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DÉFINITION DES FAMILLES DE PRODUITS À L'AIDE DE LA LOGIQUE FLOUE

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DÉFINITION DES FAMILLES DE PRODUITS À L'AIDE DE LA LOGIQUE FLOUE

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A mis padres, Consuelo e Isidro quienes con amor y cariño me han ayudado a lograr todas mis metas.

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RÉSUMÉ

Dans cette thèse, la contribution principale porte sur la conception des familles de produits par l'application de la logique floue, ceci afin d'améliorer le processus de prise de décisions. Nous considérons que la formation des familles de produits, permet aux entreprises d'offrir une grande variété de produits. Cela permet alors de satisfaire une grande variété de différents types de clients sur un marché cible, et d'éviter une diversification coûteuse par la conception et la fabrication de produits personnalisés pour chaque client. La logique floue permet d'entrer l'information à fournir en des termes linguistiques familièrement exprimés par les personnes. C'est-à-dire qu'elle permet de considérer une information plus conforme à celle exprimée par les consommateurs; elle n'est pas limitée au maniement de variables binaires comme la logique booléenne. La logique floue à travers la formulation de différentes fonctions d'appartenance, est capable d'évaluer une variété de réponses pour une variable et pas seulement un «oui» ou un «non».

Après l'analyse de littérature en ce qui concerne la logique floue et le développement des familles de produits. Nous concluons que le processus de prise de décisions est fondamental pour une formation effective des familles de produits et que le classement flou représente la base des processus de prise de décisions aidés par la logique floue. Pour cela, dans ce travail, différents outils assistés par la logique floue ont été développés et appliqués en cherchant à atteindre l'objectif principal.

Premièrement, une procédure de classement flou a été améliorée pour permettre d'évaluer les relations de préférences entre plusieurs nombres flous avec différentes fonctions d'appartenance. L'amélioration de cette procédure a été la définition de vingt-neuf cas généraux pour représenter les différentes situations qui peuvent se présenter entre deux nombres flous. Ces cas généraux ont été aussi présentés comme un cadre de référence qui permet d'inclure d'autres fonctions d'appartenance.

Postérieurement, en ce qui concerne la conception de familles de produits, différents outils ont été développés, appliqués et finalement intégrés dans une méthodologie globale pour la

formation de familles de produits. Ces outils incluent : un procédé de classement flou pour la prise de décision dans la conception des produits pour comparer différents produits, une méthode pour la sélection de produits basée sur les préférences floues des clients, une méthode pour configurer un produit pour un pour un client spécifique, une méthode pour configurer différents produits pour satisfaire les différents segments du marché et finalement l'intégration de tous ces outils dans une méthodologie globale de conception des familles de produits à l'aide de la logique floue. Tous ces travaux contribuent à la conception des familles de produits en permettant le traitement d'information en termes linguistiques communément employés par les consommateurs pour exprimer ses préférences par rapport à certaines caractéristiques de certains produits et les services.

Dans le dernier chapitre de cette thèse, quelques perspectives ont été posées.

ABSTRACT

In this thesis, the main contribution is concerned to the design of product families by applying fuzzy logic, in order to improve the decision making process. We consider that the formation of product families enables companies to offer a wide variety of products allowing the satisfaction of different types of customers into the target market, and avoiding a costly diversification by designing customized products for each customer. Fuzzy logic allows entering information provided in linguistic terms familiarly expressed by the people. That is to say, it allows considering more consistent information close to the expressed by customers and it is not limited to handle binary variables as the Boolean logic. Fuzzy logic through the formulation of different membership functions can evaluate more answers of a variable instead of a just a "yes" or a "not".

After carrying out the literature review, regarding to the fuzzy logic and to the product family development. We concluded that the process of decision making is fundamental for the effectively formation of families of products, and that the fuzzy ranking is the basis of such process. In this work, various fuzzy logic-aided tools have been developed and applied aiming at achieving the main objective.

First, an improved fuzzy ranking procedure for decision making in product has been proposed to permit the evaluation of the fuzzy preference relations among several fuzzy numbers with different membership functions. This fuzzy ranking procedure has been supported by the definition of twenty-nine general cases, which is enough to consider all the possible situations between two normal fuzzy numbers. These general cases have been presented as a framework to facilitate the inclusion of other membership functions.

Later, regarding the design of product families, different tools have been developed, implemented, and integrated into a global methodology to form families of products. These tools include: a ranking procedure for fuzzy decision-making in product design to compare different products, a method to select products based on the fuzzy preferences of the customers, an iterative method to configure products for specific customers, a method to

configure different products to satisfy the different segments of the market, and finally the integration of all these tools in a global methodology for designing families of products by using fuzzy logic. This work contributes to the design of product families by enabling the handling of information in linguistic terms commonly used by the customers to express their preferences in relation to determined characteristics of certain products and services.

In the last chapter of this thesis, some perspectives have been presented.

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FL	Fuzzy Logic
PFD	Product Fuzzy Development
QFD	Quality Function Development
ANFIS	Adaptive Neuro-Fuzzy Inference System
FID	Fuzzy Indifference Degree
CS	Customer Satisfaction
MT	Mathematical Tool
MF	Membership Function
FNS	Fuzzy Number Set
ISM	Interpretative Structural Model
FCM	Fuzzy C-Means

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CHAPITRE 1 : INTRODUCTION GÉNÉRALE

1.1 Problématique

La compétitivité des marchés mondiaux force les entreprises manufacturières et de services à fournir des produits et des services de plus en plus proches des attentes de chaque client. Dans les marchés concurrentiels, grâce à la mondialisation qui ouvre les marchés, les consommateurs peuvent voir et comparer des produits fabriqués n'importe où dans le monde et deviennent plus exigeants. Lors de l'achat d'un produit, le consommateur peut ainsi choisir parmi plusieurs produits celui qui le satisfera le mieux et sélectionner le produit adéquat. Pour conserver et développer leurs parts de marché, les entreprises se doivent alors de concevoir et proposer les produits au plus proche des besoins de chaque consommateur.

Généralement, les marchés peuvent être subdivisés en plusieurs groupes de clients avec des besoins et désirs différents à l'égard de certains biens et services. Afin de considérer cette diversité de clients, il est nécessaire de concevoir les produits en fonction des différents segments du marché en tentant de les regrouper dans un nombre de segments appropriés et plus petits. Selon Pine II (1993) la personnalisation de masse permet l'identification et la réalisation des désirs et besoins de divers clients, sans sacrifier l'efficience, l'efficacité et le faible coût. Nous considérons que la personnalisation de masse représente plus qu'une stratégie d'entreprise, elle peut être considérée comme une philosophie de travail appuyée par plusieurs stratégies de standardisation, telles que les plateformes, la communité «commonality», la modularité, l'extensibilité «scalability» et la différenciation retardée «postponement».

Dans cette direction, pour éviter une diversification coûteuse en essayant de fabriquer un produit pour chaque client, les entreprises se tournent vers les familles de produits (Agard, 2004). Selon Jose et Tollenaere, (2005) une famille de produits est un ensemble de produits qui ont des caractéristiques communes et qui sont différenciés par quelques autres. Au niveau du producteur, ceci peut avantageusement être supporté par une plateforme de produits (les éléments en commun) qui s'enrichissent d'options et variantes modulaires. Également, selon Erens et Verhulst, (1997) une famille de produits peut être définie comme un ensemble de produits qui partagent des interfaces internes identiques. Ces interfaces doivent être standardisées dans chacun des domaines fonctionnels, technologiques et physiques pour permettre l'échange de composants. Plus récemment, Moon et al., (2006) a défini une famille de produits comme un groupe de produits liés qui sont basés sur une plateforme de produit, facilitant la personnalisation de masse en offrant une variété de produits de manière rentable pour les différents segments de marché.

Le développement de produits au sein d'une famille, réutilisant une plateforme commune entre produits, permet aux entreprises de réduire le coût de développement des différentes variantes de produits (Krishnan et al., 1999). De plus en plus, les compagnies conçoivent des familles de produits dans le but de faire de la personnalisation de masse une réalité, offrant une plus grande variété de produits tout en réduisant les coûts par la standardisation des composants et des processus. Nous nous situons donc dans le contexte où l'on souhaite offrir une grande diversité de produits (apparente) à partir d'une famille de produits. Selon Agard et Tollenaere (2003) les deux stratégies principales largement appliquées pour réaliser la personnalisation de masse sont la différenciation retardée et la conception modulaire.

Notre proposition consiste à aider l'entreprise et le consommateur à configurer au mieux les options et variantes qui permettront à un exemplaire de produit d'être au plus proche des besoins de chacun. Pour cela nous proposons d'utiliser la logique floue, qui offre l'avantage de tolérer une description des besoins du consommateur sous des formes flexibles. La logique floue permet d'entrer l'information à fournir en des termes linguistiques familièrement exprimés par les personnes. Par exemple, le futur acheteur pourra être modérément ou très intéressé à certaines caractéristiques d'un produit tel que la taille ou le poids, au lieu de donner des valeurs binaires «binary» (oui, non) ou des valeurs constantes «crisp» (200 kg) non négociables. Ce type d'information permet de prendre des décisions meilleures et plus précises, en raison de la large gamme de réponses possibles qui peut être traitée au lieu de simplement être ou ne pas être intéressé à une caractéristique du produit, comme permis par les outils traditionnels.

1.2 Objectifs et contributions de la recherche

Le but de cette recherche est d'exploiter les avantages de la modélisation par la logique floue pour aider à la configuration des familles de produits. Ce but s'est décliné en plusieurs étapes.

