Evaluation and Selection in Product Design for Mass Customization

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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 chapter presents a knowledge-supported approach to concept evaluation and selection in design for the mass customization process. The focus of this chapter is on the development of a knowledge intensive support scheme and a comprehensive systematic fuzzy clustering and ranking methodology for concept design evaluation and selection. In the chapter, product family design is viewed as a selection problem with the following key stages: product family (design alternatives) generation, product family design evaluation, and selection for customization. First, the fundamental issues underlying product family design for mass customization are identified and 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 that models imprecision inherent in decision-making with fuzzy customers' preference relations and carrying out fuzzy analysis and evaluation in solving the multi-criteria decision making problem during the early design stage is proposed and discussed in detail. The neural network technique is used to adjust the membership function. The proposed model is illustrated by a case study of knowledge support for power supply product evaluation, selection, and customization.

Keywords: Product family (line), mass customization, design evaluation, decision-making, fuzzy clustering, fuzzy ranking, and knowledge support

1. Introduction

Today's highly competitive, global marketplace is redefining the way companies do business. Mass customization (Pine, 1993) provides 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 an increasing 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 as much variety as possible in the marketplace 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 or similar 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 design 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 the academia and in the 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. The aim of this chapter is to develop methodologies and technologies of knowledge support for modular product family evaluation and selection in customer-driven design for mass customization. The focus of this chapter is on the development of a comprehensive systematic fuzzy clustering and ranking methodology for product family evaluation and selection in the context of design for mass customization.

The organization of this chapter 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 and its knowledge support framework. 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 chapter.

2. Current Status of Research

In this section, previous research work related to knowledge supported product family design for mass customization and design alternative evaluation and selection, is briefly reviewed. We first review the literature on design alternative evaluation and selection. Next we review the application of design alternative evaluation and selection to product family design 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): 1) multi-criteria utility analysis, 2) fuzzy set analysis, 3) design analytic methodology, 4) hybrid approach, and 5) information content approach. The first three approaches are generally used. The following review focuses mainly on these first three approaches.

Multi-criteria utility analysis, originally developed by von Neumann and Morgenstern (1947), is an analytical method for evaluating a set of alternatives, given a set of multiple criteria. It has been widely applied in the areas of engineering and business for decision-making (Hwang and Yoon, 1981). Thurston

(1991) has applied this technique to the material selection problem that evaluates alternatives based on utility functions that reflect the designer's preferences for multiple criteria. Mistree *et al.* (1992, 1995) modeled design evaluation as a compromise decision support problem (DSP) 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 in a quantitative form. They are not appropriate for use in the early design stages, where some qualitative design criteria, *i.e.*, intangible criteria, are involved and difficult to quantify (Thurston and Carnahan, 1992).

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," "medium," *etc.* Fuzzy analysis has proven to be quite useful in decision-making problems with multiple goals or criteria (Zimmermann 1987, 1996). Wood and Antonsson (1989) have demonstrated its viability in performing computations with imprecise design parameters in mechanical design. Wood *et al.* (1990) compared fuzzy sets with probability methods and concluded that fuzzy set analysis is most appropriate when there are imprecise design descriptions, while probability analysis is most appropriate for dealing with stochastic uncertainty. Thurston and Carnahan (1992) revealed that fuzzy set analysis is more useful and appropriate at very early stages of the preliminary design process. Knosala and Pedrycz (1992) utilized the analytic hierarchical process method (Satty 1991) to construct membership functions for the performance and weight of each criterion, and then applied the fuzzy weighted mean of the overall evaluation to ranking alternatives. Carnahan *et al.* (1994) represented evaluation results and weights regarding each criterion with linguistic terms and ranked alternatives based on the fuzzy weighted mean of distance from a fuzzy goal. While fuzzy analysis excels in capturing semantic uncertainty with linguistic terms, it requires discreet deliberation in dealing with crisp information. A domain-specific method is needed to fuzzify each tangible criterion whose evaluation is naturally estimated as an ordinary real variable (Carnahan et *al.* 1994). Another challenge is the incomparability between various criteria (Wang 1997, Siskos et *al.* 1984). This necessitates 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.

To reflect customer preferences in multi-criteria design evaluation, the relative importance or weighting factor for each criterion has been considered by numerous evaluation procedures (Jiao and Tseng 1998). Frazell (1985) assigned weights to criteria on a 0-100 scale. Sullivan (1986) presented a similar method called the linear additive model, in which ranking is included. Huang and Ghandforoush (1984) presented another procedure for quantifying subjective criteria. They computed intangible criteria measures as the multiplication of the intangible criterion weights by the subjective customer rating. Dixon *et al.* (1986) measured the performance by degree of satisfaction, ranging from excellent to unacceptable. They combined this measure with priority categories of high, moderate, or low to evaluate a 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 (Saaty 1991), which occurs when the solution does not match the decision maker's preference and results from the randomness of the decision maker's judgments. 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). The AHP determines weights by means of pair-wise comparisons between hierarchical decision levels. It has been proven to be a more rigorous procedure for determining customer preferences, and has been approached from the fuzzy point of view by Boender *et al.* (1989). Carnahan *et al.* (1994) proposed an approach to fuzzify the weights after they have been obtained by the AHP.

