Evaluation and Selection in Product Design for Mass Customization: A Knowledge Decision Support Approach

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Abstract

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. This paper presents a knowledge decision support approach to product family design evaluation and selection for mass customization process. In the paper, product family design is viewed as a selection problem with major stages: product family (design alternatives) generation and product family design evaluation and selection for customization. First, the fundamental issues underlying product family design for mass customization are discussed. Then, a knowledge support framework and its relevant technologies are developed for module-based product family design for mass customization. A systematic fuzzy clustering and ranking model is proposed and discussed in detail to model imprecision inherent in decision-making with fuzzy customers' preference relations and carry out fuzzy analysis and evaluation and selection of product family for customization. Neural network technique is also adopted to adjust the membership function to enhance the model. The focus of this paper is on the development of a knowledge intensive support scheme and a comprehensive systematic fuzzy clustering and ranking methodology for product family design evaluation and selection. A case study and the scenario of knowledge support for power supply product evaluation, selection, and customization are provided for illustration.

Keywords: Product platform, product family design, customer-driven design, mass customization, design evaluation, multi-criteria decision-making, fuzzy clustering, fuzzy ranking, and knowledge support

Nomenclature

CDFMC: Customer-driven design for mass customization

PP: Product platform

PFA: Product family architecture

cDSP: Compromise decision support problem

QFD: Quality function deployment

CFD: Concurrent function deployment

AHP: Analytic hierarchy process

CB: Common base

DE: Differentiation enabler

PV: Product variant

PDS: Product design specification

EDS: Engineering design specification

EDSV: Engineering design specification vector

OFR: Operational functional requirement

GFR: General functional requirement

VoCs: Voice of customers

FMCDM: fuzzy multi-criteria decision-making

$\eta_{M:}$ Market efficiency

$\eta_{I:}$ Investment efficiency

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

$\mu_{R_{ij}}(r_{ij})$: Membership function of r_{ij}

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

$\mu_R(r_i)$: Fuzzy rating membership function

f_h: Heuristic evaluation function

1. Introduction

Today's highly competitive, global marketplace is redefining the way companies do business. Mass customization (Pine, 1993) embarks a new paradigm for manufacturing industries, whereby variety and customization supplant standardized products, heterogeneous and fragmented markets spring from once homogeneous markets, and product life cycles and development cycles spiral downward (Tseng and Jiao 1996,1998). It has recently received much attention and popularity from both industry and academia, and has been considered as a new battlefield for manufacturing enterprises (Wortmann et al. 1997). Mass customization aims at delivering a sufficient product variety to satisfy diverse customer needs while maintaining near mass production efficiency (Tseng and Jiao 1996). Essentially, it is an oxymoron of variety to cater for customization and the low costs of variety fulfillment. To adopt the mass customization paradigm, many companies are being faced with the challenge of providing sufficient variety for the market with as little variety as possible between products in order to maintain economies of scale while satisfying a wide range of customer requirements.

A product family (line) refers to a collection of product variants that have the same functions but with different combinations of attribute levels. In a market characterized by a large variety of customer preferences and with competitions, companies introduce a product family to satisfy as best as possible the preferences of different customers and also achieve their business goals (Li and Azarm 2002). 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 (Tseng and Jiao 1996). Customized product development is resembled as configuration design, in which 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 configuration design 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. Thus, product /family evaluation plays an important role in this process as a poor selection of either a building block or module or a configuration structure is difficult to be compensated for at later design stages and can give rise to expensive redesign costs (Pahl and Beitz 1996). Because of its paramount importance in configuration design, the alternative evaluation and selection problem has received enormous attention both in academia and in industry. Although a number of methods have been investigated, there is still much to be desired due to the hindrance inherent in the conceptual evaluation and selection process. Difficulties associated with such a task lie in problem-solving complexity, various decision criteria, and product performance assessment (Jiao and Tseng 1998; Zha and Lu 2002a,b).

Contemporary design has become increasingly knowledge-intensive (Tong and Sriram 1991a,b; Sriram 2002). Knowledge-intensive support becomes more critical in the design process and has been recognized as a key solution towards future competitive advantages in product development. To improve the product family design for mass customization process, it is imperative to provide knowledge support and share design knowledge among distributed designers. In our previous work (Zha and Lu 2002a,b), a general high-level knowledge intensive support framework was proposed for customer-driven, modular platform-based product family design and design for mass customization. Some fundamental research issues were identified and addressed. A prototype web-based knowledge system to support product family design has been developed and tested with a power supply product family. On the basis of the previous work, this paper aims to develop a knowledge support paradigm for product family design evaluation and selection in customer-driven design for mass customization (CDFMC). The focus of this paper is on the development of a comprehensive systematic fuzzy clustering and ranking methodology for product family design evaluation and selection in the context of CDFMC.

The organization of this paper is as follows. Section 2 reviews the previous research related to product family design evaluation and selection. Section 3 addresses issues and technologies for customer-driven modular product family design for mass customization. Section 4 discusses a knowledge support scheme for product family evaluation in design for mass customization. A fuzzy clustering and ranking methodology is proposed and discussed in detail. Section 5 provides a case study and a scenario of knowledge support for product customization in power supply family design. Section 6 presents the research results and discusses the benefits or advantages of the proposed approach. Section 7 summarizes and concludes the paper.

2. Current Status of Research

This section briefly reviews previous research work and current status of research related to product family design for mass customization and design alternative evaluation and selection.

2.1 Design Alternatives Evaluation and Selection

The literature on design alternative evaluation and selection can be generally classified into five categories (Jiao and Tseng 1998a): multi-criteria utility analysis, fuzzy set analysis, design analytic methodology, the hybrid approach, and the information content approach, but the first three approaches are prevalent. The following review will be mainly on these first three approaches.

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 (1991) 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.* (1992,1995) 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 (Thurston and Carnahan 1992).

Fuzzy analysis, based on fuzzy set theory (Zadeh 1965), 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," and "medium." It has been 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 (Zimmermann 1996). The fuzzy set analysis approach is most appropriate when there are imprecise design descriptions, whereas the probability analysis approach 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 for the fuzzy set analysis approach 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 (1985) 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 (Knosala and Pedrycz 1992). It is difficult for a fuzzy goal-programming model to consider all sources of uncertainty coherently at the preliminary design stage (Carnahan, Thurston and Liu 1994). In addition, the computational complexity is a key issue, especially in case of a large number of design alternatives and criteria being involved (Wang 1997; Boender et al 1989). 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), concept selection matrix (Pugh 1991), Taguchi robust design method (Taguchi 1986), 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.

To reflect customer preferences in multi-criteria design evaluation, numerous evaluation procedures take into account the relative importance or weighting factor for each criterion (Jiao and Tseng 1998). Frazell (1985) assigned weights to criteria on a 0-100 scale. Sullivan (1986) presented a linear additive model, in which ranking is included. Huang and Ghandforoush (1984) proposed another procedure for quantifying subjective criteria, in which they compute 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, i.e., 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 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 (Saaty 1991). The analytical hierarchy process (AHP) was developed to deal with the decision-maker's inconsistency and to mimic the human decision-making process (Saaty 1991). It determines weights by means of pair-wise comparisons between hierarchical decision levels. The AHP 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 an approach to fuzzify the weights after they have been obtained by the AHP.

2.2 Product Family Design Evaluation and Selection for Mass Customization

Various approaches and strategies for designing families of products and mass customized goods are reported in the literature. These techniques appeared in varied disciplines such as operations research (Gaithen 1980), computer science (Nutt 1992), marketing / management science (Kotler 1989; Meyer and Utterback 1993; Pine 1993; Wheelwright *et al.* 1989, 1992; Sanderson 1991; Rothwell and Gardiner 1990), or engineering design (Stadzisz and Henrioud 1995; Ishii and Eubanks 1995; Martin and Ishii 1996; Chen *et al.* 1996; Fujita and Ishii 1997; Fujita *et al.* 1998; Tseng and Jiao 1996, 1998; Simpson *et al.* 1998, 2001; Ulrich *et al.* 1995; Gonzale-Zugasti 2000; Zha and Lu 2002a,b).

In order to evaluate a family of products for mass customization, suitable metrics are needed to assess the appropriateness of a product platform and the corresponding family of derivative products (Krishnan and Gupta 2001). The metrics should also be useful for measuring the various attributes of the product family and assessing a platform's modularity. With respect to the process of product family design for customization, the evaluation of product family design was viewed from three different level perspectives: product platform, product family and product variant (Zha and Sriram 2003). The product variant level evaluation is actually the same as or similar to the individual product design evaluation. Various traditional design evaluation approaches reviewed above are applicable, and the metrics for this level of evaluation include cost, time, assemblability, manufacturability, etc. The platform and family level evaluation is focused on the overall benefit of product family development to the company, and the metrics at these levels reflect the main goal of designing products/families is to maximize the benefits to the company. Currently, there are many marketing or business, econo-technical metrics that can be used for measuring performance or evaluation in customer-driven design for mass customization on the first two levels (Simpson 1998; Zha and Sriram 2003). For example, platform efficiency and platform effectiveness defined by Meyer et al. (1997) can be used to measure R&D performance, focused on platforms and their follow-on products (variants) within a product family. Other methods include cycle time efficiency, technological competitive responsiveness, and profit potential (Meyer and Lehnerd 1997).

Specifically, the approaches for product family design evaluation and selection have been received much attention of researchers from both engineering design (for designer) and management and marketing (for customer). From an engineering design perspective, multi-objective optimization models have been used to obtain a performance optimal product family (line) in order to satisfy a range of customer requirements, and to quantify the influence of a product platform (Nelson et al 1999, Li and Azarm 2000,2002; Simpson 1998; Simpson *et al.* 2001). In addition, the engineering design literature reports on models that account for cost, expected profit, risks, and benefits of delayed decisions in producing a product family (line) (Fujita et al 1998; Gonzale-Zugasti 2000). From the management and marketing perspective, research efforts have been made mainly on product line positioning (Green and Krieger 1985; Kohli and Sukumar 1990; Dobson and Kalish 1993). In the product line-positioning problem, a line of products is selected from a set of already available design alternatives, considering cost, customers' preferences and market competition to optimize a business goal such as profit or market share. Li and Azarm (2002) proposed an integrated approach for a product line design selection based upon marketing potential of candidate product lines, those that have from an engineering design point of view the best possible variants. The integrated approach accounts for a large variety of customers' preferences, market competitions, and commonality (i.e., multi-component variants that share one or more components across the product line). However, the previous work did not sufficiently account for uncertainties of parameters such as customer preferences, product's life cycle, market size, and discount rate, etc.