Nous avons tout d'abord développé une méthode qui a contribué à améliorer la modélisation des besoins des clients. Cette méthode permet le classement «ranking» de nombres flous nécessaires pour la comparaison entre différentes caractéristiques. Ceci a donné lieu à une première publication (Barajas, M., & Agard, B., 2009a. Improved fuzzy ranking procedure for decision making in product design. *International Journal of Production Research*, accepté) qui constituera le chapitre 3 du présent document.

La méthode précédente a été adaptée pour comparer des options de produits (Barajas, M., & Agard, B., 2008a. A ranking procedure for fuzzy decision-making in product design, *IDMME - Virtual Concept, Beijing, China*), puis pour sélectionner une alternative de produits basée sur les préférences des clients (Barajas, M., & Agard, B., 2008b. Selection of products based on customers preferences applying fuzzy logic*, IDMME - Virtual Concept, Beijing, China*).

Dans le cadre des familles de produits, nous avons développé une méthode qui permet de configurer un produit pour un consommateur unique (Barajas, M., & Agard, B., 2009e. Iterative product configuration with fuzzy logic. International Conference on Industrial Engineering and Systems Management – IESM' 2009, Montréal, Canada, May 13-15). Aussi une méthode pour configurer des gammes de produits dans des marchés différents a été proposée (Barajas, M., & Agard, B., 2009d. Fuzzy product configuration based on market segmentation to form a family of products, 42nd CIRP Conference on Manufacturing Systems, Grenoble, France, June 3-5.

Tout ceci a donné lieu à une méthodologie globale de conception des familles de produits à l'aide de la logique floue (Barajas, M., & Agard, B. 2009b. A methodology to form product families through fuzzy product configuration, Rapport de recherche du CIRRELT-2009-30, soumis à *International Journal of Engineering Design*, en revue) qui constituera le chapitre 4 de ce document. Alors que plusieurs autres travaux ont contribué à rendre les principes de la personnalisation de masse une réalité, nos travaux portent sur le développement et l'application des différents outils assistés par la logique floue pour améliorer le processus de prise de décision en considérant des informations vagues ou imprécises dans toutes les phases de la conception d'une famille de produits.

Nous avons contribué d'un coté à la conception des familles de produits en offrant de nouveaux outils d'aide à la décision, d'un autre coté nous avons contribué à l'avancement des connaissances et outils disponibles en logique floue, il est maintenant possible de classer «rank» une plus vaste diversité de nombres flous.

Liste des contributions originales :

1. Barajas, M., & Agard, B. (2009a). Improved fuzzy ranking procedure for decision making in product design. International *Journal of Production Research*, doi: 10.1080/00207540903117873.
2. Barajas, M., & Agard, B. (2009b). A methodology to form product families through fuzzy product configuration, Rapport de recherche du CIRRELT-2009-30, soumis à *International Journal of Engineering Design*, en revue.
3. Barajas, M., & Agard, B. (2009c). The use of fuzzy logic in product family development: literature review and opportunities, Rapport de recherche du CIRRELT-2009-31, soumis à *Journal of Intelligent Manufacturing,* en revue

4. Barajas, M., & Agard, B. (2009d). Fuzzy product configuration based on market segmentation to form a family of products, *Proceeding of the 42nd CIRP Conference on Manufacturing Systems, Grenoble, France.*
5. Barajas, M., & Agard, B. (2009e). Iterative product configuration with fuzzy logic. International *Proceeding of the International Conference on Industrial Engineering and Systems Management – IESM' 2009, Montréal, Canada.*
6. Barajas, M., & Agard, B. (2008a). A ranking procedure for fuzzy decision-making in product design, *Proceeding of the IDMME - Virtual Concept 2008, Beijing, China.*
7. Barajas, M., & Agard, B. (2008b). Selection of products based on customers preferences applying fuzzy logic, *Proceeding of the IDMME - Virtual Concept 2008, Beijing, China.*

1.3 Plan de lecture de la thèse

Le présent document est constitué de 7 sections principales. Après l'introduction générale qui présente la problématique ainsi que les objectifs et les contributions de cette thèse, nous avons présenté le chapitre 2 «revue de littérature» qui décrit l'état de l'art ; ce chapitre est constitué d'un article (Barajas and Agard, 2009c) qui analyse les différentes thématiques en rapport avec le développement des familles de produits, ainsi que l'application de la logique floue dans différents sujets en rapport à la conception des familles de produits.

Le chapitre 3 «Démarche du travail de recherche» présente les différentes étapes effectuées pour atteindre les objectifs de la recherche ainsi que les principaux résultats.

Le chapitre 4 «Improved fuzzy ranking procedure for decision making in product design» est aussi constitué d'un article (Barajas and Agard, 2009a) qui présente une méthode pour ordonner n'importe quelle quantité de nombres flous normaux en utilisant des nombres flous trapézoïdaux comme forme générale pour représenter des nombres flous triangulaires et rectangulaires. Cette méthode a pu être employée pour prendre des décisions importantes autour de différents processus tels que la conception de produits. Le calcul de la relation de préférence floue et l'application du modèle de préférence de pseudo-ordre constituent la base de la méthode.

Le chapitre 5 «A methodology to form product families through fuzzy product configuration» est constitué d'un article (Barajas and Agard, 2009b) qui présente une méthodologie globale pour la conception des familles de produits en profitant de la configuration floue des produits. Dans cette méthodologie, la logique floue est considérée comme un moyen d'améliorer le processus de prise de décision en raison de sa capacité à gérer l'information avec plus de précision que de la logique binaire. Cette méthodologie est présentée en trois parties principales: la considération du marché, la formation de famille de produits par la configuration de produits, et la considération de la variété de produits.

Le chapitre 6, intitulé « Discussion générale » présente les apports de notre travail de recherche. Ces apports se situent dans deux directions : la contribution à la logique floue et la contribution à la conception des familles de produits; ceci constituera les deux développements présentés dans ce chapitre.

À la fin, les conclusions et perspectives sont présentées dans le chapitre 7 de cette thèse.

CHAPITRE 2 : REVUE DE LITTÉRATURE

2.1 Abstract

Over the past few years, a number of key issues related to the product family design process have been addressed, and a great deal of work has been done to improve it. Many different philosophies, approaches, frameworks, methods and methodologies have been employed in this effort, such as mass customization, modularity, delayed differentiation, commonality, platforms, product families, and so on. The purpose of this paper is to analyze how fuzzy logic has been applied and how it can help to improve the entire process of product family development. Given its powerful capability to represent aspects that binary variables cannot, we show how fuzzy logic has been used to take advantage by considering the vague parameters related to the human character in different processes. Our aim is to contribute to the understanding and improvement of product family development process by identifying essential applications of fuzzy logic in such process. An extended overview of the product family development process is provided, and also this work highlights the role of fuzzy logic in it. Fourteen fuzzy logic tools and thirteen topics into the product family development process are identified and summarized as a framework to analyze the role of fuzzy logic in the product family process and at the same time to identify further application opportunities in such process.

Keywords: literature review, product family development, fuzzy logic, shortcomings, opportunities.

2.2 Introduction

Competitive companies are involved in a race to increase customers' satisfaction as well as enlarge their market share. They are pushed to improve their products in terms of quality, price, variety, safety, flexibility, delivery time, etc. To achieve these goals, many companies have applied design strategies that incorporate all the actors (customers and suppliers) and their perspectives into the business game as effectively as possible.

On this way, mass customization permits the identification and fulfilment of individual wants and needs of various customers, without sacrificing efficiency, effectiveness and low cost (Pine II, 1993). Product portfolio is a parameter that should be optimized looking for a balance between customer desires and the product family design in different domains, such as the physical, technical and functional domains, and yet at the same time keeping costs low (Jiao et al., 1998). To make mass customization a reality, many strategies have been developed in recent decades, such as modular design, delayed differentiation, platforms, and product families, among others. By developing products as a family, reusing a common product platform, firms can reduce the cost of developing individual product variants (Krishnan et al., 1999). The development of product families has been recognized as a mean for optimizing internal complexity and external variety (Meyer et al., 1997). A product family can result in a large variety of products supported with managed development and manufacturing costs.

Even if many important topics around product family development have been significantly explored, there are still some unexplored topics such as Fuzzy logic (FL), it has the capacity to manage vague parameters related to the human character in the decision-making process; this powerful capability represents a critical aspect that could advantageously improve the process of designing a product family.

Processes used in companies present a systemic behaviour; they are interconnected to some degree. Product family development (PFD) presents a similar behaviour; all its processes are interconnected, this makes an integral application of FL necessary, instead of isolated applications. This represents a major challenge, but the improvements will be very useful. Unfortunately, most of presently published works contain isolated applications of FL rather than an integral application.

This paper presents a review of the literature on the main topics related to the PFD process, analyzing the application of FL. This work is organized as follows: Section 2 provides an overview of the PFD process and the role of FL in it, including consideration of the customers' desires, design of the product family and creation of its architecture, evaluation of the product family, and redesign of the product family. Each phase is explained below, and several tools, such as product development, mass customization, platforms, commonality, modularity, scalability and postponement, are explained as well. Section 3 presents an analysis of the role of FL in the PFD process. This analysis is presented in three parts. These are: classification of the work carried out on PFD, current applications of FL in the PFD process, and identification of the shortcomings and opportunities inherent in applying FL to improving the process. Section 4 concludes the paper.

2.3 Product family development

A great deal of work has been carried out to try to improve and optimize some aspects in different phases of the PFD process. These include various philosophies, strategies, approaches, frameworks, methods, models, algorithms and methodologies. Prior to analyze this work, it is important to define what "product family" covers.

