1989, "Multi-criteria Decision Analysis with Fuzzy Pairwise Comparisons," Fuzzy Sets and Systems, Vol.29, pp.133-143.
- [18] Clausing, D., 1994, Total Quality Development: A Step-by-Step Guide to World Class Concurrent Engineering, New York: ASME Press.
- [19] Prasad, B., 1996, Concurrent Engineering Fundamentals, Volume 1-2, NJ: Prentice Hall PTR.
- [20] Pugh, S., 1991, Total Design: Integrating Methods for Successful Product Engineering, Addison-Wesley Publishing Co. Inc.
- [21] Taguchi, G., 1986, Introduction to Quality Engineering, Tokyo, Japan: Asian Productivity Organization.
- [22] Simpson, T. W., 1998, "A Concept Exploration Method for Product Family Design," Ph.D Dissertation, Woodruff School of Mechanical Engineering, Georgia Institute of Technology.
- [23] Jang, J.-S. Roger, 1993, "ANFIS: Adaptive-Network-Based Fuzzy Inference System," IEEE Trans. Syst., Man, and Cybernetics, 23, pp.665-685
- [24] Zha, X.F., Lu, W.F., 2002, "Knowledge Intensive Support for Customer-Based Design for Mass Customization," Artificial Intelligence in Design (AID'02), Kluwer Academic Publisher, pp. 407-430
- [25] Zha, X.F., 2001, "Neuro-fuzzy Comprehensive Assemblability and Assembly Sequence Evaluation," Artificial Intelligence for Engineering Design, Analysis and Manufacturing, Vol.15 (5), pp.367-384
- [26] Zha, X.F., Lu W.F., 2003, "Knowledge Support for Concept Evaluation and Selection in Design for Mass Customization," Proceedings of International Conference on Engineering Design (ICED03), Stockholm, August 19-21
- [27] Xiao, A., Choi, H., Allen, J.K., Rosen, D.W., Mistree, F., 2002, "Collaborative Decision Making Across Digital Interfaces," Proceedings of ASME DETC 2002, Paper No.: DETC2002/DAC-34073, Montreal, Canada
- [28] Sriram, R.D., 2002, Distributed & Integrated Collaborative Engineering Design, Sarven Publishers, Glenwood, MD, USA

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