The literature review indicates that several quantitative frameworks have been proposed for product family design evaluation and selection. They provide valuable managerial guidelines in implementing the overall platform-based product family development. However, there are very few systematic qualitative or integrated intelligent methodologies to support the product development team members to adopt the platform product development practice, despite the progress made in several research projects (Zha and Lu 2002a,b; Zha and Sriram 2003; Simpson et al. 2003).

3. Customer-Driven Product Family Design for Mass Customization

The approach advocated in this work is for companies to realize a family of products that can be easily modified and quickly adapted to satisfy a variety of customer requirements or target-specific market niches. Details about the knowledge supported product family design for mass customization are discussed below.

3.1 Strategies and Technical Challenges for Mass Customization

The essence of mass customization is to satisfy customers' requirements precisely without increasing costs, regardless of how unique these requirements may be. That is, a manufacturer has to perceive and capture latent market niches and correspondingly develop its technical capabilities to meet diverse customer needs. The capture of target customer groups means emulating or outclassing competitors in either quality or cost or quick response or a combination of one or more. Therefore, the requirements of mass customization lie in three aspects: 1) time to market (quick responsiveness), 2) variety (customization), 3) flexibility, and 4) economies of scale (mass efficiency). The oxymoron of mass customization depends on the leverage of these requirements. There are eight identified strategies that have worked in many circumstances (Baudin 2001):

(1) *Analysis of the structure of customer demands*. The premise is that it is only necessary to make what customers do order, not everything they might. Most of the actual customer demands tend to cluster around a few configurations, and production must be organized to take advantage of this structure.

(2) *Standardization of components*. Customized products do not always have to be made from scratch. Instead, they can be made from a small number of standard components.

(3) *Use of products catalogs with a discrete set of sizes*. Products made in size increments meet the needs of almost all consumers.

(4) *Postponement of customization to the end of the process*. Customization is best employed at or near the end of the manufacturing process. Postponing customization, however, may require substantial process engineering efforts.

(5) *Identification of a common process*. Treat customized products like options on standard products.

(6) *Maintenance of a database for past designs*. It can be an enormous time saver in meeting requirements that appear to be new. The challenge is finding ways to organize this data for easy retrieval of similar designs rather than exact matches.

(7) *Design a customized manufacturing process*.

(8) *Setup of a simple production control system*.

Considering the above requirements, the main technical challenge in developing a coherent framework for mass customization is in the ability to simultaneously satisfy the following requirements within a single approach (Tseng and Jiao 1996):

(1) *Reusability and commonality*. Optimizing reusability and commonality to achieve low cost and high efficiency, i.e., the economy of scale, an advantage characterized by mass production.

(2) *Product platform.* Providing a technical foundation for realizing customization, managing varieties and leveraging core capabilities to optimize flexibility and foster a customer-focused and product-driven business.

(3) *Integrated product development*. Facilitating meta-level integration throughout the product development process and over the product life cycle to achieve quality and increased responsiveness.

3.2 Customer-Driven Design for Mass Customization

With regards to the above challenges and strategies, this research investigates mass customization from a product development perspective, namely customer-driven design for mass customization (CDFMC), based on the belief that mass customization can be effectively approached from a design perspective (Tseng and Jiao 1996,1998). Essentially, the attempt includes customers into the product development life cycle through proactively connecting customer needs to the capabilities of a company. The primary focus of CDFMC is to elevate the current practice from designing individual products to designing product families. In addition, CDFMC advocates extending the traditional boundaries of product design to encompass a larger scope spanning from sales and marketing to distribution and services (Tseng and Jiao 1998). To support customized product differentiation, a product family platform is required to characterize customer needs and subsequently to fulfill these needs by configuring and modifying well-established building blocks.

Figure 1 outlines the concept for CDFMC used in this research. It is an adaptation of the process model presented by Barkmeyer et al. (1997). Recognizing the rationale of family-based product design with respect to mass customization, the whole process of CDFMC ranges from capturing voices of customers (VoCs) and market trends for generating product design specifications, designing product platform for generating product variety or family, to deriving and customizing product variants by evaluating and selecting a product family for customers' satisfaction. It can be divided into two major stages: 1) product/family planning, and 2) family design. The product planning stage embeds the voices of customers into the design objective and generates product design specifications. The product family design stage realizes sufficient product variety to satisfy a range of customer demands. The bottom of Figure 1 illustrates the concept of module-based product family design process.

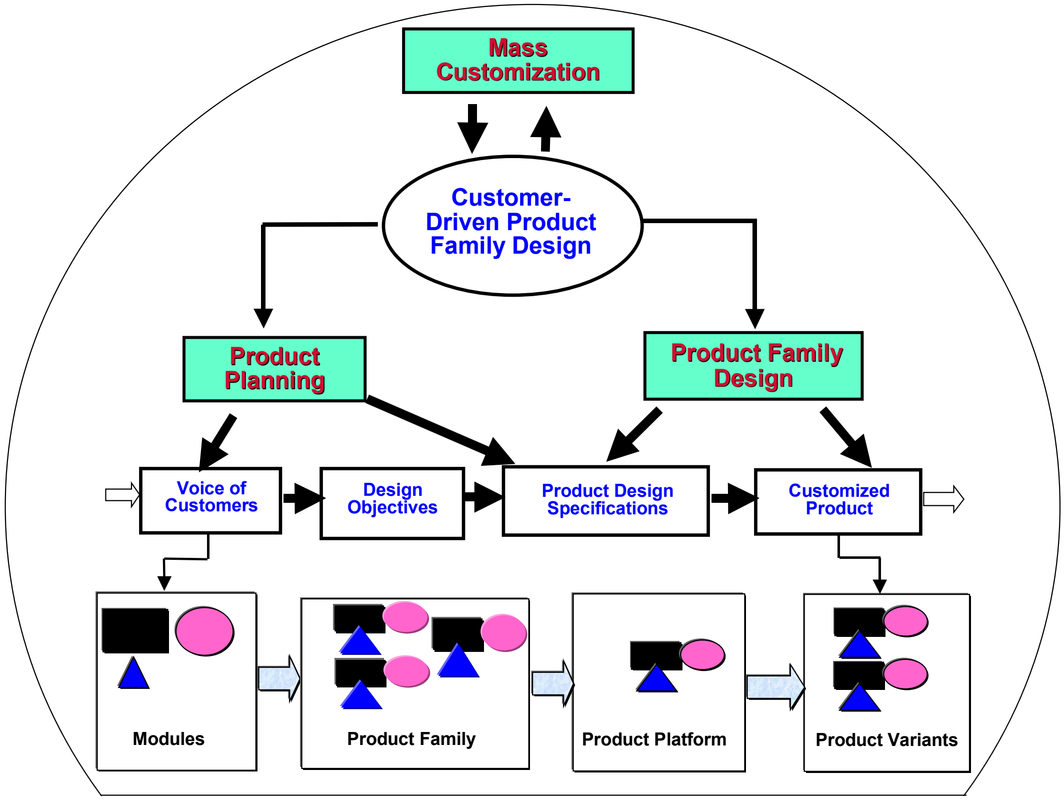


Figure 1: Framework for CDFMC based on the module-based product family design

Figure 2 illustrates a product family architecture (PFA) to support mass customisation (Du et al. 2000). From the customers' point of view, products are functional features, $\{f\}$, and the related feature values, $\{f^*\}$. A product family, $\{PV_1, PV_2, PV_3, \ldots, PV_i, \ldots, PV_m\}$, is designed to address the requirements of a market segment {Customer $_1$, Customer $_2$, Customer $_3$, …, Customer $_i$, …, Customer $_m$}, wherein the customers share some similar/common requirements, f_0^*, and have their special requirements, $\{f_1^*, f_2^*, f_3^*, \ldots, f_n^*\}$, in the mean time. Customer requirements characterized by the different combinations of functional features can be satisfied by the product variants derived by the common bases, {CB), and differentiation enablers, {DE}, of the product family. It is the configuration mechanisms that determine the generative aspect of a product family, which guarantee the technical feasible and market wanted product variants are derived. Details about the PFA and its three elements: the common base, the differentiation enabler, and the configuration mechanism, can be found in (Tseng and Jiao 2002).

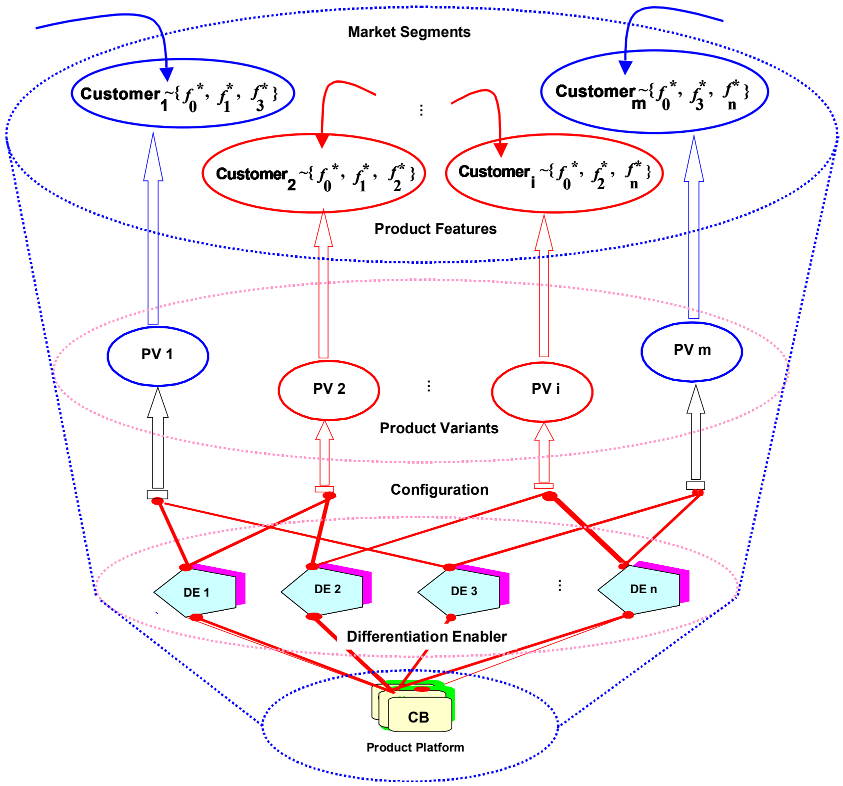


Figure 2: Architecture of product family for mass customization

3.3 Module-Based Product Family Design Process

The fundamental issues underlying the whole product family design for mass customization process include product information modeling, product family architecture, product platform and variety, modularity and commonality, product family generation, and product assessment and customization, etc. (Jiao and Tseng 1998b; Zha and Lu 1992a,b). An effective product family platform can allow a variety of derivative products to be created more rapidly and easily, with each product providing the features and functions desired by a particular market segment (Simpson 1998; Simpson *et al.* 2001). Usually, product families have an impact on a firm's ability to efficiently deliver high product variety and can have profound implications for subsequent product development activities. The product family design is tightly linked to several issues of importance to the entire enterprise: product change, product variety, component standardization, product performance, manufacturability, and product development management.