According to Erens and Verhulst (1997) a product family can be defined as set of products that share identical internal interfaces. These interfaces must be standardized in each of the functional, technological and physical domains to allow the full exchange of components. More recently, Moon et al., (2006) defined a product family as a group of related products based on a product platform, facilitating mass customization by providing a variety of products cost-effectively for different market segments.

In this work, the process of PFD is presented in four main phases. These are: consideration of customer desires, design of the product family and its architecture, evaluation of the product family, and redesign of the product family. An overview of the PFD process is depicted in Figure 2.1.

Figure 2.1 shows the three main views that appear in most works related to product families. These are the functional, technical and physical views that should be considered before creating the product family design. The following section explains the main phases of the product family overview.

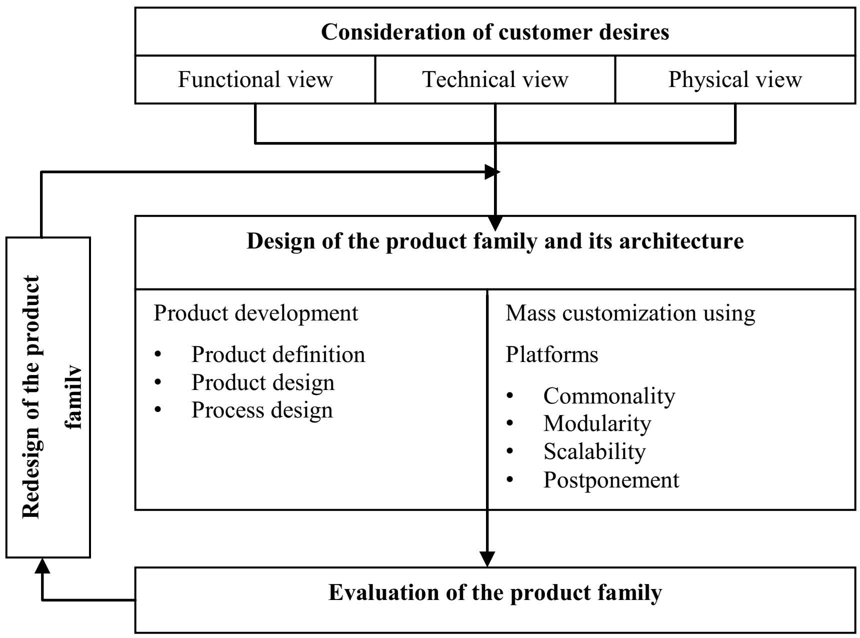


Figure 2.1 Overview of the product family development

2.3.1 Consideration of customer desires

Companies around the world aim to satisfy the customer desires. They try to avoid all the drawbacks, such as loss of a segment of the potential market and shortening of the life cycle of the product due to a deficient identification of the customer needs.

The design of a product family requires a product's architecture in three domains (Erens and Verhulst, 1997). In the functional view, the functional merit of a Product Family Architecture (PFA) is judged by the capability of its product portfolios to target identified market niches. The technical view looks to highlight differentiation (variety) in product design resulting from different solution technologies applied to meet diverse customer needs. Finally, the physical view in a PFA displays the variety resulting from manufacturing concerns. This view represents product information by means of a description of the physical realization of a product design, and bears a strong relationship to product construction.

For several years now, a powerful tool used to translate the customer's needs and wishes into product specifications has been Quality Function Deployment (QFD). This tool has recently evolved through the addition of other improvements, such as FL methods. FL uses the customer inputs to reveal the relative importance of their needs and to facilitate their implementation. Several works have been developed in this way, (Kalargeros and Gao, 1998; Fung et al., 1999; Wang, 1999; Vanegas and Labib, 2001a; Fung et al., 2002; Chen et al., 2004a; Ramasamy and Selladurai, 2004; Shipley et al., 2004; Chen et al., 2004b; Koga and Ohta, 2005) trying to simplify and rationalize the application of QFD using FL tools. They consider fuzzy inference techniques to accommodate the possible imprecision and vagueness, fuzzy outranking to prioritize the design requirements, fuzzy numbers to represent the imprecise nature of judgments and to define the relationships between engineering characteristics and customer attributes, fuzzy regression to identify the relational functions between, and among, engineering characteristics and customer requirements. At the same time, environmental issues are being increasingly addressed. For example, Chen et al., (2005) proposed a novel fuzzy expected value operator approach to model the QFD process in a fuzzy environment.

2.3.2 Design of the product family and its architecture

The design of PFA is one of the most critical tasks faced by the design team. There are many types of architectures for individual products or for product portfolios, among them modular, integral and mixed configurations, as well as an adjustable configuration (Gonzalez-Zugasti et al., 2000). To deal with PFA design, some approaches (Du, 2000; Dahmus et al., 2001) and different methodologies (Jiao, 1998; Jiao and Tseng, 1999; Siddique and Adupala, 2005) have been proposed as a way to reach the mass customization through the product families.

Different approaches (Anderson, 1997; Hsiao and Liu, 2005; Zhang, 2006) and diverse methodologies (Dong et al., 2001; Agard and Kusiak, 2004a) haven been presented to design product families. They manage the required variety to satisfy the different segments of the market. A very few part of these works applied the FL as a tool for developing product families. Two works in this sense have been proposed recently. The first one (Dong et al., 2001) was a product family configuration method based on constraints and fuzzy decisions, in which fuzzy optimum selection is used in the reasoning process to select between similar current components. The second one (Zhang, 2006) proposed an approach to develop a new product family which consists of a process evaluation method to determine whether or not some factors contribute to the new product family; it follows an application of the fuzzy analytic hierarchy process to weight the importance of the factors.

2.3.2.1 Product development

The product development process represents an essential part of the product family design and it can be divided into three consecutives stages (Jiao and Zhan, 2005): (1) product definition—mapping customer needs in the customer domain to functional requirements in the functional domain; (2) product design—mapping functional requirements in the functional domain to design parameters in the physical domain, these stages are highly supported by QFD; and (3) process design—mapping design parameters in the physical domain to process variables in the process domain.

2.3.2.1.1 Product definition

According to Anderson (1997) one important phase in the product development is product definition. Product definition is characterized by the portfolio of products that represents the target of mass customization which then becomes the input to the downstream design activities and is propagated to product and process platforms (Jiao and Zhang, 2005).

2.3.2.1.2 Product design

Product design is an engineering process involving iterative and complex decision-making. It usually starts with the definition of a need, proceeds through a sequence of activities to find an optimal solution to the problem, and ends with a detailed description of the product (Deciu et al., 2005).

A great deal of research has been carried out in the effort to improve the product design process. It seeks to apply many concepts, such as standardization or mass customization, modular products, product platform, component sourcing, evolutionary product, real-time design, information exploitation, etc. Among this research works are devoted to mass customization, and some of it related to the development of product families as a tool to achieve mass customization.

Different approaches, methods, and models have been proposed for the product design process (Deciu et al., 2005; Shaowei, 2006; Chen and Weng, 2006; Kuo et al., 2006) based on different fuzzy models, such as fuzzy goal programming models to determine the level of fulfilment of the design requirements, green fuzzy design analysis for evaluating product design alternatives based on environmental considerations using FL, and the fuzzy multi-attribute decision-making to select the most desirable design alternative.

Other technologies, like the Internet, are being used in this field, some examples of which include: (Siddique and Ninan, 2005), who presented an Internet-based framework which uses a grammatical approach to represent and develop models of customized products. Another example of an Internet application is a web-based virtual design environment method which allows customers to participate in product design and help designers conveniently adjust the structure of their products (Shen et al., 2005).

2.3.2.1.3 Process design

The optimization of product and process designs is very important to make the performance minimally sensitive to the various causes of variation (Nepal, 2005). A model to evaluate the investment in process improvement as a means of responding to changing market forces characterized by the mass customization paradigm was published by Burgess (1997). A careful design of product assembly sequence helps to create generic subassemblies which reduce subassembly proliferation and the cost of offering product variety (Gupta and Krishnan, 1998). A manufacturability evaluation decision model based on FL and multiple-attribute decision-making in a concurrent engineering environment was proposed by Jiang and Chi-Hsing (2001). In the same context (Park and Simpson, 2005) presented a production cost model based on a production cost framework associated with manufacturing activities. Also, Da Cunha and Agard (2005) proposed a simulated annealing algorithm to address the problem of module design, focusing on minimizing mean assembly time.

2.3.2.2 Mass customization using platforms

Many manufacturers define product families in order to introduce some degree of standardization. These product families could be further partitioned into subfamilies to better match distinct market segments. Then, each subfamily can be customized according to the needs and preferences of a specific customer segment (Agard and Kusiak, 2004b). Two strategies widely applied to achieve the mass customization are the delayed product differentiation and modular design (Agard and Tollenaere, 2003b). Also, (Agard and Kusiak, 2004b) suggested that data mining can be applied to standardize the components, products and processes thanks to knowledge extracted from databases.

Two dimensions for classifying product families were proposed by Wijnstra (2005). The first deals with coverage of the product family platform. The second deals with the variation mechanisms used to derive a specific product from the generic platform. The key to a successful product family is the common product platform around which the product family is derived (Messac et al., 2002).

There are two recognized approaches to product family design (Simpson, 2004). The first is a top-down (proactive platform) approach, wherein the company's strategy is to develop a family of products based on a product platform and its derivatives. The second is a bottom-up (reactive redesign) approach, wherein a company redesigns and/or consolidates a group of distinct products to standardize components and thus reduce costs.