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

2.2 Product Family Design Evaluation and Selection

In the literature, the problem on product family design evaluation and selection has 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 et al 1998,2001). 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 the best possible variants from an engineering design point of view. 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; 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 paradigm of mass customization is variety and customization through flexibility and quick responsiveness. 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 or company has to perceive and capture latent market niches and correspondingly develop its technical capabilities to meet diverse customer needs. Perceiving latent customization requires the exploration of market niches. The capture of target customer groups means emulating or outclassing competitors in either quality or cost or quick response or 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.* 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 design repository*. A database of previous designs should help in rapidly determining an appropriate starting point for a new design.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 challenges and strategies presented in the previous section, this research investigates mass customization from a product development perspective, namely customer-driven design for mass customization (CDFMC). Our approach is based on the belief that mass customization can be effectively approached from a design perspective (Tseng and Jiao 1996,1998). Essentially, we attempt to include customers into the product development life cycle through proactively connecting customer needs to the capabilities of a company. The main emphasis 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.

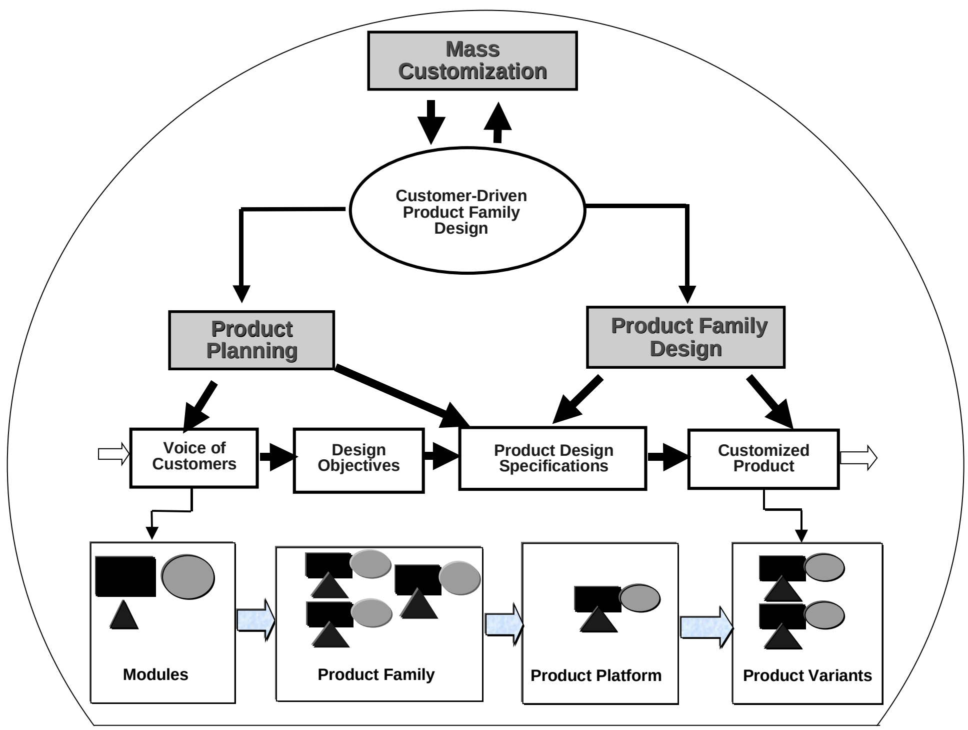


Figure 1: Framework for CDFMC based on the module-based product family design

Figure 1 outlines the concept for CDFMC used in this research (this is an adaptation of the process model presented in (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 and market trends for generating product design specifications, designing product platform for generating product variety or family, to deriving and customizing products (variant) by evaluating and selecting product family for customers' satisfaction. CDFMC can be divided into two major stages: 1) product 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- a family of products to satisfy a range of customer demands. Figure 2 illustrates a product family architecture (PFA) to support mass customization. From customers' point of view, products are functional features and the related feature values. A product family is designed to address the requirements of a market segment wherein the customers share some similar requirements and have their special requirements 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 and differentiation enablers of the product family. It is the configuration mechanisms that determine the generative aspect of a product family, which guarantee that the technically feasible and market-wanted product variants are derived.