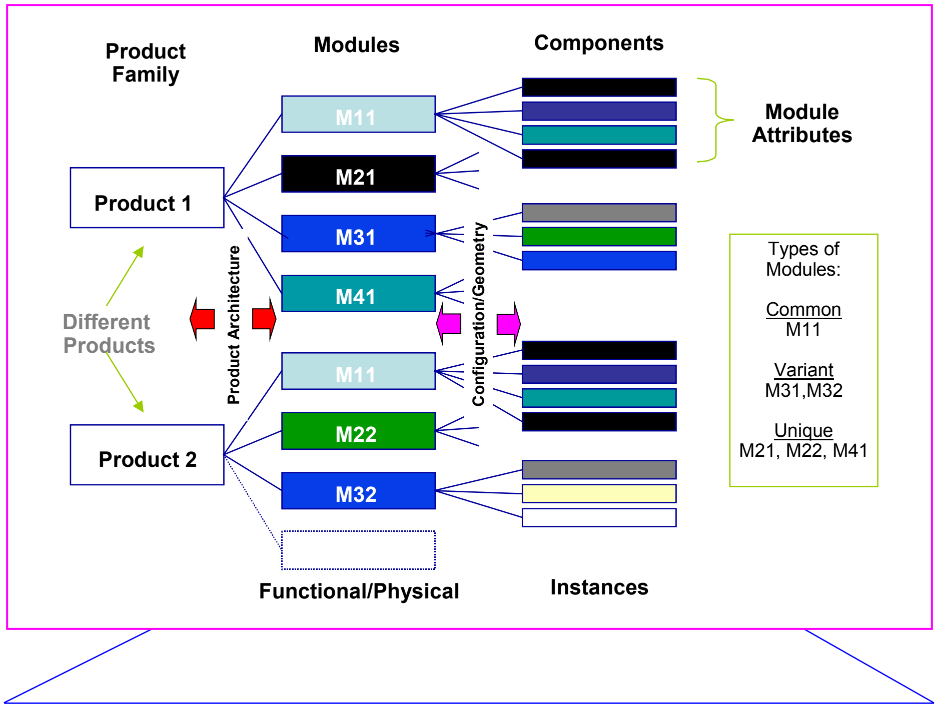


Figure 3: Product families, modules, and attributes (Modified from Fujita and Ishii 1997)

From the aspect of product design, component standardization through a modular architecture has clear advantages in the areas of cost, product performance and product development. Decomposing the problem into modules and defining how modules are related to one another creates the model of a design problem. Modular systems provide the ability to achieve product variety through the combination and standardization of components (Kusiak and Huang 1996). Fujita and Ishii (1997) decompose product families into systems, modules, and attributes. Under the hierarchical representation scheme as shown in Figure 3, product variety can be implemented at different levels within the product architecture. This is actually a modularization process from a certain perspective, as shown in Figure 4. The modularization process can be fulfilled through the following steps (Zha and Lu 2002a,b):

(1) The requirement analysis and modeling is carried out both from task or customer and designer viewpoints using design function deployment technique. A function-function interaction matrix is generated.

(2) The combination of heuristic and quantitative (fuzzy) clustering algorithms is used to modularize the product architecture, and a modularity matrix is constructed (see Section 4.3).

(3) All modules in the product are identified through the modularity matrix, and the types of all these modules can be further identified according to the module classifications.

(4) The functional modules are mapped to structural modules using the function-structure interaction matrix. Module attribute parameters or features can represent its structure.

(5) The hierarchical building blocks (modules) are used to represent the product architecture from both the functional and the structural perspectives.

(6) A hybrid of the genetic algorithm and the simulated annealing algorithm is used to optimize product architecture to achieve one main objective. Other design objectives are transformed into constraints for modules and their attributes as well as their assemblies or configurations. In addition, the cost or profit models can also be built as system constraints.

(7) The product family architecture is rebuilt to form a hierarchical architecture by using the optimized modules from both the functional and the structural perspectives.

(8) The product family module space forms a product platform. The product family portfolio is derived from the product family module space.

(9) Standardize interfaces to facilitate addition, removal, and substitution of modules.

(10) The product family can be generated by modules configuration/reconfiguration.

(11) Product variants are evaluated and selected to satisfy the customer requirements.

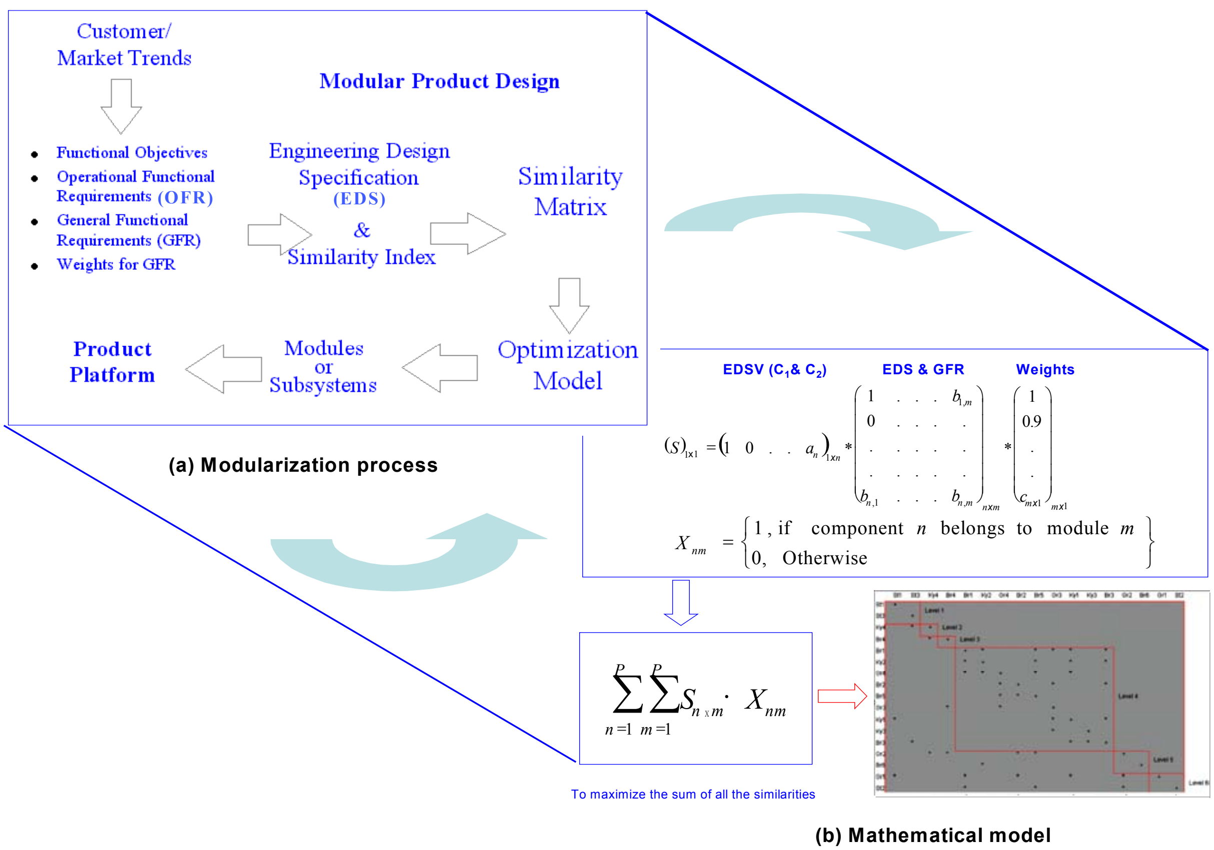


Figure 4: Modularization process in modular product family design

Therefore, the major steps for creating a modular product family can be outlined as follows: 1) Decompose products into their representative functions; 2) Develop modules with one-to-one (or many-to-one) correspondence with functions; 3) Group common functional modules into a common product platform; and 4) Standardize interfaces to facilitate addition, removal, and substitution of modules. The module-based product family design process develops a re-configurable product platform that can be easily modified and upgraded through the addition, substitution, and exclusion of modules to realize module-based product family. The product customization stage aims at obtaining a feasible architecture of a product variant (i.e., a family member) through reasoning product family module space according to customer requirements (Meyer and Ishii 1997). There are two steps involved in this stage. First, customer requirements such as function, assembly, and reuse need to be converted to constraints (Suh 1990). Then, the reasoning is performed at two levels: namely, module and attribute levels, to determine (evaluate and select) the feasible product variants.

3.4 Knowledge Support Framework for CDFMC

The conceptual framework shown in Figure 1 demonstrates the process of customer-driven product family design for mass customization, which ranges from capturing voices of customer, analyzing market trends, generating design objectives and product design specifications (PDS) to customizing products for customer satisfaction. To assist the designer during this process, a knowledge support framework is further developed based on the rationale of customer-driven design for mass customization, as illustrated in Figure 5.