In a general way, an important number of works has been published for developing platforms. These works include methods for identifying a platform using data mining techniques and fuzzy clustering (Moon et al., 2006), methods for the platform development applying preference aggregation, optimization, and cluster analysis (Gonzalez-Zugasti et al., 2001; Dai, 2005; Dai and Scott, 2006).

More specifically, four basic platform strategies have been applied successfully for the platform development. These are commonality, modularity, scalability and postponement (Huang et al., 2005). A brief summary of the work carried out related to these strategies follows.

2.3.2.2.1 Commonality

The success of the product family relies heavily on properly balancing the commonality of the product platform with the individual product performance within the product family. To help resolve this trade-off, (Simpson et al., 2001) presented a product variety trade-off evaluation method for assessing alternative product platform concepts with varying levels of commonality.

Jiao and Tseng (2000) identified two sources of commonality: in the component part, and in the process part. In this way, Thevenot and Simpson (2004) compared and contrasted six of the commonality indices from the literature based on the ease with which data can be collected, and their repeatability and consistency.

An analytical approach focuses on the demand side-effects of commonality and on the integration of the cost side-effects of commonality was presented by Kim (1998). It suggests a notion of customer valuation change due to commonality and demonstrates the effect of the valuation change on optimal product design. In the same way, Dai (2005) proposed a method to make an appropriate commonality decision in order to achieve a meaningful trade-off between the technical and monetary aspects of the product family.

For modelling the commonality of components, two models were presented by Mishra (1999). These methods are: the multiple product-multiple common components, and the multiple product-single common components. A methodology for performing commonality optimization in choosing product components to be shared without exceeding user-specified bounds on performance and allowing the maximization of commonality at different levels of acceptable performance was proposed by Fellini (2003) and Fellini et al., (2005).

2.3.2.2.2 Modularity

According to Jose and Tollenaere (2005), modularization was first mentioned in the literature in the 1960s. Modularity was proposed to group components of products in a module for practical production objectives. Today, modularity and standardization are promising tools in PFD, because they make it possible to design a variety of products using the same modules of components, called platforms. Salvador et al., (2002) explored how manufacturing characteristics affect the appropriate type of modularity to be embedded in the product family architecture, and how the types of modularity relate to component sourcing.

Different approaches have been proposed (He and Kusiak, 1997; Rai and Allada, 2003; Zhang et al., 2006) for tackling the modular product family design using various tools, such as multi-objective optimization, and search-based algorithms. Some methods for developing a modular product family have been presented as well. Wang et al., (2005) proposed a method based on simulated annealing algorithm to develop a modular product family. Also, Sered and Reich (2006) proposed a method called SMDP (standardization and modularization driven by process effort), which focuses the engineering effort on product platform components when applying standardization or modularization. Xianghui et al., (2007) presented a methodology for identifying the constituent modules of product families including four principles such as identification and isolation of individualized components into modules, identification and isolation of components with high possibility of replacement into one module, improvement of the functional independency of the modules, and improvement of the structural independency of the modules. Da Cunha et al., (2007) proposed various heuristic algorithms to design modular elements in a mass customization context, focusing on minimizing the manufacturing and transportation cost in a supply chain.

2.3.2.2.3 Scalability

To facilitate the product family design process based on a scalable product platform, (Simpson and Mistree, 1999) introduced the product platform concept exploration method. In the same way, Callahan (2006) developed a model called the extended generic product structure. This model focuses on capturing reusable and non-reusable design definitions, as well as the hierarchical product design structures composed from them. Messac et al., (2002) proposed a product family penalty function to optimize the product family design process. This function determines which parameters should be common throughout the product family, and which should be the scaling variables. If a parameter cannot be made constant across the products without adversely affecting the design objectives, then it should be considered a good candidate for becoming a scaling parameter. Also, a methodology to identify a scaling factor for product family-based product and process design employing the tools of experimental design and analysis was presented by Sopadang et al., (2001-2002).

2.3.2.2.4 Postponement

The development of product families allows high volumes to be produced at low cost through standardization. The downside is that this approach represents a move away from real needs in an increasingly heterogeneous and evolving market. To compensate for this negative effect, companies produce standardized goods, but incorporate a degree of differentiation, which makes it possible to personalize each product in the final phase of the production process. This strategy is called delayed differentiation (Lee and Tang, 1997), and it is based on the modular design (Kusiak, 1999). Delayed differentiation makes it possible to produce almost-finished goods which can be personalized in the last phase.

According to Feitzinger and Lee (1997) the key to effective mass customization is postponing product differentiation for a specific customer until the latest possible point in the supply chain or network. Postponement can be defined as an organizational concept whereby some of the activities in the supply chain are not performed until customer orders are received (Van Hoek, 2001). Companies can then finalize the output in accordance with customer preferences, and even customize their products. Postponement has become mandatory for many companies, due the current levels of market globalization, increasing demand for product variety and customization, rapid technological innovation, shortening product life cycles and intense competition (Biao et al., 2004). Su et al., (2005) have been developed some models to represent two possible mass customization postponement structures, Time Postponement and Form Postponement, and study their performance in terms of total supply chain cost and the expected customer waiting times.

2.3.3 Product family evaluation

A knowledge decision support approach to product family design evaluation and selection for the mass customization process was presented by Zha et al., (2004). In this approach, product family design is viewed as a selection problem with the following stages: product family generation, product family design evaluation and selection for customization. This approach supports the imprecision inherent in decision-making with fuzzy customer preference relations, and uses fuzzy analysis techniques for evaluation and selection. Also, this work focuses 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.

In the same way, Thevenot and Simpson (2006) introduced a comprehensive metric for commonality to evaluate product family designs on a 0-1 scale; this is based on the components in each product, their size, geometry, material, manufacturing process, assembly and costs, and the allowed diversity in a family. This method improves the accuracy, repeatability and robustness of the results by minimizing user input, and helps designers resolve the trade-off between variety and commonality in a product family.

2.3.4 Product family redesign

Thevenot et al., (2005) developed a methodology for product family redesign that is based on the use of a genetic algorithm and commonality indices—metrics to assess the level of commonality within a product family. It consists of four phases, as follows. Phase 1: Data input. This phase is designed to obtain the necessary data for the product family concerned. Phase 2: Commonality assessment. In this phase, the commonality within a product family is measured. Phase 3: Product family design optimization. Phase 4: Data output and redesign recommendations. More recently, a systematic method to generate recommendations during the process of product family redesign using a new commonality index, the comprehensive metric for commonality was introduced by Thevenot (2006), it is made up of the same four phases.

Nanda et al., (2005) proposed two approaches for redesigning a product family: (1) a component-based approach, and (2) a product-based approach. In the component-based approach, the emphasis is placed on a single component which could be shared among different products in a PF to increase commonality. In the product-based approach, multiple products from a PF are selected, and commonality is improved among the selected products. In the same way, Thevenot et al., (2007) proposed a five steps framework for product family redesign. These steps are: (1) collect information, (2) store information, (3) retrieve information, (4) reuse information for product family redesign, and (5) represent information.

2.4 Fuzzy logic in product family

2.4.1 Summary and analysis

The product family is a powerful tool that makes it possible to take advantage of product similarities to reduce design and manufacturing costs. Moreover, the design of product families can be improved in many processes in a wide range of areas by the application of FL. FL allows opinions, knowledge and expertise to be provided in linguistic way. This information can be used for making better and more accurate decisions. FL is increasingly used in decision-aided systems, since it offers several advantages over other traditional decision-making techniques. The fuzzy decision support system can easily deal with incomplete and/or imprecise information.

During the process of product family design, it is necessary to consider many important aspects, such as operational capabilities (normally called "design for operations" in a company context), product life cycle, and external factors. Not to do so can result in a reduction in productivity and quality, and also may generate an incremental rise in costs. The life cycle of a product is important because it distinguishes the differences between products in their various phases.

A summarized list of the works considered in this paper is displayed in Table 2.1. This table indicates in which publications the topics are addressed. The topics considered are product definition, product design, process design, product family architecture, mass customization, platform, commonality, modularity, scalability, postponement, product family design, product family evaluation and product redesign. Furthermore, for each work, the type of tool offered is identified. The classification is divided into the following categories: approach, framework, method, methodology, algorithm, and model. Finally, the last column in the table indicates whether or not the work has a FL application.