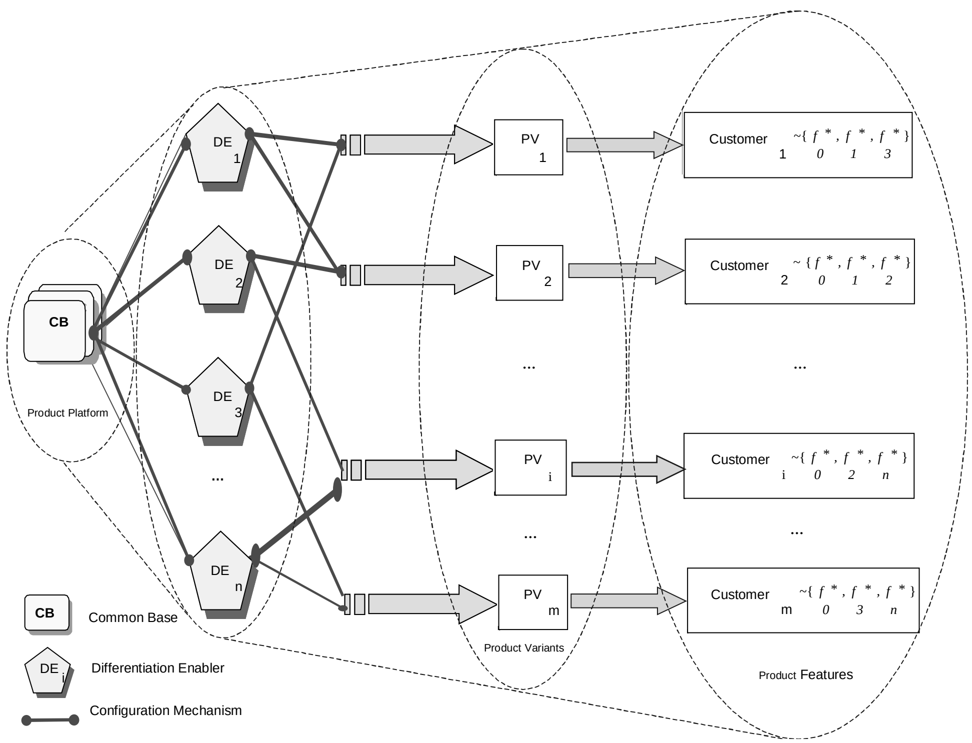


Figure 2: Architecture of product family for mass customization

3.3 Module-Based Product Family Design

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 this hierarchical representation scheme, as shown in Figure 3, product variety can be implemented at different levels within the product architecture. The steps for creating a module-based product family are as follows (Zha and Sriram 2003):

(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 is to develop 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 customization stage aims at obtaining a feasible architecture of product family member through reasoning product family module space according to customer requirements (Meyer et al 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 feasible product family member architecture.

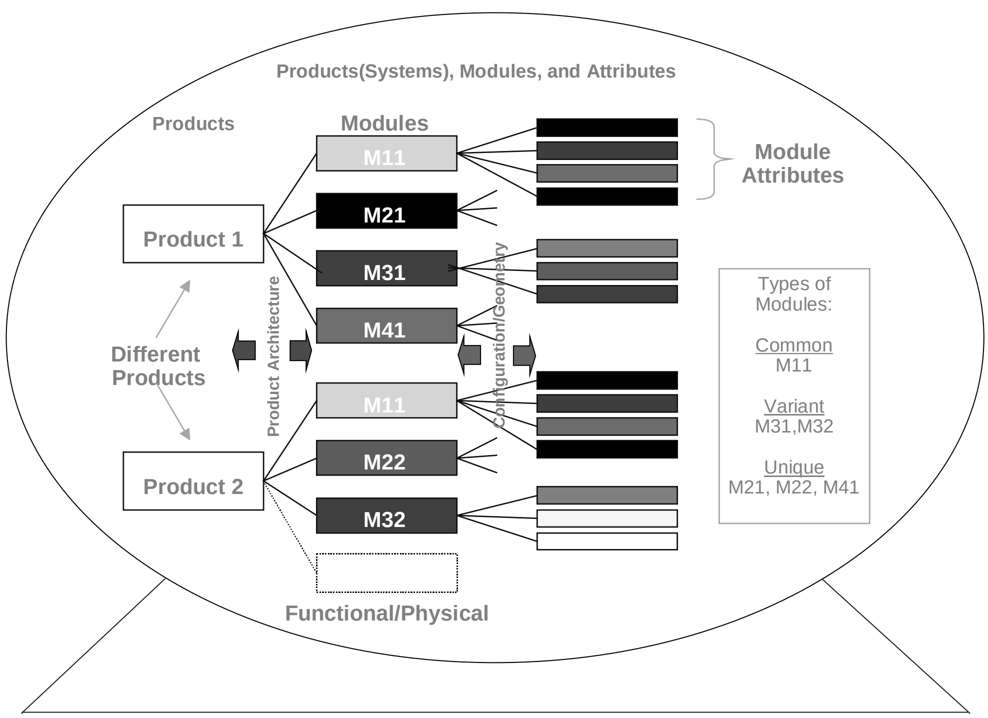


Figure 3: Products, modules, and attributes

3.4 Knowledge Support Framework for CDFMC

The conceptual framework shown in Figure 1 demonstrates the process of customer-driven 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 4.

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).