Product family design knowledge is classified into two categories: 1) product/family information and knowledge, and 2) product/family design process knowledge. These two categories of knowledge are utilized to support customer-driven design for mass customization that has two application scenarios: product planning and product family design (Zha and Sriram 2003). With understanding of the fundamental issues in modular product family design, the knowledge support scheme aims to provide support for customer requirements' modeling, product architecture modeling, product platform establishment, product family generation, and product family assessment for customization. The knowledge support scheme for modular product family design and its key research issues are described in (Zha and Lu 2002b).

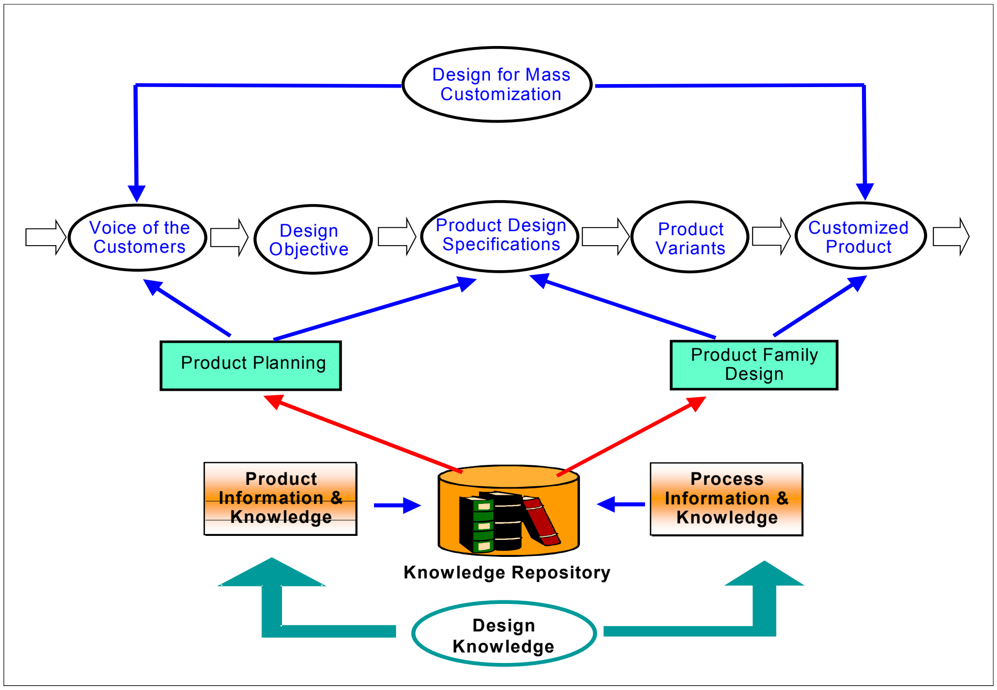


Figure 5: Knowledge support framework for CDFMC

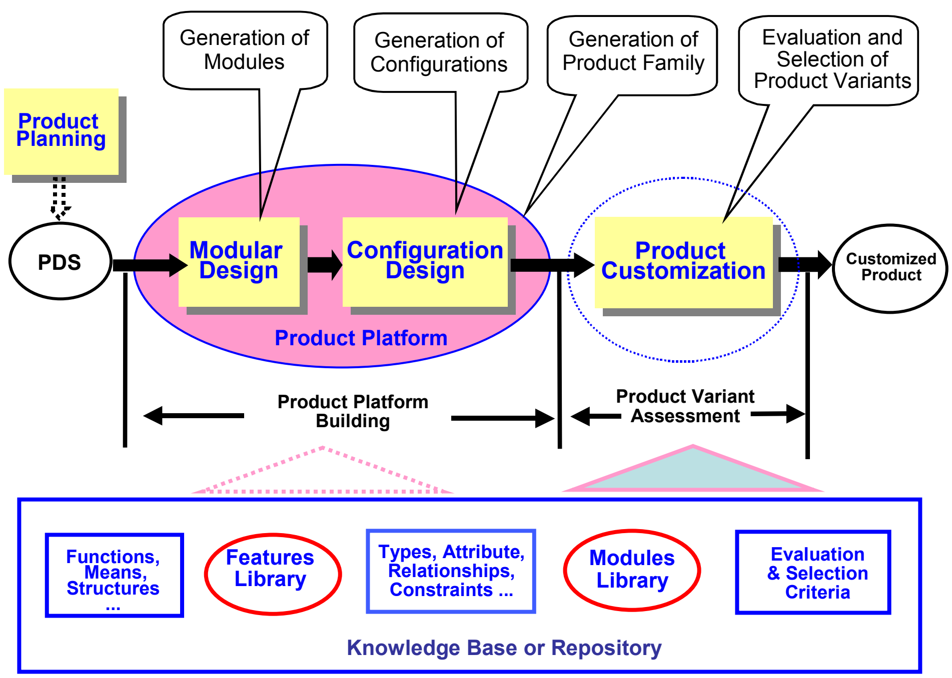


Figure 6: Modular product family design for mass customization process

As shown in Figure 6, the product family design process in the context of CDFMC can actually be divided into two major stages: 1) product platform building, and 2) product variant assessment. The generation of product platform and family in the product platform building stage is implemented through product (family) planning for design specifications and modular and configuration design, while the product family evaluation and selection for customization is implemented by assessing product variants generated from a product platform. The fundamental issues involved in the product family design process have been addressed in (Zha and Lu 2002a,b; Zha and Sriram 2003), which include a knowledge-intensive support strategy and its implementation for platform-based product design and development.

During the process of modular product family design, a family of products 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 customization requirements. The essence of CDFMC lies in synthesizing 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: family generation, evaluation and selection. A wrong or even a poor selection of either a building block or a 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, product family design evaluation and selection is crucial for CDFMC. To this end, a knowledge support scheme is developed in this research. Therefore, the remainder of this paper will focus on how the product family design knowledge base or repository (Zha and Sriram 2003) supports the designer to perform product family evaluation and selection.

4. Knowledge Supported Product Family Design Evaluation and Selection

This section begins with a summary of the knowledge decision support scheme for product family design evaluation and selection. It then presents evaluation/customization metrics applied in the product family design for mass customization process. Finally, it describes a fuzzy clustering and ranking model for classification, evaluation and selection of product family design alternatives.

4.1 Knowledge Support Scheme

As discussed above, the product customization stage aims to obtain a feasible product variant through reasoning and decision support in the product family module space according to customer requirements and design constraints. The design space for product configuration during module reasoning is very large for a complex system. The designer is required to consider not only the product functionality, but also some other criteria including compactness and other life-cycle issues, such as assemblability, manufacturability, maintainability, reliability, and efficiency. Some criteria may contradict each other. Designers should analyze the trade-off among various criteria and make the “best” selection from a number of design alternatives.

With respect to the traditional approaches (Pahl and Betiz 1996; Jiao and Tseng 1998), we propose a knowledge-based decision support approach for product family evaluation and selection for customization, as shown in Figure 7. Typically, this stage characterizes a feasible set of products generated from product platform as an input to 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 customers' requirements and design constraints. The knowledge resources utilized in this process may extensively include differentiating features, customers' requirements, desirabilities, preferences and importance (weights), trade-offs (e.g., market vs investment), and utilities functions, and heuristic knowledge, rules, etc. 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 with handling these fuzzy knowledge. The kernel of the knowledge decision support scheme is fuzzy clustering and ranking algorithms for design evaluation and selection that will be discussed below.

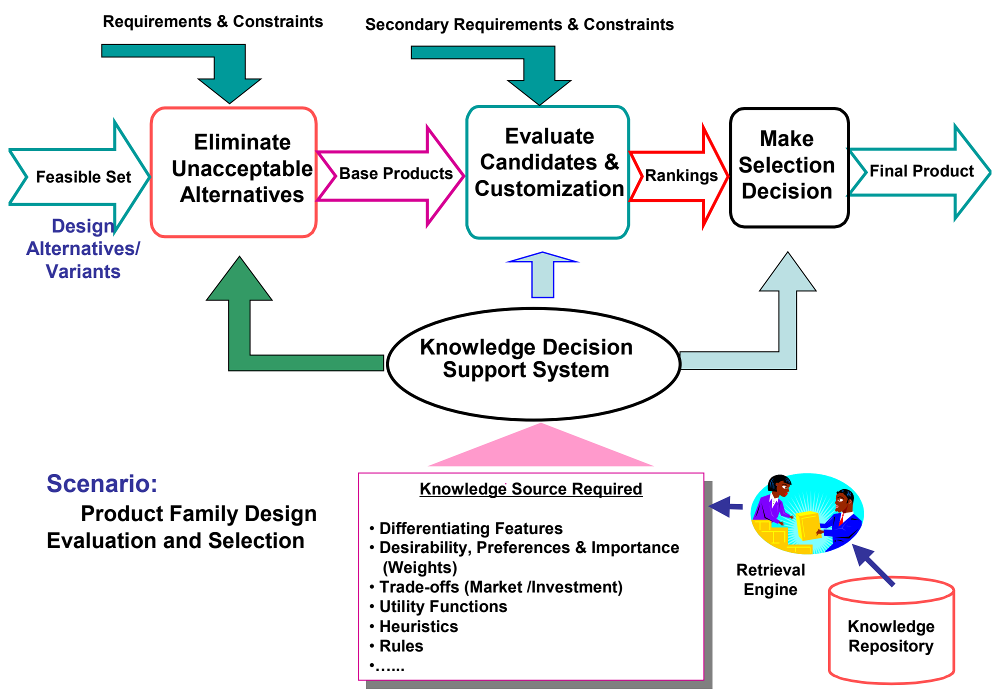


Figure 7: Knowledge-based decision support scheme

4.2 Evaluation /Customization Metrics

In this research, the evaluation of product family design is viewed from three different level perspectives: product platform, product family and product variant (Zha and Sriram 2003). The metrics for the product variant level of evaluation include cost, time, assemblability, manufacturability, etc. For the platform-based family level evaluation, many marketing or business, econo-technical metrics are used, including platform efficiency and platform effectiveness, and cycle time efficiency. In addition, the following two typical metrics have also been used (Zha and Sriram 2003):

(1) Market efficiency. This metric embodies a tradeoff between the marketing and the engineering design, which offers the least amount of variety to satisfy the greatest amount of customers, i.e., targets the largest number of market niches with the fewest products.