Table 2.1 Classification of developed works related to product family development

Publications	Consideration of customer desires	Product definition	Product design	Process design	Product family architecture	Mass customization	Platform	Commonality	Modularity	Scalability	Postponement	Product family design	Product family evaluation	Product family redesign	Approach	Framework	Method	Methodology	Model	Algorithm	Fuzzy application
Agard & Kusiak 2004a						*						*			*			*			
Agard & Kusiak 2004b			*			*												*			
Agard &Tollenaere 2003			*			*			*		*	*						*	*		
Anderson 1997		*	*	*	*	*			*			*			*						
Biao Yang *et al*. 2004						*					*					*					
Burgess 1997				*		*													*		
Büyüközkan & Feyzioğlu 2004a		*	*												*						*
Büyüközkan & Feyzioğlu 2004b															*						*
Callahan 2006			*							*		*							*		
Chen *et al*. 2004a	*	*	*														*				*
Chen & Weng 2006		*	*																*		*
Chen 1999																			*		*
Chen *et al*. 2005	*	*	*												*				*		*
Chen *et al*. 2006	*	*	*														*				*
Chen *et al*. 2004b	*	*													*				*		*
Da Cunha & Agard 2005				*					*											*	
Da Cunha *et al*. 2007				*		*			*											*	
Dahmus *et al*. 2001		*	*		*		*		*						*						
Dai 2005							*	*				*			*		*				*
Dai & Scott, 2006			*				*					*			*		*				
Deciu *et al*. 2005			*			*									*				*		*
Dong *et al*. 2001		*										*				*	*				*
Du, X. 2000			*		*	*		*	*						*						
Erens & Verhulst 1997	*	*	*		*	*			*												
Ertay & Kahraman 2007	*	*	*																		*
Feitzinger & Lee 1997						*					*										
Fellini *et al*. 2005							*	*				*			*						
Fellini 2003							*	*	*			*						*			
Feyzioğlu & Büyüközkan 2006																*					*
Fung *et al*. 2002	*	*	*																*		*
Fung *et al*. 1999	*	*													*						*
Gonzalez-Zugasti *et al*. 2001			*				*					*							*		
Gonzalez-Zugasti *et al*. 2000					*		*								*		*				
Gungor & Arikan 2000																	*				*

Table 2.1 (contd.) Classification of developed works related to product family development

Publications	Consideration of customer desires	Product definition	Product design	Process design	Product family architecture	Mass customization	Platform	Commonality	Modularity	Scalability	Postponement	Product family design	Product family evaluation	Product family redesign	Approach	Framework	Method	Methodology	Model	Algorithm	Fuzzy application
Gupta & Krishnan 1998				*								*			*			*		*	
Hanumaiah *et al*. 2006	*	*		*											*	*		*			
He & Kusiak 1997				*					*						*						
Hsiao & Liu 2005												*			*						
Huang *et al*. 2005						*	*	*	*	*	*										
Jiang & Chi-Hsing 2001				*															*		*
Jiang & Yan 2003				*			*					*									
Jiao & Tseng 2000				*		*		*				*									
Jiao *et al*. 1998		*				*						*			*						
Jiao 1998		*	*	*	*	*	*	*	*	*						*		*			*
Jiao & Tseng 1998			*															*			*
Jiao & Tseng 1999					*	*												*			*
Jiao & Zhang 2005	*	*	*	*		*												*			*
Jose & Tollenaere 2005			*				*		*			*									
Kalargeros & Gao 1998	*	*															*				*
Kim 1998			*					*							*						
Kim *et al*. 2000	*	*	*																*		*
Koga & Ohta 2005	*	*															*				*
Krishnan *et al*. 1999							*					*							*		
Kuo *et al*. 2006			*														*				*
Kusiak 1999			*	*					*												
Lee & Tang 1997						*					*								*		
Lin & Chen 2004		*	*												*						*
Messac *et al*. 2002			*				*	*		*		*			*						
Meyer *et al*. 1997							*					*					*				
Mishra 1999								*											*		
Moon *et al*. 2006						*	*		*			*					*				*
Nanda *et al*. 2005								*				*		*	*	*		*			
Nepal 2005			*	*					*							*		*			*
Park & Simpson 2005				*								*				*	*				
Pine II 1992		*	*			*			*												
Rai & Allada 2003									*			*			*	*	*				
Ramasamy & Selladurai 2004	*	*															*				*
Salvador *et al*. 2002		*	*		*	*			*			*									

Table 2.1 (contd.) Classification of developed works related to product family development

Publications	Consideration of customer desires	Product definition	Product design	Process design	Product family architecture	Mass customization	Platform	Commonality	Modularity	Scalability	Postponement	Product family design	Product family evaluation	Product family redesign	Approach	Framework	Method	Methodology	Model	Algorithm	Fuzzy application
Sered & Reich 2006				*		*	*		*			*					*				
Shaowei 2006			*														*		*		*
Shen *et al*. 2005		*	*																		
Shipley *et al*. 2004	*	*	*																*		*
Siddique & Adupala 2005				*	*							*				*	*				
Siddique & Ninan 2005			*			*									*	*					
Simpson 2004						*	*					*									
Simpson & Mistree 1999							*			*		*					*				
Simpson *et al*. 2001			*				*	*				*			*		*				
Sivard 2001							*		*			*							*		
Sopadang *et al*. 2001-2002			*	*						*		*					*				
Su *et al*. 2005						*					*								*		
Thevenot *et al*. 2007														*		*					
Thevenot *et al*. 2005								*						*				*			
Thevenot & Simpson 2004							*	*				*									
Thevenot & Simpson 2006			*					*				*	*				*				
Thevenot 2006			*					*						*			*				
Van Hoek 2001											*					*					
Vanegas & Labib 2001	*	*															*				*
Vanegas & Labib 2001b			*														*				*
Vanegas & Labib 2005			*												*						*
Wang *et al*. 2005									*			*					*				*
Wang 1999	*	*													*						*
Wijnstra 2005						*	*					*									
Xianghui *et al*. 2007									*			*						*	*		
Zha *et al*. 2004			*			*							*		*	*			*		*
Zhang 2006												*			*						*
Zhang *et al*. 2006									*			*			*						

Although FL may not yet have been applied to the entire process of development of product families, it has, however, been used more and more in recent years to perform several tasks in that process.

It is interesting to note that an important number of publications into the analyzed sample in Table 2.1 contain at least one FL application. The most of these are partial applications; that is to say, different FL tools are used in one or more phases in the PFD process. Product definition, consideration of customer desires, product design, and mass customization are the topics addressed in most FL applications. On the contrary, the topics that are less addressed with FL applications are postponement, and product family redesign with not any work found with FL.

Also, topics such as process design, product family architecting, platforms, commonality, modularity, scalability, and product family evaluation presented a minimal number of works addressed in this way. Even if some considered works presented any application of FL into the product family design process, these applications are very partial and still necessitate developing new powerful tools for the entire PFD process.
Several fuzzy logic tools may be identified through the papers examined in this review. In this work, thirteen fuzzy logic tools around PFD have been identified and these are explained as follows.

(1) Fuzzy analytical hierarchy process. Fuzzy analytical hierarchy process has been used for different purposes such as distribution of weights for the establishment of fuzzy relationship matrix into the modular product family development process (Wang et al., 2005), to weight the importance of the factors determine whether or not some factors contribute to the new design of a product family (Zhang, 2006), to construct the hierarchical structure of environmentally conscious design indices into the green fuzzy design analysis (Kuo et al., 2006), to choose the best project alternative in the decision-making process (Büyüközkan and Feyzioğlu, 2004a), and to describe more accurately the evaluation and decision-making process (Büyüközkan and Feyzioğlu, 2004b).

(2) Fuzzy clustering. Jiao and Tseng (1999) employed the fuzzy cluster analysis to evaluate the similarities of customers needs by applying c-means clustering analysis. In the same way, Moon et al., (2006) used fuzzy c-means clustering to determine initial clusters

representing modules and to identify the platform and its modules by a platform level membership function and classification. Jiao and Zhang (2005) adopted a fuzzy clustering approach to create a hierarchical decomposition of the given set of objects, and to form groups in different levels of similarity. Zha et al., (2004) developed a knowledge-intensive support scheme and a comprehensive systematic fuzzy clustering and ranking methodology for product family design evaluation and selection.

(3) Fuzzy goal programming. Fuzzy goal programming has been adopted to determine the fulfillment levels of the engineering design requirements, where the coefficients in these models are also fuzzy in order to expose the fuzziness of the linguistic information (Chen and Weng, 2006), and to simultaneously optimize multiple objectives for product modularization (Nepal, 2005).

(4) Fuzzy inference. Fuzzy inference has been significantly used for numerous purposes such as determination of the priority of customer demands (Chen et al., 2004a), to accommodate the possible imprecision and vagueness during the interpretation of the voice of the customers during the interpretation of the qualitative and sometimes imprecise customer requirements (Fung et al., 1999), to process new product ideas into the product evaluation process by using a neuro-fuzzy inference system (Büyüközkan and Feyzioğlu, 2004b; Feyzioğlu and Büyüközkan, 2006), to adjust the membership function to enhance their systematic fuzzy clustering and ranking model by adopting a neural network technique (Zha et al., 2004), to perform the learning process of the fuzzy inference system by using adaptive neuro-fuzzy inference systems (ANFIS) (Büyüközkan and Feyzioğlu, 2004a; Büyüközkan and Feyzioğlu, 2004b; Feyzioğlu and Büyüközkan, 2006).

(5) Fuzzy multiple attribute decision-makings. The consideration of multiple attributes during the decision-making process has been considered an important issue to make accurate decisions. Jiang and Chi-Hsing (2001) used fuzzy logic decision model and fuzzy multiple attribute decision making model to construct the goal decision and activity decision spaces respectively into the proposed manufacturability evaluation decision model.

Shipley et al., (2004) used a fuzzy-set based multi-criteria decision-making process to determine the distributions of effort directed toward technical changes. Kuo et al., (2006) used fuzzy multi-attribute decision-making techniques to develop a method for green fuzzy design analysis, which involves simple and efficient procedures to evaluate product design alternatives based on environmental consideration to select the most desirable design alternative.

(6) Fuzzy numbers. Fuzzy numbers have been widely applied for different purposes. Vanegas and Labib (2001a) used fuzzy numbers to represent the imprecise nature of the judgments, and to define more appropriately the relationships between engineering characteristics and customer attributes in QFD, Vanegas and Labib (2001b) to develop a new fuzzy weighted average during the engineering design evaluation process trying to reduce the obtained imprecision during such process, Vanegas and Labib (2005) to capture the relative importance of the considered criteria and performance levels of the different alternatives in the evaluation process for engineering design, and Chen et al., (2006) to express and represent the input data in order to calculate the importance of the technical attributes in the fuzzy QFD. Others applications include Lin and Chen (2004) used fuzzy numbers to describe the criteria ratings and their corresponding importance in the proposed method for new product screening, Büyüközkan and Feyzioğlu (2004a) to represent the performance of different ideas into the fuzzy preference relation. Büyüközkan and Feyzioğlu (2004b) to express the assessments of the decision makers into the fuzzy analytical hierarchy process, and Ramasamy and Selladurai (2004) applied fuzzy triangular membership functions to represent the customer attribute and engineering characteristic into the rule-based fuzzy logic system to examine their relationships.