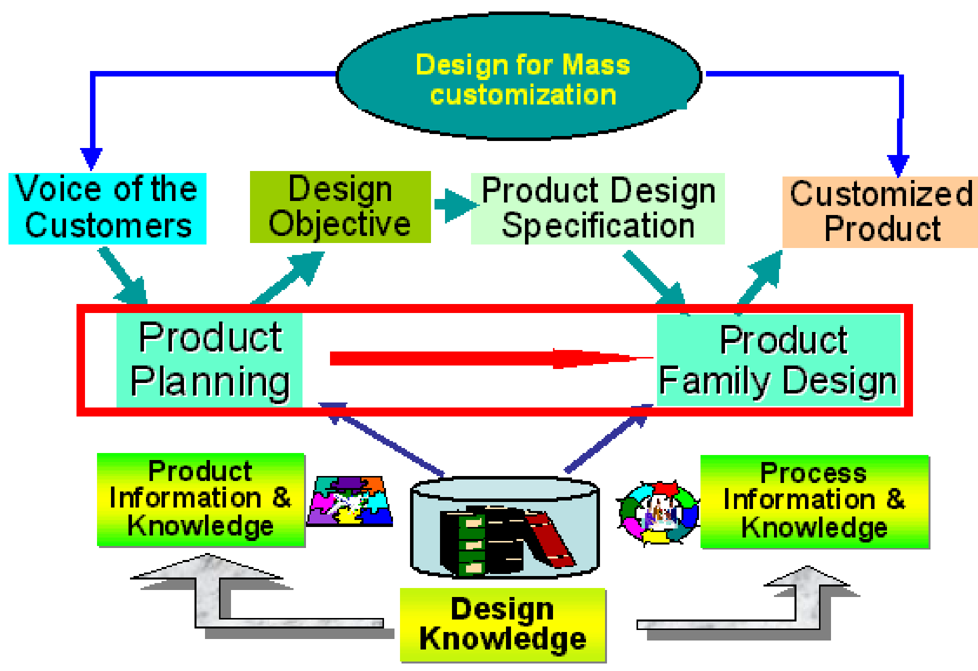


Figure 4: Knowledge support framework for CDFMC

As shown in Figure 5, 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 evaluation and selection of product family for customization is implemented by assessing product variants generated from product platform. The fundamental issues involved in product family design process have been addressed in (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 for mass customization, 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 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: 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. The remainder of this chapter will focus on how the decision support knowledge in product family design knowledge base or repository (Zha and Sriram 2003) supports the designer to perform product family evaluation and selection.

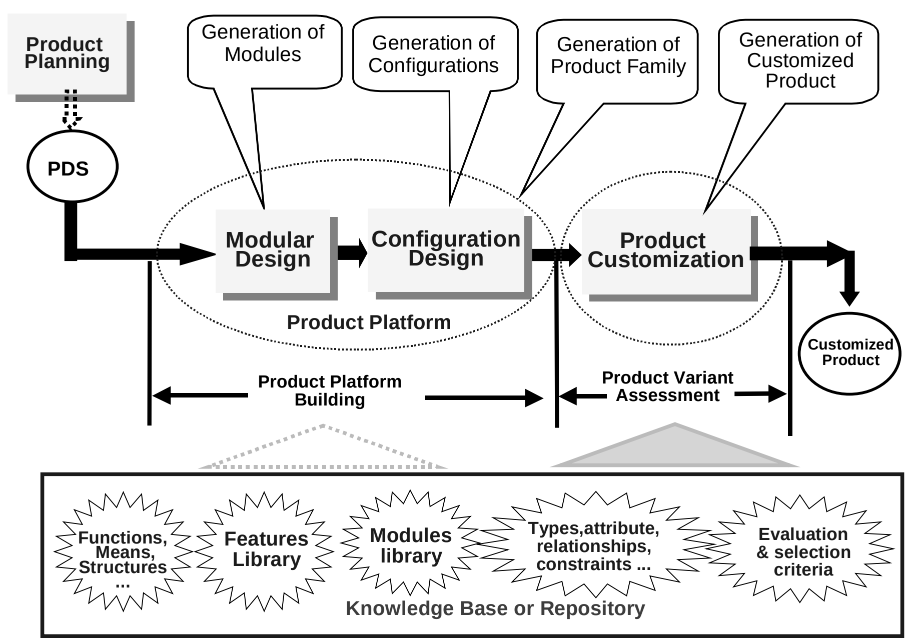


Figure 5: Modular product family design for mass customization process

4. Product Family Design Evaluation and Selection

This section begins with a summary of knowledge decision support scheme for product family design evaluation and selection. It then presents evaluation/customization metrics applied in 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 Decision Support Scheme

The product family evaluation and selection for customization stage aims at obtaining a feasible architecture of product family members through reasoning and decision support in the product family module space according to customer requirements. The customization process includes two steps. First, the customer requirements such as functions and assemblies need to be converted to constraints and rules. Then, the reasoning or decision support is performed at two levels, namely module level and attribute level, to determine the feasible product family member architecture at the conceptual level. 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, manufacturiability, 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.