(2) Investment efficiency. This metric embodies a tradeoff between the manufacturing and the engineering design, which invests a minimal amount of capital into machining and tooling equipment while still being able to produce as large a variety of products as possible.

Therefore, they can be represented by the following two equations:

$$\eta_M = N_{TM}/N_M \tag{1}$$

$$\eta_I = C_M/N_v, \tag{2}$$

where, N_{TM} and N_M are the number of the targetable market niches and the total market numbers, respectively; C_M and N_v are the manufacturing equipment costs and the number of the product varieties, respectively. Of course, a tradeoff also exists between the market efficiency and the investment efficiency as an increase in the investment efficiency through a decrease in product variety can cause a decrease in the market efficiency.

4.3 Fuzzy Clustering and Ranking for Product Family Design

In this section, a fuzzy clustering and ranking methodology is proposed for product family design evaluation and selection in the context of CDFMC. The algorithms are constructed using fuzzy sets theory to solve a fuzzy clustering/classification and multi-criteria decision-making (FMCDM) problem. The fuzzy clustering algorithm is used to classify design alternatives or variants and determine similarity and commonality between modules, product variants and product families. The fuzzy multi-criteria decision-making problem can be defined as follows: given a set of design alternatives, evaluate and select a design alternative that satisfies customer needs, meets design requirements and complies with the technical capabilities of a company.

4.3.1 Fuzzy Clustering Analysis for Design

Based on the systematic approaches (Pahl and Beitz 1996; Suh 1990), a reasonable number of possible design alternatives can be obtained using the design solution generation techniques at the conceptual design stage. Each sub-function may correspond to a collection of available solution principles to determine design alternatives or variants through mappings from functions to forms. If there are a total of n sub-functions, each of them has m_i possible solution principles. Combining these solutions, all theoretically possible overall solution variants can be obtained as schematically illustrated in Table 1. Consequently, the cluster analysis for pattern recognition (Kandel 1982; Gui 1993) can be used to sort a product family design data set, for example, a number of possible solution principles to sub-functions or their possible combinations, into families. This is very crucial for determining the similarity between modules and also the commonality between product variants and product families.

Generally, given that there are m design patterns, a_1, a_2, ..., a_m, contained in the design pattern space S, the process of clustering can be formally stated as: to seek the regions $s_1, s_2, \ldots, s_k$ such that every a_i, i=1,...,m, fall into one of these regions and no a_i falls into two regions, that is, $s_1 \cup s_2 \cup \ldots \cup s_k = S$, $\forall i \neq j$, $s_i \cap s_j = \phi$. From this definition, clustering algorithms must be based on some natural associations according to some similarity measures and the patterns are described by a set of numerical measures or linguistic variables. The similarity measure or dissimilarity measure is usually given in a numeric form to indicate the degree of resemblance between modules or product variants in a family:

(1) The Euclidean distance is one of the simplest ways/metrics to measure the similarity. Therefore, a design object (e.g., a module, product variant or product family) in the design space may be viewed as a pattern point described by a vector in a pattern space. The shorter the distance between two points, the more they resemble each other. However, the concept of similarity is very fuzzy. The selection of variables and similarity measures often subjectively reflects the investigator's judgment, rather than rigorous mathematical guidelines.

(2) Another practical way to measure similarity is to predefine a fuzzy similarity matrix based on some concerns and then to store it in the computer. Matrix M_F (A×B) shows a fuzzy matrix to represent the similarity between types of modules or products in a family, as illustrated in Figure 8. Each entry in the matrix m_{ij} indicates the degree of fuzzy resemblance of product variant i and j. The closer the number in the matrix is to 1, the more similar the corresponding module or product variant is. Figure 9 gives an instance of a fuzzy similarity matrix for conceptual layout variants in a gear reducer family.

It is noted that given any two objects (modules or product variants) at some level they can be grouped into the same cluster. If these two objects are always kept within one family at all later levels, then the clustering sequence is hierarchical. The hierarchical clustering sequence or procedure can be divided into two distinct classes, bottom-up (agglomerative) and top-down (divisive). The former starts with singleton clusters and forms the sequence by successively merging clusters, whereas the latter starts with all the objects in one cluster and forms the sequence by successively splitting clusters. These two classes of hierarchical procedures are both employed in this research. The top-down (decisive) method is applied in the modularization process discussed in Section 3.3, and its algorithm and mathematical model is illustrated in Figure 4b. The bottom up (agglomerative) method is applied mainly for classification of modules and product variants. The algorithm follows four steps (Gui 1993): 1) Find the smallest element in distance matrix D_i to merge corresponding to two objects; 2) Select a point as reference in the merged group using some rule, e.g., nearest neighbor or centroid cluster; 3) Recalculate distance matrix between the new group and remainders, named D_{i+1}, and 4) Repeat step 1 until all the objects merge into one group.

Table 1: Various combinations of solution principles, of which hatched areas belong to the same family

Solutions							
Sub-functions		1	2	…	*j*	…	*m*
1	F_1	S_{11}	S_{12}		S_{1j}		S_{1m}
2	F_2	S_{21}	S_{22}		S_{2j}		S_{2m}
:	:	:	:	:	:	:	:
i	F_i	S_{i1}	S_{i2}		S_{ij}		S_{im}
:	:	:	:	:	:	:	:
n	F_n	S_{n1}	S_{n2}		S_{nj}		S_{nm}

	PV-B1	PV-B2	PV-Bi	PV-Bm
PV-A1	1	0.8	0.95	1
PV-A2	0.9	0.7	0.96	0.9
PV-Ai	0.65	0.65	0.87	0.8
PV-An	0	1	0.6	1

(a)

	PV-A1	PV-A2	PV-Ai	PV-An
PV-A1	1	0.86	0.95	0.9
PV-A2	0.86	1	0.96	0.9
PV-Ai	0.95	0.96	1	0.8
PV-An	0.9	0.9	0.8	1

(b)

Figure 8: Fuzzy similarity matrices between product variants (PV-A, PV-B) in a family

	L-R	R-L	L-L	R-R	R-LR	L-LR	LR-L	LR-R	LR-LR
L-R	1.0	0.9	0.85	0.85	0.7	0.7	0.65	0.65	0.4
R-L	0.9	1.0	0.9	0.9	0.8	0.8	0.7	0.7	0.4
L-L	0.85	0.85	1.0	0.95	0.7	0.7	0.6	0.6	0.5
R-R	0.85	0.9	0.95	1.0	0.8	0.8	0.7	0.7	0.6
R-LR	0.7	0.8	0.7	0.8	1.0	0.9	0.8	0.8	0.6
L-LR	0.7	0.8	0.7	0.8	0.9	1.0	0.8	0.8	0.7
LR-L	0.65	0.7	0.6	0.7	0.8	0.8	1.0	0.8	0.7
LR-R	0.65	0.7	0.6	0.7	0.8	0.8	0.8	1.0	0.8
LR-LR	0.4	0.4	0.5	0.6	0.6	0.7	0.7	0.8	1.0

Figure 9: A fuzzy similarity matrix between conceptual gear-reducer layout variants in a family (L: Left, R: Right)

4.3.2 Fuzzy Ranking for Design

After obtaining the design alternatives or variants, the next procedure is to examine them against marketing, econo-technical and even ergonomic criteria as well as aesthetic criteria. This is actually a multi-criteria decision-making problem. One of the well-known methods for multi-criteria decision-making is the procedure for calculating a weighted average rating $\bar{r}_i$ by use of the value analysis or cost-benefit analysis introduced in (Pahl and Britz 1996):

$$\bar{r}_i = \sum_{j=1}^{n}(w_j r_{ij}) / \sum_{j=1}^{n} w_j \tag{3}$$

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, this procedure 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. Thus, the fuzzy approach for ranking a set of alternatives (variants) against a set of criteria is needed. In what follows, we describe a fuzzy ranking approach developed based on the fuzzy set and theory (Zadeh 1965; 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 r_{ij} to certain C_j of alternative a_i is 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,...,w_n} are 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:

$$g_i(z_i) = \sum_{j=1}^{n}(w_j r_{ij}) / \sum_{j=1}^{n} w_j \tag{4}$$

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

$$\mu_{Z_i}(z_i) = \overset{\circ}{\bigwedge}_{j=1,...,n} \mu_{W_j}(w_j) \overset{\circ}{\bigwedge}_{k=1,...,n} \mu_{R_{ik}}(r_{ik}) \tag{5}$$

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

$$\mu_{R_i}(r_i) = \sup_{Z_i g(z_i) = r_i} \mu_{Z_i}(z_i), r_i \in R \tag{6}$$

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 $\mu_R(r_i)$ is the best one. The following procedure further evaluates the two fuzzy sets as:

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

$$\mu_{I/R}(i \mid r_1,...r_m) = \begin{cases} 1 & if \quad r_i > r_k, \forall k \in (1,2,...,m) \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

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

$$\mu_R(r_1,...r_m) = \overset{\circ}{\bigwedge}_{i=1,...,m} \mu_{R_i}(r_i) \tag{8}$$

A 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.,

$$\mu_I(i) = \sup_{r_1,...r_m} \mu_{I/R}(i \mid r_1,...r_m) \overset{\circ}{\wedge} \mu_R(r_1,...r_m) \tag{9}$$

Comparing with Eq.(3), the fuzzy ranking for design is more flexible and presents uncertainty better. Based on this method, the designer can use linguistic rating and weights such as "good," "fair," "important," "rather important," for design alternatives evaluation. Therefore it looks natural and attractive in practical use.