(7) Fuzzy optimization. Some important applications of fuzzy optimization include Dong et al., (2001) employed fuzzy optimum selection in the reasoning process, where the constraint satisfaction and fuzzy optimum selection interact to search the optimum solution, Fung et al., (2002) applied a fuzzy non-linear optimization model for QFD planning to obtain a set of feasible solutions to support more practical and cost-effective QFD planning

under resource constraints, and Chen et al., (2004a) applied fuzzy optimization theory with symmetric or non-symmetric triangular fuzzy coefficients to model the relational functions between engineering characteristics and customer requirements in QFD methodology.

(8) Fuzzy outranking. Wang (1999) proposed a new fuzzy outranking approach and an outranking decision model to select the critical design requirements for product development in the imprecise and uncertain design environment in the QFD planning process. Focusing on the application of the outranking approach, Gungor and Arikan (2000) used the outranking approach to model an imprecise preference structure in a project selection problem, Büyüközkan and Feyzioğlu (2004a) applied the outranking concept into the pseudo-order fuzzy preference model to discriminate the set of alternatives without the information about their information. An interesting comparison of three different outranking methods (Roy's, Brans et al.,'s and Siskos et al.,'s) to evaluate the design requirements was made by Ertay and Kahraman (2007) concluding that all the methods outrank the same alternative.

(9) Fuzzy preference. Jiao (1998) developed a fuzzy ranking methodology by employing the fuzzy preference relation to model the fuzziness in conceptual design evaluation. Some applications of fuzzy preference include Jiao and Tseng (1998) applied fuzzy preference relation for modelling the fuzziness in the proposed fuzzy ranking methodology for concept evaluation in configuration design, Gungor and Arikan (2000) to represent the imprecise preference relation between design alternatives. Büyüközkan and Feyzioğlu (2004a) used the pseudo-order fuzzy preference model to discriminate between different ideas without the relative importance of each considered criterion of evaluation into their proposed approach for new product development.

(10) Fuzzy quality function deployment. Ramasamy and Selladurai (2004) proposed a fuzzy logic-quality function deployment to determine optimum rating of engineering characteristics by using a rule-based fuzzy logic system. Also, Shipley et al., (2004)

presented a model to develop the QFD into a fuzzy-set based multi-criteria decision-making process to determine the distributions of effort directed toward technical changes.

(11) Fuzzy ranking. A fuzzy ranking methodology by employing the fuzzy preference relation to model the fuzziness in conceptual design evaluation in configuration design for mass customization was developed by Jiao (1998). Jiao and Tseng (1999) developed a fuzzy ranking approach and methodology using information-content measure for solving the multi-attribute design evaluation problem. More recently, focusing on the PFD process Zha et al., (2004) developed a ranking methodology for the product family design evaluation and selection.

(12) Fuzzy regression. Chen (1999) developed a fuzzy regression applying nonlinear programming to solve the fuzzy ranking problem. Kim et al., (2000) employed fuzzy regression to consider mathematically the inherent fuzziness during the estimation of the functional relationship between customer requirements and engineering characteristics in the QFD application. Chen et al., (2004b) considered the fuzzy linear regression with symmetric triangular fuzzy coefficients to model the relational functions between engineering characteristics and customer requirements considered traditionally in QFD methodologies.

(13) Fuzzy weighted average. Vanegas and Labib (2001b) developed a new fuzzy weighted average to produces fuzzy numbers as a better basis for making decisions more credible, and with less imprecision. Fuzzy weighted average has been used for different purposes such as the ranking of projects in the new product development process (Büyüközkan and Feyzioğlu, 2004a), the aggregation of fuzzy numbers into the product rating process (Lin and Chen, 2004), to calculate the overall performance of the alternatives considered in the evaluation of designs (Vanegas and Labib, 2005), to determine the fuzzy technical importance rating of design requirements in their fuzzy QFD proposed approach (Chen and Weng, 2006), and to rank technical attributes in fuzzy QFD and to calculate their importance (Chen et al., 2006).

The following Table 2.2 shows how the different FL tools have been developed and applied to support different important topics related with the PFD process.

Table 2.2 Fuzzy logic applications into Product Family Development

Fuzzy logic tools	**Product family development topics**												
	Product definition	Product design	Process design	Product family architecture	Mass customization	Platform	Commonality	Modularity	Scalability	Postponement	Product family design	Product family evaluation	Product family redesign
Fuzzy analytical hierarchy process		*						*			*		
Fuzzy clustering	*	*	*	*	*	*		*			*	*	
Fuzzy goal programming	*	*						*					
Fuzzy inference	*	*											
Fuzzy multiple attribute decision-makings		*	*		*								
Fuzzy numbers	*	*											
Fuzzy optimization	*	*									*		
Fuzzy outranking	*	*											
Fuzzy preference			*	*	*	*	*	*	*			*	
Fuzzy product knowledge		*	*					*					
Fuzzy quality function deployment model	*	*											
Fuzzy ranking	*	*	*	*	*	*	*	*	*			*	
Fuzzy regression	*	*											
Fuzzy weighted average	*	*											

Table 2.2 also aims to show the status of current applications of FL along the entire PFD process, presenting an interesting summary that lists and classifies the most and less developed topics throughout PFD. In Table 2.2, it is easy to note that topics as product definition, product design, and modularity are the topics with the most addressed topics in current applications of FL, topics as product family evaluation and scalability are topics with minimal applications of FL, and topics as product family redesign and postponement are not addressed topics in current FL application.

Table 2.1 and Table 2.2 allow noting how FL has been applied. Significant applications in mass customization and product family design can be noted, but it must be pointed out that, in this work, mass customization and product family design are addressed as general topics. Mass customization is made up of other subtopics, such as platforms, commonality, modularity scalability and postponement. Product family design involves all the subtopics, from consideration of customer desires and product development to product family architecture and mass customization. Although FL has been widely used in the product development process with several works related to QFD, it can be further exploited to embrace all the topics in the PFD process. In the same way, Table 2.1 and Table 2.2 can be analyzed to identify shortcomings in the application of FL and, consequently, to detect significant applications of FL in all the subprocesses in PFD. Even though many works in the sample are related to product family design, just a few parts of them correspond to work with a FL application.

2.4.2 Opportunities for fuzzy logic applications

As it can be noted in Table 2.1 and Table 2.2, some topics such as postponement and product family redesign do not contain any application of FL, but sometimes this situation can be understandable due to the nature of the topic. Product family evaluation and redesign are topics which have not been developed much with application of FL. Hence, there is an opportunity to take advantage of FL in future developments related to these topics. With the exception of consideration of customer desires, product definition and product design, there is a significant opportunity to use FL in the rest of the topics, specifically in the evaluation and redesign phases. Table 2.3 aims to identify some opportunities for fuzzy logic application through the different PFD phases and topics depicted in Figure 2.1.

Table 2.3 presents four phases (in bold type) and ten topics related to the PFD process listed in the first column. The second column presents the identified potential applications to these phases and topics. Each is described as follows.

Consideration of customer desires: FL may be applied in different PFD issues, including generic product structuring, association methods, and optimization trying to avoid a deficient identification of the customer needs. More specifically *Quality Function Deployment* has been a powerful tool widely used to translate the customer's needs and wishes into product specifications. As mentioned in the previous phase, the customer desires consideration can be improved through the FL applications in different issues such as generic product structuring, and QFD optimum targets determination.

Design of the product family and its architecture: The design of a product family architecture is one of the most critical tasks faced by the product family design team. Some important issues such as generic product structuring, optimization, decision-making tools, and activity-based costing can be enhanced by applying FL as a way to reach the mass customization benefits.

In *product definition* issues such as generic product structuring, optimization, decision-making tools, activity-based costing may be improved with FL application to obtain generic products by optimizing common components groped in modules to minimize the labour and resources requirement per unit.

In *product design* multi-criteria analysis, preference aggregation, decision-making tools, activity-based costing, optimization, association methods, product family penalty function, product variety tradeoff evaluation are some of possible issues that could be enhanced by applying FL. These issues are important to properly parameterize the product designs according to the customer desires, and at the same considering functional requirements of the product. In the *process design*, for mapping design parameters to process variables in the process domain, some issues such as optimization, analytical hierarchal process, activity-based costing, assembly simulation, scaling factor identification can be improved by the incorporation of FL. Also in *mass customization,* generic product structuring, optimization, decision-making, activity-based costing, association methods, and variation mechanisms are some of the issues where FL can be applied to make the mass customization a success reality.

Table 2.3 Classification of potential fuzzy logic applications in product family development

PFD phases and topics	**Potential fuzzy logic applications**
Consideration of customer desires	Generic product structuring, optimization, association methods.
Quality Function Deployment	Generic product structuring, method for determining optimum targets in QFD.
Design of the product family and its architecture	Generic product structuring, optimization, decision-making tools, activity-based costing.
Product definition	Generic product structuring, optimization, decision-making tools, activity-based costing.
Product design	Multi-criteria analysis, preference aggregation, decision-making tools, activity-based costing, optimization, association methods, product family penalty function, product variety tradeoff evaluation.
Process design	Optimization, analytical hierarchal process, activity-based costing, assembly simulation, scaling factor identification.
Mass customization	Generic product structuring, optimization, decision-making, activity-based costing, association methods, variation mechanisms.
Platform	Generic product structuring, optimization, decision-making, activity-based costing, product family penalty function, association methods, product platform concept exploration.
Commonality	Generic product structuring, optimization, decision-making, preference aggregation, cluster analysis, commonality indices, activity-based costing, product family penalty function, commonality indices - metrics.
Modularity	Generic product structuring, optimization, decision-making, activity-based costing, association methods, multi-objective analysis.
Scalability	Optimization, decision-making, activity-based costing, product family penalty function, scaling factor identification.
Postponement	Optimal characterization and optimization.
Product family evaluation	Comprehensive commonality metrics, and knowledge decision support systems.
Product family redesign	Optimization, commonality indices - metrics to assess the level of commonality, comprehensive metric for commonality.