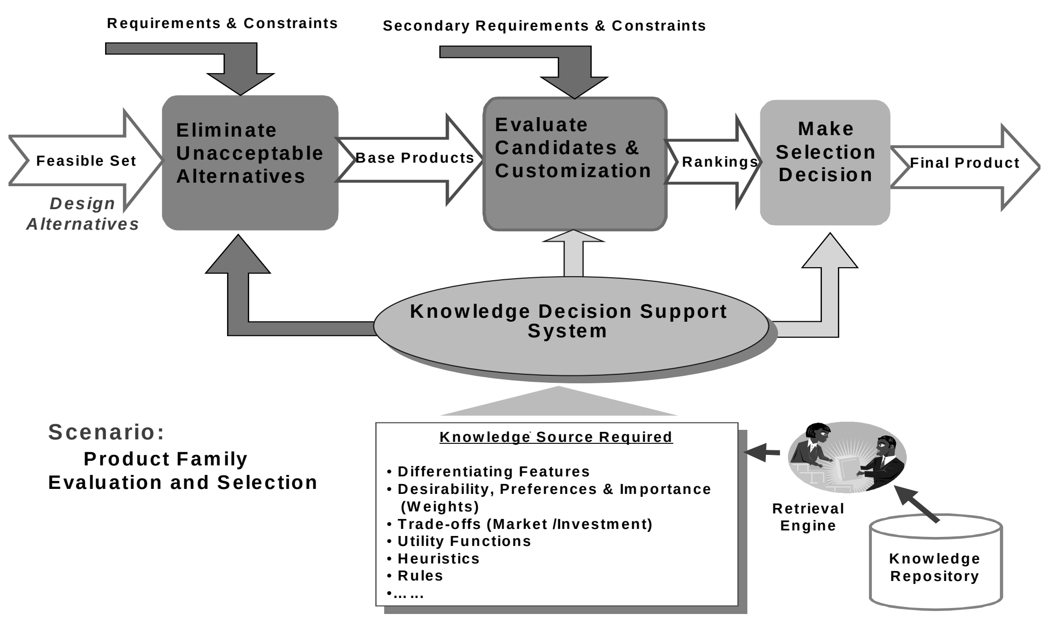


Figure 6: Knowledge decision support for product evaluation

In contrast to the traditional approaches (Pahl and Betiz 1996; Jiao and Tseng 1998), we propose a knowledge-based approach to product family evaluation and selection for customization. Figure 6 shows a knowledge decision support scheme. As shown in Figure 6, this stage characterizes a feasible set of products generated from product platform as an input to the final customized product as an output. It will experience the elimination of unacceptable alternatives, the evaluation of candidates for customization, and the final decision under the customers' requirements and design constraints. The knowledge resource utilized in the process may extensively include differentiating features, customers' requirements, desirabilities, preferences and importance (weights), trade-offs (e.g. market vs investment), utility functions, and heuristic knowledge, rules, etc. The kernel of the knowledge decision support scheme is based on fuzzy clustering and ranking algorithms for design evaluation and selection. These will be discussed below.

4.2 Customization/Evaluation Metrics

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 and customization, we viewed the evaluation of product family design 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 are applicable, and the metrics for this level 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). In this research, the following two typical metrics have been used in platform-based family level evaluation (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 Design Ranking Methodology

Due to the fuzziness of voice of customers (VoCs) or customer requirements/preferences, it is difficult to model and assess the performance of a product platform/family and product variants. 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 and determine similarity between modules and commonality between products 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 approach (Pahl and Beitz 1996), a reasonable number of possible design alternatives can be obtained using the design solution generation techniques at the conceptual design stage. Each sub-function usually corresponds to a collection of available solution principles. If there are a total of n sub-functions, each of them has m_i possible solution principles. After a complete combination, we have several theoretically possible overall solution variants as schematically illustrated in Table 1. Clustering is a widely used method for pattern recognition (Kandel 1982). The use of cluster analysis in this research is to sort a product data set, for example, a number of possible solution principles to sub-functions or their possible combinations, into families such that the members of the same family (or group) are similar in some respect and unlike those from other families. This is very crucial for determining similarity between modules and also commonality between products and product families.

Assuming there are m patterns, $a_1,a_2,...,a_m$, contained in the pattern spaces S. The process of clustering can be formally stated as: to seek the regions $s_1,s_2,...,s_k$ such that every a_i, $i=1,...,m$ fall into one of these regions and no a_i falls into two regions, that is $s_1\cup s_2\cup ...\cup s_k=S$, $\forall i\neq j$, $s_i\cap s_j=\phi$. This definition indicates that clustering algorithms are based on natural association 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 numerical form to indicate degree of resemblance between objects (or modules, or product variants) in a group (or family), or between an object and a group, or between object groups.

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

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}

The simplest way to measure similarity is to use Euclidean distance. A design object (module, product variant or product family) in a design space may be viewed as a pattern point in a pattern space, described by a vector. 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. Another practical way to measure similarity is to predefine a fuzzy similarity matrix based on some concerns and then to store it in computer. Matrix M_F (A×B) shows a fuzzy matrix to represent the similarity between types of modules or products in a family (Figure 7). 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 is. Figure 8 gives an instance of fuzzy similarity matrix for conceptual layout variants in a gear reducer product family.

Given any two modules or product concepts at some level they will be grouped into the same cluster if these two are always kept within one group or family at all later levels. The clustering sequence or procedures are said to be hierarchical, which are divided into two distinct classes, bottom-up and top-down. 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. The algorithm of clustering used in this research follows four steps:

(1) Find the smallest element in the distance matrix (d_i) to merge corresponding to two objects.

(2) Select a point as a reference in the merged group using an appropriate rule, e.g., nearest neighbor or centroid cluster.

(3) Recalculate the distance matrix between the new group and these remainders, named d_{i+1}.

(4) Repeat step 1 until all the objects merge into one group.

	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 7: Fuzzy matrix of similarity relations between types of 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 8: Fuzzy matrix of similarity relations between types of conceptual layout variants in a gear reducer product family (L: Left, R: Right)

4.3.2 Fuzzy Ranking for Design

Using the design solution clustering techniques discussed above, a reasonable number of possible design alternatives can be obtained. The remaining procedure is to examine the design alternatives 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 $\overline{r}_i$ by use of the value analysis or cost-benefit analysis introduced in (Pahl and Britz 1996):

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

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 $\overline{r}_i$ 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. In what follows, the problem of fuzzy ranking a set of alternatives against a set of criteria is described. 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

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

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:

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

A combination of these two fuzzy sets induces a fuzzy set I which can determine the 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, such as, "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.