4.3.3 Simplified Fuzzy Ranking for Design

In some cases, a simplified model is employed in integrating linguistic terms and fuzzy numbers into the fuzzy preference model. The universe of discourse is a finite set of fuzzy numbers used to express an imprecise level of performance rating and weight of each criterion. A range of imprecise levels is the linguistic terms, "very low," "low," "fairly low," "medium," "fairly high," "high," and "very high." The linguistic scale is used to transform these linguistic terms of partial performance ratings R_{ij}, and weights W_j of the criteria into triangular or trapezoidal fuzzy numbers defined in the interval [0,1]. R_{ij} denotes the linguistic performance rating with respect to a criterion C_j for a retrieved product variant PV_i, W_j denotes the linguistic weight of a criterion C_j. The aggregation of fuzzy numbers in an analytic form requires a complex arithmetic process. Thus, in this research, an approximate centroid-based defuzzification method is used to defuzzify the fuzzy numbers into crisp values early on, then the defuzzified results can be aggregated easily and the execution is very fast (Zhang et al 2002). For example, if a fuzzy set is represented as a trapezoidal fuzzy number, see Figure 10, then it can be parameterized by a quadruple (x_1, x_2, x_3, x_4) and its crisp defuzzied value (approximate centroid) is $(x_1+x_2+x_3+x_4)/4$. A triangular fuzzy number (x_1, x_2, x_3) can also be represented as (x_1, x_2, x_2, x_3) by a trapezoidal fuzzy number form with its crisp defuzzied value becoming $(x_1+x_2+x_2+x_3)/4$.

With the approximate centroid-based defuzzification method the fuzzy linguistic performance rating R_{ij} and fuzzy linguistic weight W_j can be transformed respectively into the crisp performance rating $r_{ij} \in [0,1]$ and crisp weight $w_j \in [0,1]$. Now the numerical weighted performance rating $\bar{r}_i \in [0,1]$ of a design alternative can be calculated simply using the classic weighted average aggregation method. The key points of this simplification can be understood as: it is a simple scenario; it can also be used for defuzzification.

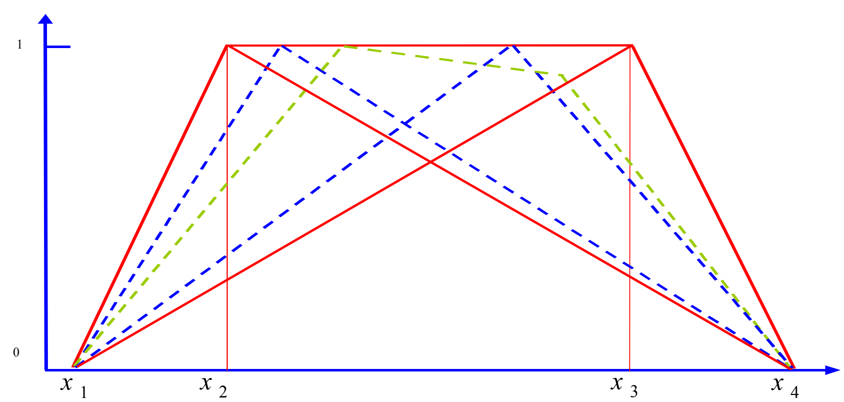


Figure 10: Linguistic scale representation for fuzzy customer preferences and performances

4.4 Evaluation of Product Family Design Alternatives

4.4.1 Heuristic Evaluation Function

With respect to the traditional approaches (Pahl and Betiz 1996; Jiao and Tseng 1998), we propose an approach to concept evaluation and selection for product customization from the knowledge support viewpoint. The knowledge resource utilized in the process extensively include differentiating features, customers' requirements, desirabilities, preferences and importance (weights), trade-offs (e.g. market vs investment), and utilities functions, and heuristic knowledge, rules, etc. It is important to have a powerful search strategy that will lead to a near optimum solution in a reasonable amount of time. A* search (Sriram 1997) provides a method to achieve this. 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 used as the heuristic evaluation function by considering all the weighted performance ratings of product variants.

4.4.2 Evaluation Index

After calculating the numerical weighted performance ratings of all design alternatives, the evaluation index is calculated and used as a heuristic evaluation function f_h, by considering all the weighted performance ratings $\bar{r}_i$ (i=1, 2, 3,…, m) of its constituent members and the number k of its unsatisfied customer requirements, as follows:

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

where, $\bar{r}_i \in [0,1]$ is the numerical weighted performance rating of product variants PV_i; $1/\bar{r}_i = (1,+\infty)$ is defined as the performance cost of product variants PV_i. A higher weighted performance rating of a product variant 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 so 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, also called the evaluation index or the heuristic evaluation function. In the above formula, a higher $\bar{r}_i$, i.e., the better-aggregated performance of each retrieved product variants PV_i, and lower m or k, *i.e.,* higher compactness of design alternative, result in a lower f_h (lower evaluation index of a design alternative). 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 can be selected, by taking into account multi-criteria factors, including design compactness and efficiency (market vs investment) or other life-cycle issues, for instance, manufacturability, assemblability, maintainability, and reliability.

4.5 Neural Network Adjustment for Membership Functions

Due to the complexity and uncertainty of design problems, it is required to further improve the above comprehensive fuzzy clustering and ranking methods. One of aspects of 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 (Zimmermann 1987, 1996). It can be easily implemented and adjusted by using neural networks. The fuzzy system (e.g., rule block) is the kernel of the whole fuzzy neural network model. It forms the basic scheme of knowledge representation exploited in the fuzzy evaluator.

The neuro-fuzzy hybrid approach uses neural network to optimize certain parameters of an ordinary fuzzy system, or to preprocess data and extract fuzzy rules from data (Zha 2001). The fuzzy evaluator described above 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 fuzzy rule 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 a 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. With simplicity but without loss of generality, the former approach is adopted in this research. Suppose that $[\alpha_1,\alpha_2]$ contains the support of all the A_i we might have as input to the system, and $[\beta_1,\beta_2]$ contains the support of all the B_i we can obtain as outputs from the system, i = 1, 2,…,n. If $m\geq2$ and $n\geq2$ be positive integers, then

$$x_j = \alpha_1 + (j-1)(\alpha_2 - \alpha_1)/(n-1),$$

$$y_i = \beta_1 + (i-1)(\beta_2 - \beta_1)/(m-1),$$

where, $1\leq i\leq m$, and $1\leq j\leq n$. Thus, a discrete version of the continuous training set can be composed of the following input/output pairs: $\{(A_i(x_1),\ldots,A_i(x_n)), (B_i(y_1),\ldots,B_i(y_m))\}$, i = 1,…,n. Using the notations $a_{ij}=A_i(x_j)$, $b_{ij}=B_i(y_j)$, the fuzzy neural network turns into an n inputs and m outputs crisp network, which can be trained by the generalized delta rule. Figure 11 shows a network trained on membership values of fuzzy numbers.

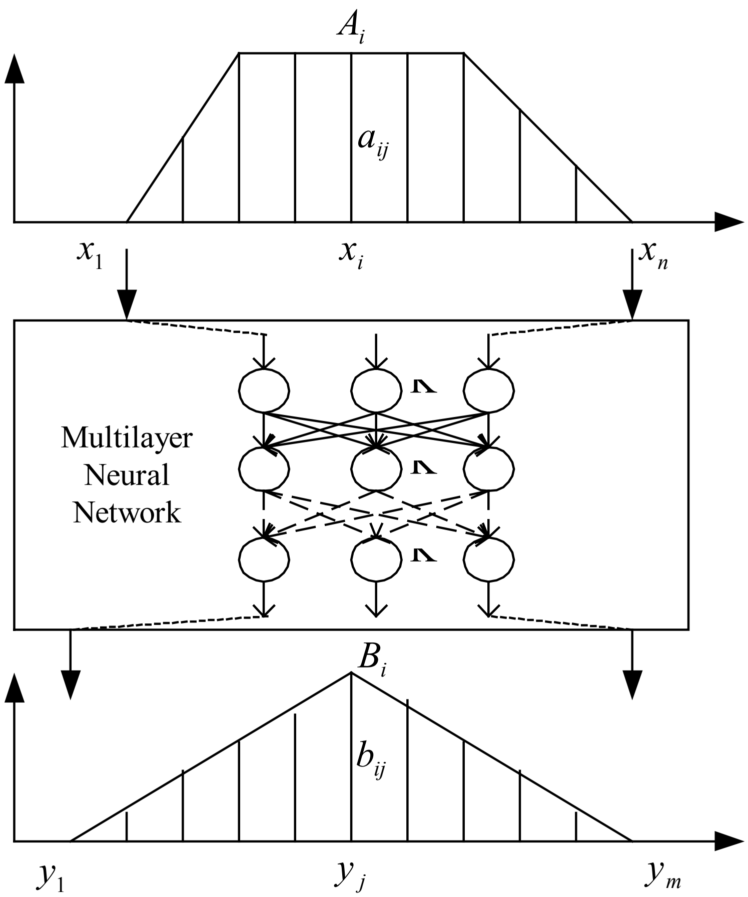


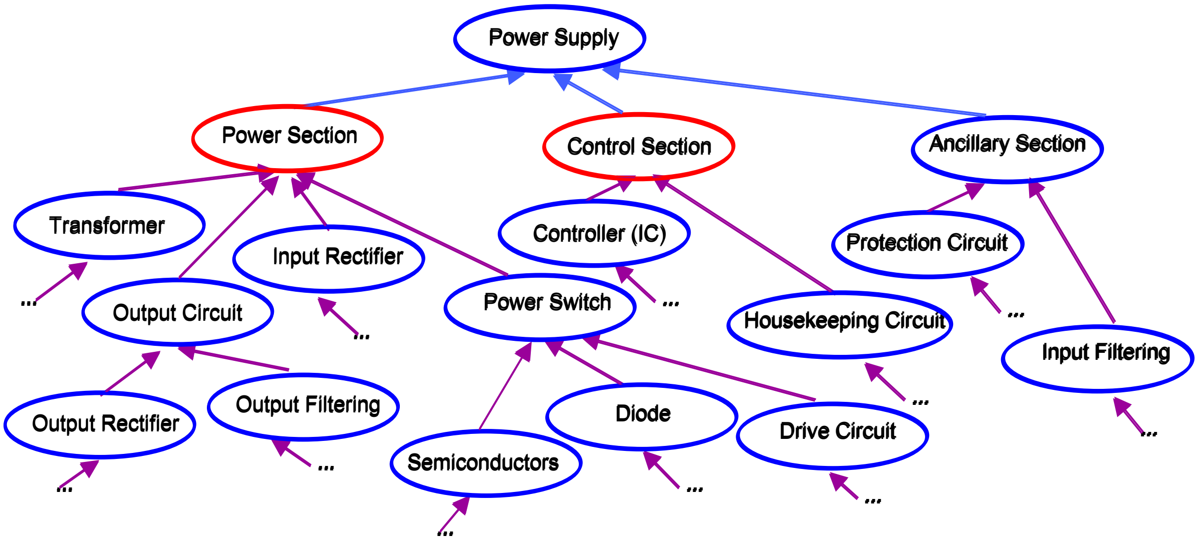
Figure 11: A network trained on membership values for fuzzy numbers