One of the most important aspects to obtain a successful product family is the *product platform* around which the product family is derived. FL may be applied into different issues including generic product structuring, optimization, decision-making, activity-based costing, product family penalty function, and association methods to get a common product platform for all the product family.

Four basic platform strategies (commonality, modularity, scalability, and postponement) have been applied successfully for the platform development. Each is discussed as follows. A proper *commonality* balance of the product platform with the individual product performance within the product family is a very important aspect for its success. Issues such as generic product structuring, optimization, decision-making, preference aggregation, cluster analysis, commonality indices, activity-based costing, product family penalty function, and the development of commonality indices and metrics may be enhanced with the application of FL to obtain more accurate common platforms. FL can be used in some issues related to *modularity* including generic product structuring, optimization, decision-making, activity-based costing, association methods, and multi-objective analysis to makes possible to design a variety of products using the same modules of components, called platforms. With *scalability,* optimization, decision-making, activity-based costing, product family penalty function, and scaling factor identification are some of the issues that may be improved by applying FL to facilitate the product family design process by developing generic product structures and scalable product platforms. Also *postponement* makes it possible to produce almost-finished goods which can be personalized in the last phase. To facilitate the product family design based on a scalable product platform, issues such as optimal characterization and optimization can be improved with the incorporation of the FL.

Product family evaluation. Comprehensive commonality metrics and knowledge decision support systems could be improved by using FL to support the evaluation of product families. Some FL tools such as fuzzy preference, fuzzy clustering, and fuzzy ranking have been partially applied in some issues related to the evaluation of product families. Others indices to evaluate the amount of modularity, scalability, manufacturability, among others may be improved by adopting FL in their processes.

Product family redesign. FL could be applied to support the phase of product family redesign in issues such as the development of multiple metrics needed to evaluate current families of products including metrics to measure the amount of commonality, modularity, scalability, postponement, manufacturability, reliability, customer satisfaction, and so on. Also, FL may be applied in the optimization of all these metrics and the optimization of the product family design process as well.

2.5 Conclusions

Product Family Development (PFD) is a broad subject, which includes a number of topics that have been considered throughout this work. An analysis of these topics permits to understand the importance of developing tools with greater scope. A large number of application opportunities appear to take advantage of Fuzzy Logic (FL) for improving PFD. The topics with the most potential for FL applications are presently postponement and product family redesign, as no studies have been found that contain a FL application. Topics with potential are still product family architecture, platforms, commonality, modularity, scalability, product family evaluation and process design. Even though there is some application of FL in these topics, this application is minimal. By contrast, consideration of customer wishes, product definition and product design have already received large development.

The analysis about the application of FL in different topics through all phases in PFD process allowed constructing a summary to prioritize such topics (Table 2.2), this summary shows opportunities for application of FL in such process. That is, it already lists the most developed topics around the PFD process and at the same time rank those topics according the FL application permitting to identify application shortcomings (Table 2.3). By considering the shortcomings as opportunity to apply FL into the topics related to PFD process, it may allows to companies to offer better products according to the customer desires.

It is important to say that there are other important issues to consider with respect to PFD; external factors, such as legal, moral and environmental aspects, could be better modelled using FL. The most of companies are subject to rules that must be respected when designing products. From the moral perspective, it is necessary to solve the dilemmas to develop safe products for the customer. Recycling, for example, must be considered by producers, which means recovering materials to be used again. The term “design for recycling” defines the capacity to disassemble and reprocess a used product to recover any of its components that can be recycled. Most of these issues have already been considered into different topics of PFD though without applying FL.

CHAPITRE 3 : DÉMARCHE DU TRAVAIL DE RECHERCHE

3.1 Structure et méthodologie

L'approche de cette recherche part des questions fondamentales suivantes :

1. Est-ce que l'application de la logique floue dans les processus de prise de décision peut améliorer le traitement des préférences des consommateurs?

2. Est-ce que la conception des familles de produits peut être améliorée à travers le développement d'outils assistés par la logique floue?

Il s'agit, dans cette thèse, d'une recherche théorique qui vise au développement d'outils à base de logique floue pour aider à la configuration des familles de produits. Nous considérons qu'à travers le développement des familles de produits il est possible d'offrir une plus grande variété de produits conformes aux attentes des consommateurs. La logique floue est capable de gérer des informations imprécises, et cette capacité est un élément essentiel dans l'amélioration du processus de prise de décision. L'application de la logique floue à plusieurs outils de prise de décision permet la considération d'informations imprécises à partir de variables d'entrée qui peuvent être données en termes linguistiques, tels que «très important», «moyennement important», «très haut», «très bas», et ainsi de suite, comme exprimées par les humains.

Dans ce contexte nous partons de l'hypothèse suivante :

La logique booléenne ou binaire n'est pas suffisante pour traiter tous les types de réponses possibles émises par un consommateur par rapport à ses préférences pour certaines caractéristiques d'un produit.

Comme il a été mentionné dans le chapitre 1, l'objectif principal de ce travail de recherche, est d'analyser l'inclusion de la logique floue dans le processus de configuration de familles de produits pour améliorer le maniement de l'information provenant des consommateurs dans ce processus, en ayant comme but d'aider aux entreprises à former de meilleurs produits, plus conformes aux désirs et aux besoins des consommateurs.

La méthodologie appliquée pour atteindre les objectifs de cette recherche est constituée des étapes suivantes :

Étape 1. Analyse de l'état de l'art par rapport aux applications de la logique floue dans les outils existants relatifs à la conception des produits.

Étape 2. Identification des applications possibles pour exploiter les bénéfices de la logique floue dans le développement d'outils pour représenter d'une manière plus flexible les besoins et les préférences des consommateurs.

Étape 3. Développement et amélioration des outils de classement flou «fuzzy ranking» pour la prise de décision dans la conception de produits.

Étape 4. Application de la procédure de classement flou dans les processus de prise de décision pour la conception de produits.

Étape 5. Application de l'analyse des relations de préférences floues «fuzzy preference relation» pour la sélection de produits basés sur les préférences des clients.

Étape 6. Développement et application d'une méthode pour la configuration de produits à travers l'évaluation de la satisfaction du client en appliquant des outils de logique floue développés précédemment.

Étape 7. Adaptation d'une méthode de configuration de produits considérant les différents segments de marché pour concevoir les produits nécessaires pour former une famille de produits qui satisfait adéquatement les différents types de clients.

Étape 8. Développement d'une méthodologie globale pour la formation de familles de produits à travers la configuration de produits, par la logique floue, en partant de la segmentation du marché pour l'identification de caractéristiques communes et la formation de possibles modules interchangeables.

3.2 Principaux résultats de la recherche

Cinq éléments principaux constituent les apports développés dans ce travail de recherche :

1. Développement d'une méthode qui contribue à l'amélioration de la modélisation des besoins des clients.

Cette méthode permet le classement de nombres flous nécessaires pour la comparaison entre différentes caractéristiques. Elle permet d'ordonner n'importe quel ensemble de nombres flous normaux qui utilisent des nombres flous trapézoïdaux comme forme générale pour représenter des nombres flous triangulaires et rectangulaires. Cette forme générale est supportée par vingt-neuf cas, lesquels sont suffisants pour considérer toutes les situations possibles entre deux nombres flous normaux, comme trapézoïdaux, triangulaires et rectangulaires. La procédure de classement est effectuée en utilisant quatre critères d'ordre dans un modèle de préférence de pseudo-ordre considérant le type de la relation de préférence floue. L'application de la logique floue à la méthode proposée permet aux décideurs de profiter de l'information exprimée en termes linguistiques qui sont fréquemment vagues et imprécis, mais qui sont les termes communément utilisés par les consommateurs.

2. Développement d'une procédure pour la sélection de produits basée sur les préférences floues des clients.

La procédure proposée permet de sélectionner un produit pour un consommateur unique, et aussi de configurer des gammes de produits pour les différents types de clients. Pour effectuer cette procédure, un indicateur flou pour mesurer l'indifférence relative entre différentes caractéristiques des produits (FID, Fuzzy Indifference Degree) a été proposé comme une partie de la procédure de sélection de produits. Cet indicateur permet d'identifier le meilleur produit pour un client en particulier (Barajas, M., & Agard, B. 2008b).

3. Développement d'une méthode pour la configuration de produits basée sur les préférences floues des clients.

Cette méthode permet de configurer des produits pour des consommateurs uniques, à travers le remplacement des caractéristiques du produit les moins satisfaisantes pour le client par de meilleures caractéristiques. L'analyse des relations de préférence floues est employée pour évaluer les diverses configurations pendant le processus itératif de configuration du produit. Nous proposons un taux de satisfaction (Customer satisfaction, CS) pour mesurer le changement du niveau de la satisfaction du client en raison de la mise à niveau de chaque configuration de produit à chaque itération (Barajas, M., & Agard, B. 2009e).