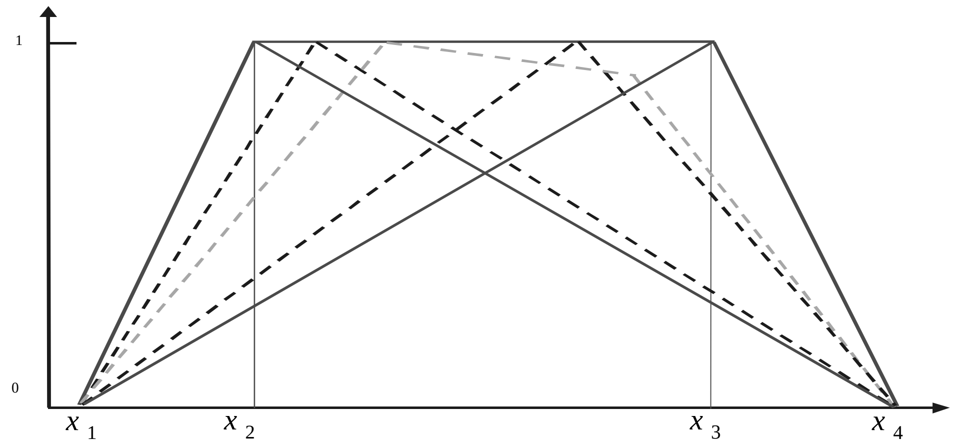


Figure 9: Linguistic scale representation for fuzzy customer preferences and performances

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, and 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 9, then it can be parameterized by a quadruple (x_1, x_2, x_3, x_4) and its defuzzied crisp value using 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 respectively transformed into the crisp performance rating $r_{ij} \in [0,1]$ and crisp weight $w_j \in [0,1]$. Therefore, 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 model can be understood as: it is a simple fuzzy ranking scenario; it can also be used for defuzzification.

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 includes differentiating features, customers' requirements, desirabilities, preferences and importance (weights), trade-offs (e.g. market vs investment), utility 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 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. Figure 6 shows a knowledge decision support scheme for product evaluation and customization process. The kernel of the knowledge decision support scheme is fuzzy clustering and ranking algorithms for design evaluation and selection that will be discussed below.

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 a design alternative, will 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 is selected, by taking into account multi-criteria factors including design compactness and other life-cycle issues, such as manufacturability, assemablility, maintability, reliability, and efficiency (market vs investment).

4.5 Neural Network Adjustment for Membership Functions

Due to the complexity and uncertainty of design problems, there is a need to improve the above comprehensive fuzzy clustering and ranking methods. This improvement can be achieved through a learning technique such as neural networks. 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 1986, 1996). It can be easily implemented and adjusted by using neural networks (Zha 1999, 2001). 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.

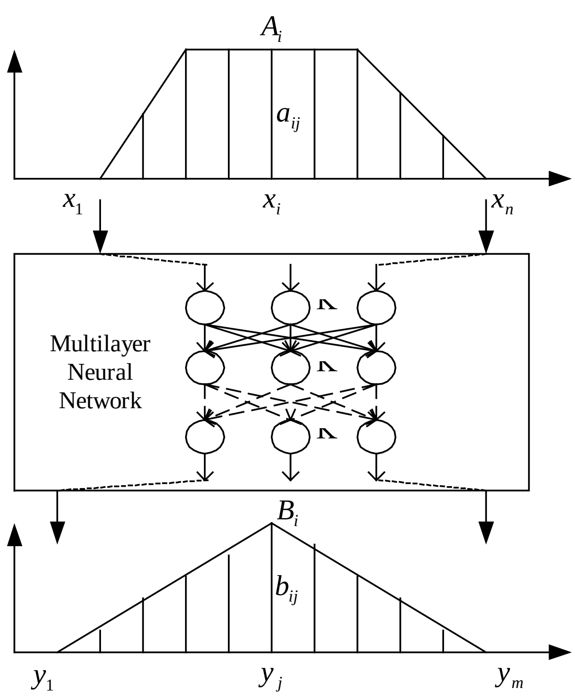


Figure 10: A network trained on membership values for fuzzy numbers

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 of 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 finite number of α-level sets. With simplicity, but without loss of generalizity, 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, $i = 1, 2,\ldots,n$. If $m\geq 2$ and $n\geq 2$ 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: $\{(A_i(x_1),\ldots,A_i(x_n)), (B_i(y_1),\ldots,B_i(y_m))\}$, $i = 1,\ldots,n$. 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 10 shows a network trained on membership values of fuzzy numbers.