5. Case Study and System Prototype

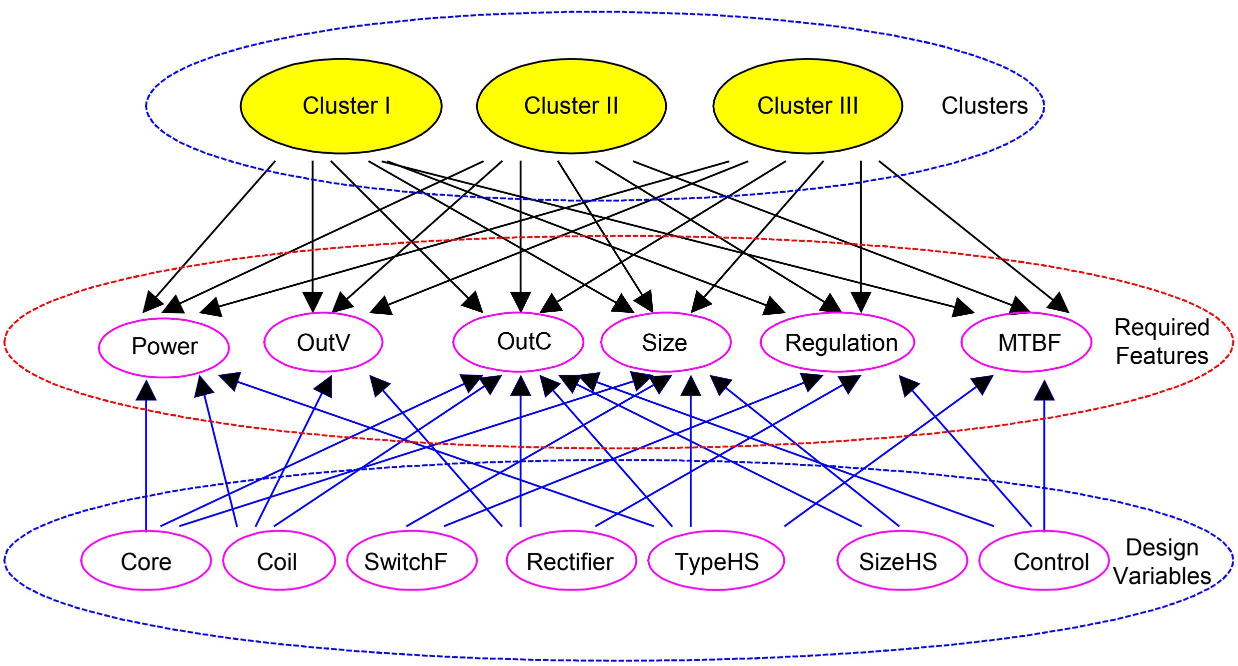
This section provides a case study of the power supply family design evaluation and selection for mass customization and introduces a prototype for a product family design advisory system for decision support.

5.1 Case Study: Power Supply Family Evaluation for Mass Customization

Power supplies are necessary components of all electronic products. Because of diverse requirements, power supply products (http://www.artesyn.com/) are often customized (Maurice, 1993; Jiao and Tseng 1998). To illustrate and validate the proposed knowledge support scheme, a scenario illustrating the knowledge support for a power supply family design evaluation and selection for customization is provided.



(a) Configuration



(b) Clusters

Figure 12: Configurations and clusters of power supply products

From a customers' point of view, a power supply product is defined 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 12 shows the relationships between RFs, DPs, configurations 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. The modular design of power supply products is based on the work in (Zha and Lu 2002a,b; Tseng and Jiao 1998b). When the product configuration is carried out, the design requirements and constraints are satisfied especially in terms of product functions or function features. Of course, from assembly or disassembly/maintenance point of view, it had better be that the parts with low exchange rate are placed inside of the product, but the locations of some parts are fixed in advance due to design constraints.

With reference to the knowledge decision support scheme for product evaluation (Figure 6), a scenario of knowledge support for power supply product evaluation for customization in Family I is shown in Figure 13. 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 Figure 14, 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.

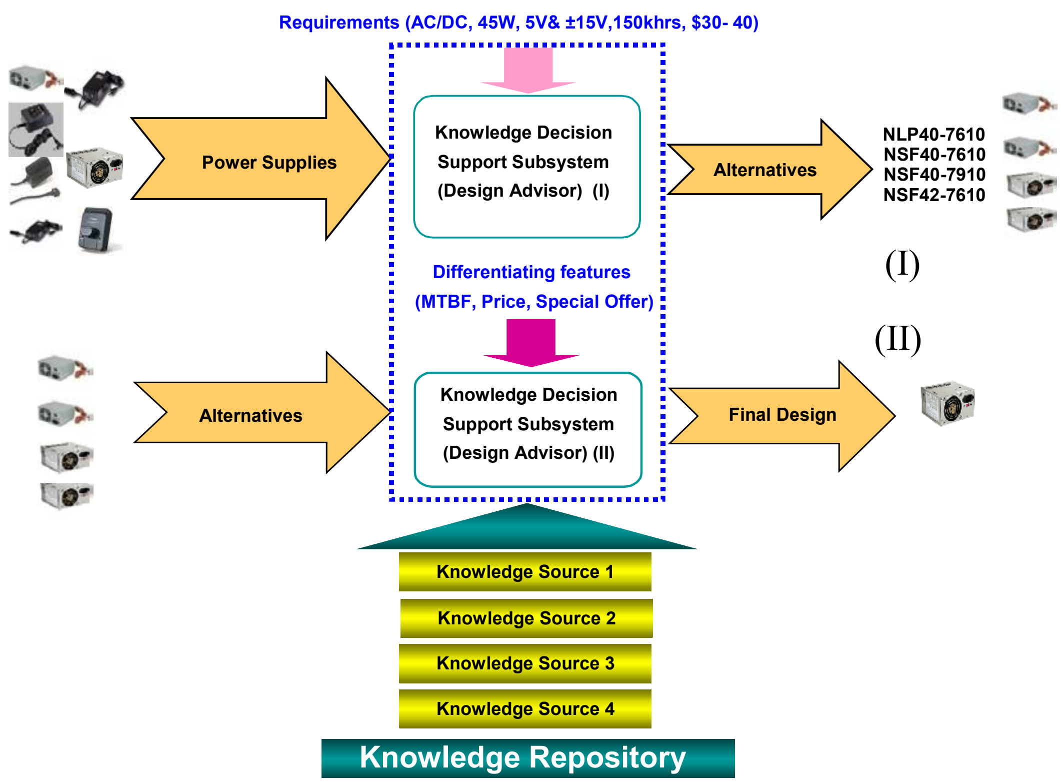


Figure 13: Scenario of knowledge support for product evaluation and selection for customization