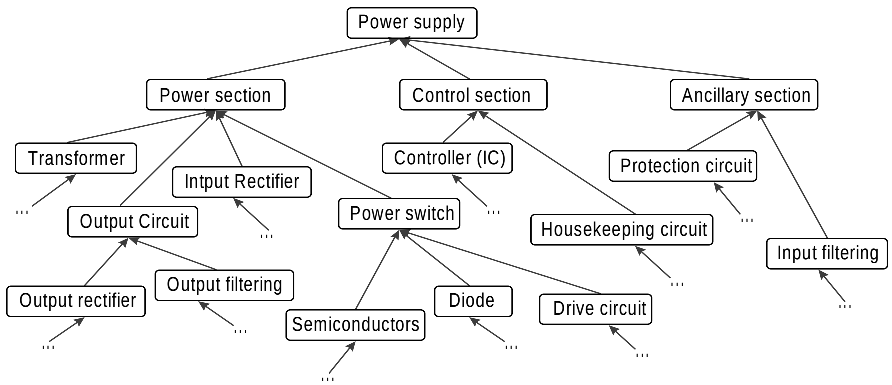
5. Case Study and System Prototype

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

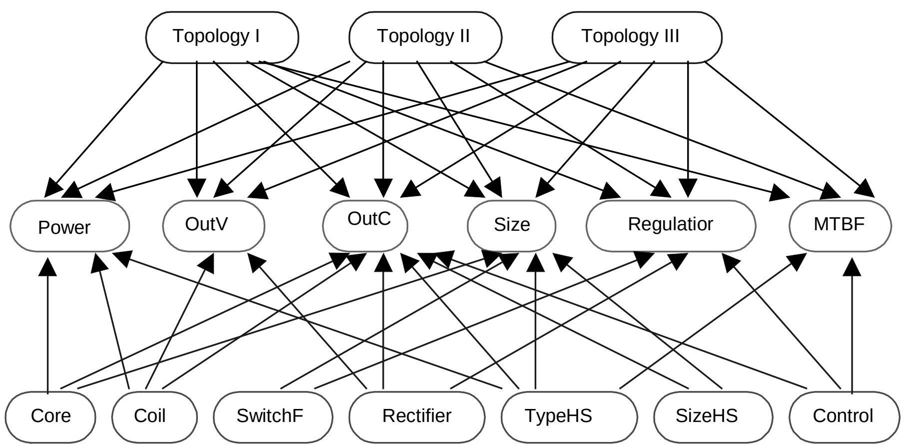
5.1 Case Study

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 power supply family design evaluation and selection for customization is provided.

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, regulator, mean time between failure (MTBF), etc. From an engineers' point of view, the power supply product is designed by determining these 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 11 shows the relationship between RFs and DPs, configurations and topologies. Three product families I, II and III are generated based on three different topologies, which have 4,5 and 3 base products (BPs) respectively. Each topology has its own range/limitation with regard to particular product features and/or design parameters. The modularization process and modular design of power supply products are based on the work in (Zha and Sriram 2003). 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 the assembly or disassembly/maintenance points of view, it had better that the parts with low exchange rate are placed at inside of product, but the locations of some parts are fixed in advance due to design constraints.



(a) Configuration



(b) Topologies

Figure 11: Configurations and topologies of power supply products

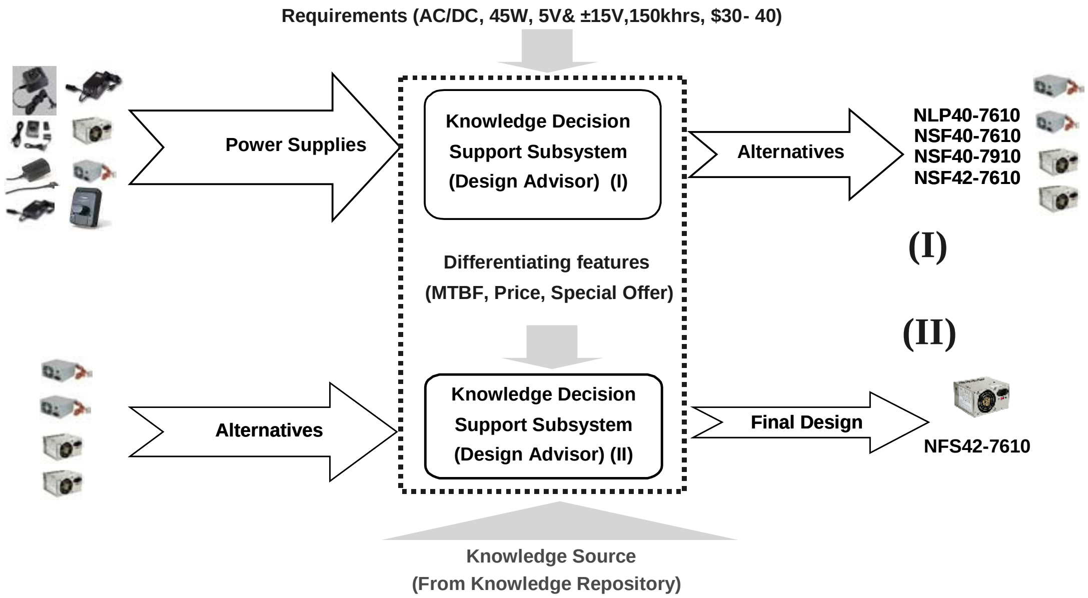
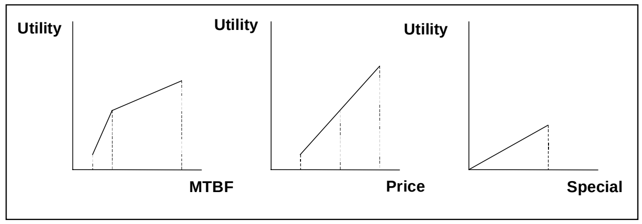


Figure 12: Scenario of knowledge support for product evaluation and selection

With reference to the knowledge decision support scheme for product evaluation (Figure 6), a scenario illustrating the knowledge support for power supply product evaluation for customization in Family I is shown in Figure 12. 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 13, including customer preferences, differentiating features (MTBF, price, and special offer) and their utility / membership functions, fuzzy rules, and 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.