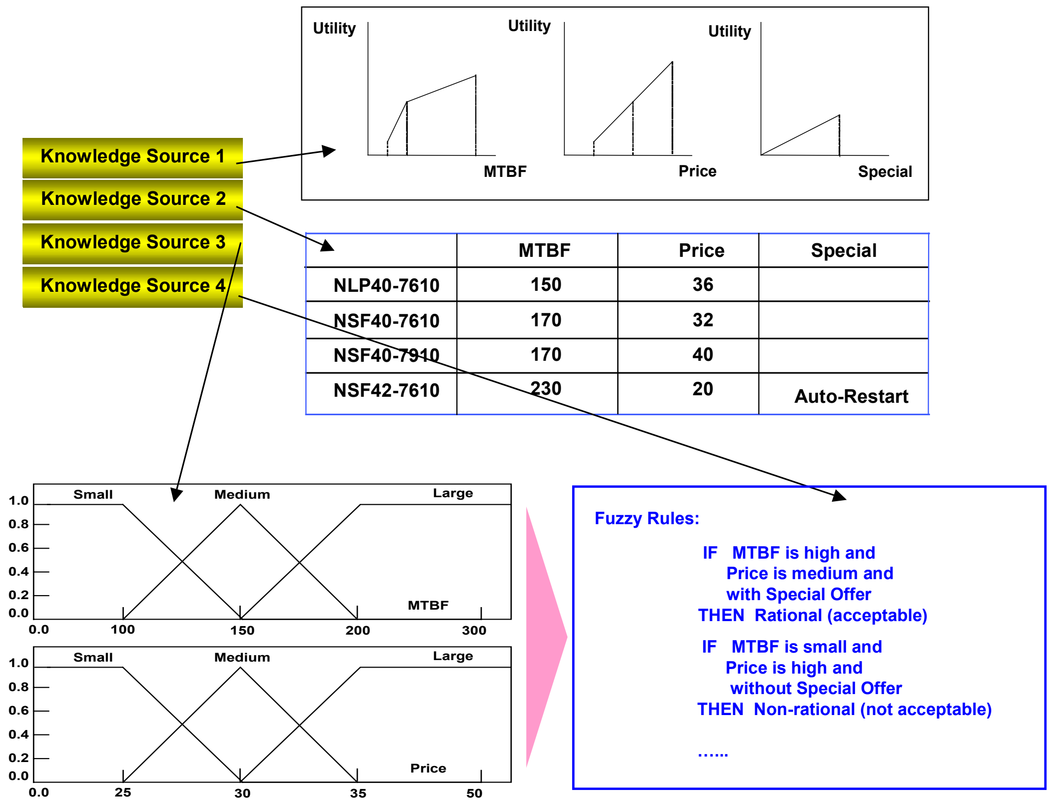
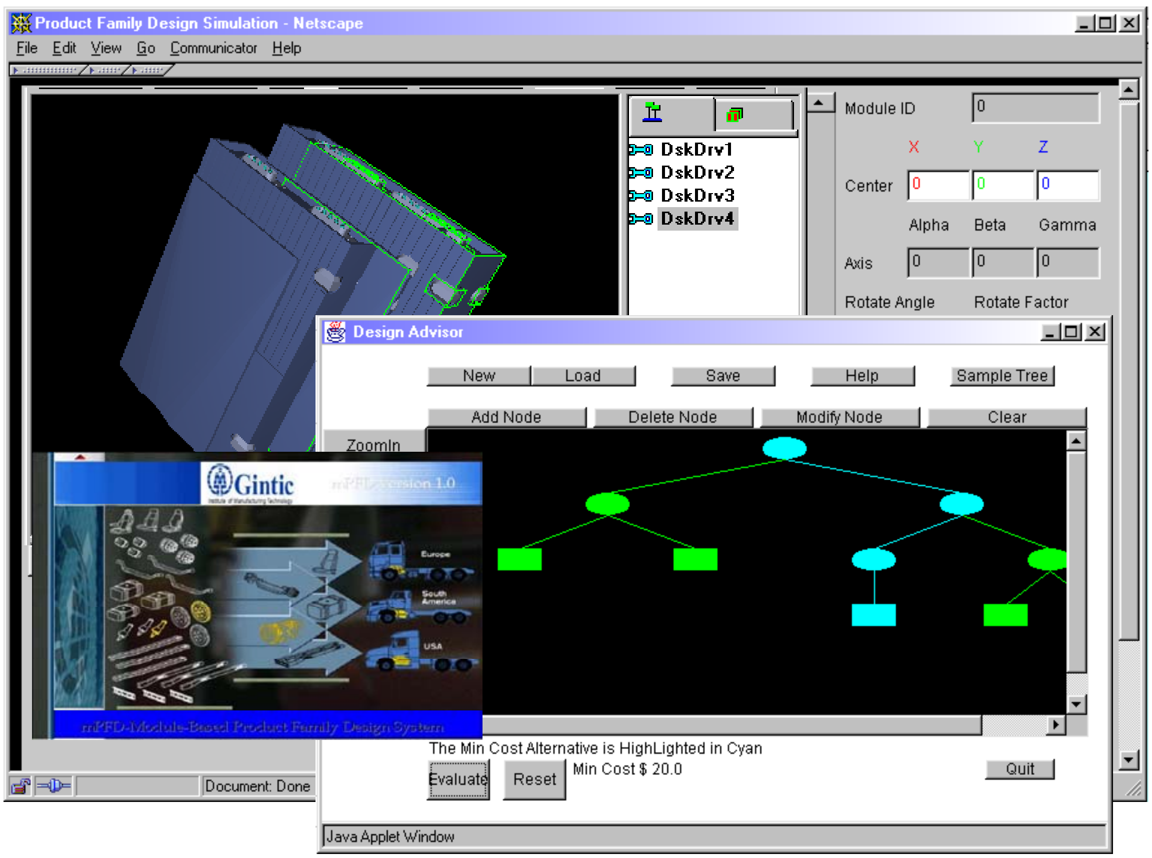


Figure 14: Knowledge used in power supply product evaluation and selection for customization

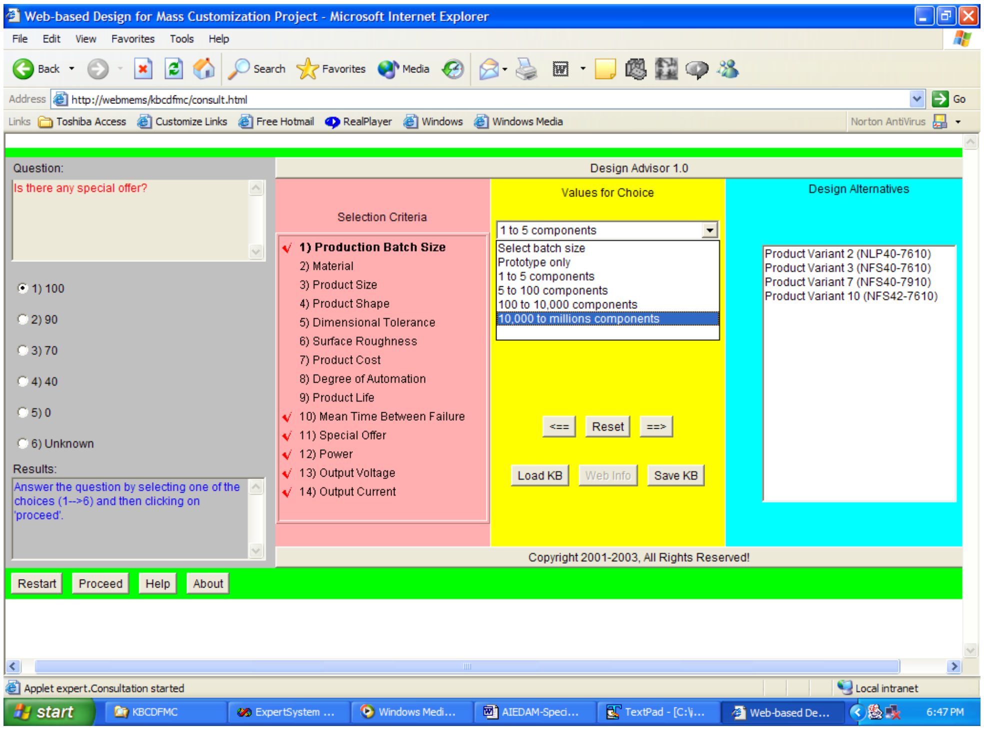
5.2 System Prototype

To verify and validate the knowledge support scheme, a prototype of a product family design decision support (evaluation and selection) system, called Design Advisor, has been developed based on the fuzzy clustering and ranking model described above. It is a web-based multi-tier system, written in Java^{TM}, incorporating Java Expert System Shell, Jess/FuzzyJess (Ernest 1999; NRCC 2003; Samuel and Bellam 2000), consisting of cluster analysis module, ranking module, selection module, neural-fuzzy module, and visualization and explanation facilities. The Design Advisor system is a subsystem of the knowledge-intensive support system for product family design described in (Zha and Lu 2002a,b; Zha and Sriram 2003). The current capabilities of the prototype include capturing and browsing the evolution of product families and product variant configurations in product families, ranking and evaluation and selection of product variants in a product family.

The comprehensive fuzzy decision support system can visualize and explain the reasoning process and make a great difference between the knowledge support system and the traditional program. In this subsystem, a tracing approach using linear chain list (Rule_Used_No) is adopted for addressing the explanation facilities: 1) How to reach the conclusions? 2) How many rules are used in reasoning? 3) Does it use Rule X? 4) Why use Rule X? and 5) When does it use Rule X? A linear chain list records the rule number of successful rules during reasoning process and stores them in a knowledge unit. The designer/user consultation is answered by a backtracking mechanism like Prolog. With this subsystem, the designer can represent the design choices available as a fuzzy AND/OR tree. The fuzzy clustering and ranking algorithms employed in the system are able to evaluate and select the (near) overall optimal design that best satisfies customer requirements. The selected design choice is highlighted in the represented tree. Figure 15 gives a screen snapshot for the prototype evaluation system used for the power supply concept evaluation and selection.



(a)



(b)

Figure 15: Screen snapshot for product family evaluation and selection session

6. Discussion

The developed approach, differing from existing methods and systems (e.g. Jiao and Tseng 1998), is knowledge based and embodies an effective and efficient method and mechanism to evaluate and select design alternatives or product variants in a product family. The system described above can provide advisory service for design of mass customized products and explain the results and what-ifs. Specifically, it is able to provide a common language at the concept level, allowing a designer to describe a design alternative or product variant so that an expert advisory system can decide and select which design alternative and product variant can satisfy the customers' requirements. This means that the system is designed as a tool for finding a "good" concept/solution for a product while still at the conceptual level of design, and making a diverse catalog of design alternatives/product variants available to designers/users so that they can experiment with different requirements/technologies in business.

The "web-top" (web-based) product families can be achieved by using the technologies of e-commerce and mass customization to design and build up a reconfigurable modular product platform on the web, and customize it based on the remote-site customers and task requirements. The widespread use of the system is likely to lead many companies to put their products database searches on-line, allowing users to filter inventories/catalogs based on user-entered requirements. Also, the system allows developers to provide intelligent knowledge services and an open environment to support and coordinate highly distributed and decentralized collaborative design and modeling activities for designers/users. A web-based interface lets designers/users customize products and submit them for review if necessary. Thus, the system provides the remote users advice that: 1) indicates which product variant is the most suited to the customers' requirement; 2) how the design could best be modified to satisfy the customers' requirements and constraints. As a result, converting a product from one task to another can be very fast in order to keep up with the rapidly changing marketplaces or applications.

7. Summary and Conclusions

This paper presented an approach on the knowledge decision support for product family evaluation and selection. A comprehensive fuzzy knowledge support scheme and the relevant technologies were developed for product family evaluation and selection in customer-driven design for mass customization. The developed systematic fuzzy clustering and ranking methodology can model the imprecision inherent in design decision-making with fuzzy preference relations and carry out fuzzy analysis and evaluation which is capable of handling linguistic as well as ordinary quantitative information thus solving the multi-criteria decision making problem. The employment of neural network can adjust membership functions of evaluation and selection criteria and rationalize the determination of customer preferences and incorporates them into fuzzy analysis. Thus, typical barriers to decision-making processes, including incomplete and evolving information, uncertain evaluations, inconsistency of team members' inputs, can be compensated. The results obtained from the case study illustrate the potential and feasibility of the knowledge-intensive decision support scheme and the fuzzy clustering and ranking methodology in product family design evaluation and selection. This work can help bring products to market faster, and with more certainty of success. Based on the results of assessment, industry best practices are identified that can help improve product quality, cost, and time-to-market and right-to-market. The developed methodology is generic and flexible enough to be used in a variety of decision problems, e.g., concept evaluation and selection.

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