	MTBF	Price	Special
NLP40-7610	150	36	
NSF40-7610	170	32	
NSF40-7910	170	40	
NSF42-7610	230	20	Auto-Restart

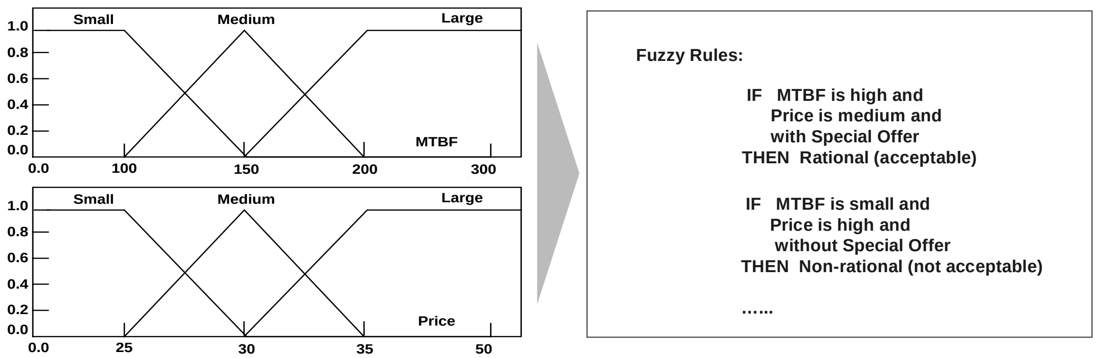


Figure 13: Knowledge used in power supply product evaluation and selection for customization

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™, 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 of the evolution of product families and of product variant configurations in product families, ranking and evaluation and selection of product variants in a product family.

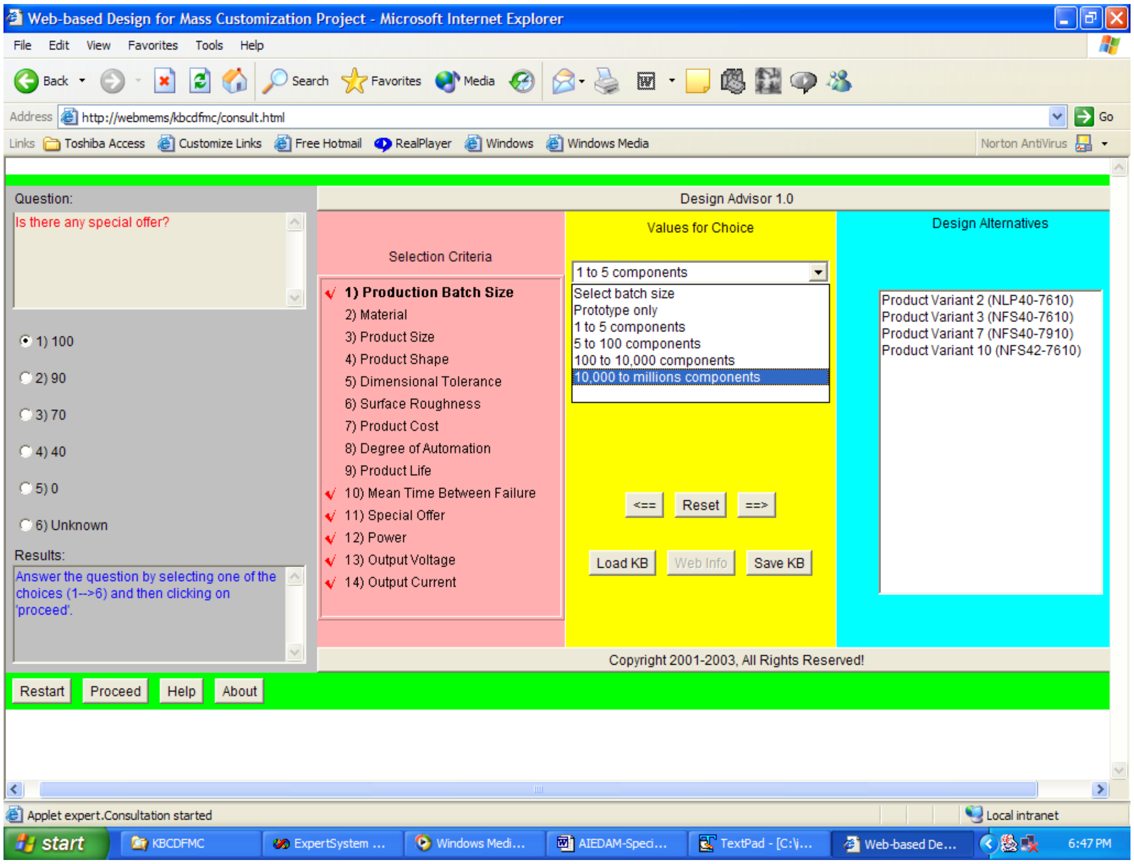


Figure 14: Screen snapshot for product family evaluation session

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 14 gives a screen snapshot of the prototype system used for power supply family evaluation and selection.

6. Discussion

The developed approach, which differs from existing methods and systems (e.g. Jiao and Tseng 1998), is knowledge supported and embodies an effective and efficient method and mechanism to evaluate and select design alternatives or product variants in product family. The system described in this chapter 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/product family 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 set up the mass customized systems on the web based on the remote-site customers and task requirements for reconfigurable modular systems. The widespread use of these systems 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/preferences. 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. 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/customer to another can be very fast in order to keep up with the rapidly changing marketplaces or applications.

7. Summary and Conclusions

This chapter presented an approach on a 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 networks can adjust membership functions of evaluation and selection criteria, rationalize the determination of customer preferences, and incorporate 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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