4. Développement d'une méthode pour la configuration de produits basée sur les préférences floues des différents segments du marché.

Cette méthode permet de configurer des produits pour les différents types de consommateurs dans les différents segments du marché, à travers la sélection d'une configuration initiale du produit, l'amélioration itérative de chaque configuration et l'évaluation de la satisfaction du client pour chaque configuration du produit améliorée. Dans cette méthode, la configuration du produit est considérée comme un aspect clé pour la formation d'une famille de produits afin de satisfaire les demandes des principaux segments du marché (Barajas, M., & Agard, B. 2009d).

5. Développement d’une méthodologie globale de conception des familles de produits à l’aide de la logique floue.

Dans cette méthodologie, la logique floue est considérée comme une manière d'améliorer le processus décisionnel en raison de sa capacité à gérer les informations d’une manière plus précise que la logique binaire. Le résultat de cette méthodologie est la constitution d’une famille de produits classés en trois types: un produit générique pour chaque segment de marché, une collection de produits personnalisés à travers des modules pour chaque segment du marché et un produit personnalisé pour un client spécifique. Cette méthodologie offre la possibilité d'offrir des produits génériques standardisés pour les différents types de consommateurs et en même temps de réduire le coût des produits en standardisant des composants et des processus de production. Il est également possible de former un produit personnalisé, bien qu'à un coût plus élevé, dû à la flexibilité d'employer des caractéristiques alternatives.

Dans le chapitre 6, une discussion générale de ces éléments est présentée. Cette discussion est effectuée dans deux perspectives, l'application de la logique floue et la conception des familles de produits.

CHAPITRE 4 : IMPROVED FUZZY RANKING PROCEDURE FOR DECISION MAKING IN PRODUCT DESIGN

4.1 Abstract

In this paper, we present a method for ranking any number of normal fuzzy numbers using trapezoidal fuzzy numbers as a general form, where rectangular and triangular fuzzy numbers are particular cases of such a form. This general form is supported by twenty-nine cases, which is enough to consider all the possible situations between two normal fuzzy numbers, such as trapezoidal, triangular, or rectangular. The ranking procedure is performed using four ordering criteria into a pseudo-order preference model considering the type of the fuzzy preference relation. Two examples are given to illustrate and validate the applicability and practicality of this fuzzy ranking method. A comparison and an analysis of the proposed method is presented to demonstrate its usefulness and its contribution to the improvement of the decision-making processes as a result of its management of vague or imprecise information, and whether or not that information should be allowed to be entered into such processes.

Keywords: fuzzy ranking; fuzzy decision-making; fuzzy numbers; fuzzy preference relations.

4.2 Introduction

Manufacturing and service organizations are always making decisions. Although they are made at different levels: strategic, tactical, or operational, in the end, all are highly important to the successful achievement of organizational goals. The decision-making process plays an important role in the success of both for-profit and not-for-profit companies, and for that it needs to be improved continuously. Because fuzzy logic is capable of managing imprecise information, and this capability is a critical aspect in the improvement of the decision making process, fuzzy logic has been increasingly used in decision making methods. The application of fuzzy logic to several decision making tools permits the consideration of imprecise information from the input variables which can be given in linguistic terms, such as “very important”, “very high”, “medium”, “very low”, and so on, aimed at representing variables from the human perspective.

Generally, the decision making process seeks to make decisions as a function of two or more variables, such as different characteristics, or alternatives, given in numerical and/or linguistic form. To consider this kind of variable, it is necessary to ‘fuzzify’ them by defining a fuzzy number for each, and is a process which should be performed by individuals with enough expertise to translate the linguistic information accurately. The ranking or ordering of this kind of number may seem to be a task that is easy to perform visually, but, in this work, we seek to replace human intervention in the ranking procedure with an appropriate alternative method.

This work is aimed at contributing to the fuzzy ranking procedure by simplifying the ordering processes using the pseudo-order preference model and a set of ordering criteria. We also contribute by presenting a complete illustration of the method and list all the possible situations (twenty-nine) that may occur between two normal trapezoidal fuzzy numbers which are capable of supporting any normal fuzzy number, such as a triangular or rectangular one. This paper is organized in the following sections. Section 2 presents the state of the art of the fuzzy decision making process and the importance of fuzzy logic in such a process. Section 3 presents the improved procedure for ranking fuzzy numbers and a simplification of the ordering procedure. Section 4 illustrates the application of the proposed ranking procedure. Section 5 presents a comparison and analysis of this and other methods. Section 6 concludes the paper.

4.3 Fuzzy logic and the decision making process

The decision making process plays an important role in the success of any company, and practically every engineering process involves different iterative and complex decision making activities. As a result, a great deal of research has been conducted on fuzzy decision making, including the use of fuzzy optimum selection (Dong et al., 2001), fuzzy multiple-attribute decision making (Kuo et al., 2006), and multiple-attribute decision making in concurrent engineering (Jiang and Chi-Hsing, 2001).

Various approaches have been proposed to contribute to decision making. One of these is the fuzzy multicriteria decision making process (Fan et al., 2002; Büyüközkan and Feyzioğlu, 2005; Işıklar and Büyüközkan, 2006; Zhang et al., 2007), which is based principally on the fuzzy preference relation. Another is the approach proposed by Sun and Wu (2006) for the ranking process based on an easy and intuitive fuzzy simulation analysis method.

The basis for the decision-making process is the ranking of fuzzy numbers (Lee and You, 2003), and (Baas and Kwakernaak, 1977; Chen and Klein, 1994) have proposed the application of fuzzy ranking for multicriteria decision making.

Several of the fuzzy ranking methods that have been developed include that of Chen and Klein (1994), who applied the α-cut and fuzzy subtraction operations to calculate the area under the new fuzzy number, and that of Wang and Parkan (2005), who introduced three optimization models to assess the relative importance weights of attributes in a multiple-attribute decision making problem.

The fuzzy preference relation has been widely used in fuzzy ranking (Delgado et al., 1988; Lee, 2000; Modarres and Sadi-Nezhad, 2001). Other works include the application of some specific concepts such as triangular membership functions (Chang, 1981), and set maximization and minimization (Chen, 1985). Lee and You (2003) presented a fuzzy ranking method for fuzzy numbers which considers a number of interesting functions and indices, such as the fuzzy satisfaction function, the fuzzy evaluation value, the degree of defuzzification, the degree of evaluation, and relative defuzzification indices. A novel method incorporating fuzzy preferences and range reduction techniques was proposed by Ma and Li (2008). Yuan (1991) presented four criteria for evaluating fuzzy ranking methods (fuzzy preference presentation, the rationality of preference ordering, distinguishability, and robustness), and suggested an improved ranking method based on the fuzzy preference relation.

Ranking methods based on the fuzzy preference relation have demonstrated their applicability in various areas. For example, Jiao and Tseng (1998) proposed a fuzzy ranking methodology for concept evaluation, which makes it possible to evaluate a conceptual design in the context of mass customization; that is, given a set of alternatives, evaluate and select the alternative that can satisfy customer needs and design requirements considering the technical capabilities of the company. According to Tseng and Klein (1988, 1989), many ranking methods for fuzzy numbers have been developed. However, these methods fail to consider many important factors, such as shapes, ranking order, the relative preference or dominance of fuzzy numbers, and the ease of computation of the ranking algorithm. This has made it necessary to develop a new, accurate, effective, and efficient algorithm capable of ranking a large number of fuzzy numbers. More recently, Lee (2000) announced that the various methods for ranking fuzzy numbers could be classified into two categories. The first is based on defuzzification, and the second is based on the fuzzy preference relation. Lee (2000) also maintains that a good ranking method should satisfy the following four criteria: a fuzzy preference presentation, rationality of preference ordering, robustness, and efficiency.

Unfortunately, while interesting, these methods have some limitations, and currently there is no general model for the ranking process. This paper proposes to contribute to remedying this situation by proposing a procedure for ranking any number of normal fuzzy numbers, which extends the previous illustration and statement based on normal triangular fuzzy numbers (Tseng and Klein, 1989). The proposed extensions use trapezoidal normal fuzzy numbers as a general base which supports both triangular and rectangular fuzzy numbers at the same time for ranking any number of fuzzy numbers.

4.4 Fuzzy ranking procedure

This section first describes the modeling of rectangular, triangular, and trapezoidal normal fuzzy numbers in the general model. Then, it describes how to use this modeling to rank any situation in which there are two fuzzy numbers, but also to rank any fuzzy numbers.

4.4.1 Trapezoidal fuzzy numbers as a general form

The improved ranking procedure in the fuzzy decision making process presented in this work is based on the algorithm proposed by Tseng and Klein (1989). In our work here, we extend this illustration by presenting a complete general form, using trapezoidal fuzzy numbers as a base, in which rectangular and triangular fuzzy numbers are particular cases of this general form.

Let A and B be two normal and convex trapezoidal fuzzy numbers where the support of A is the interval (a, d) and the support of B is the interval (e, h). The triangular fuzzy number is a particular case of the general form, when b=c for fuzzy number A or f=g for fuzzy number B. Rectangular fuzzy numbers (crisp interval) are possible when a=b and c=d for fuzzy number A, or when e=f and g=h for fuzzy number B. Also, constant values or crisp values are possible through the fuzzy line when a=b=c=d and e=f=g=h for A and B respectively.

Figure 4.1 illustrates how trapezoidal fuzzy numbers can be used as a general model for triangular and rectangular fuzzy numbers.

The rankings of all possible situations of these fuzzy numbers (see Figure 4.1) are supported with the twenty-nine cases depicted in Appendix 1, and the following section explains the ranking procedure for all of them.

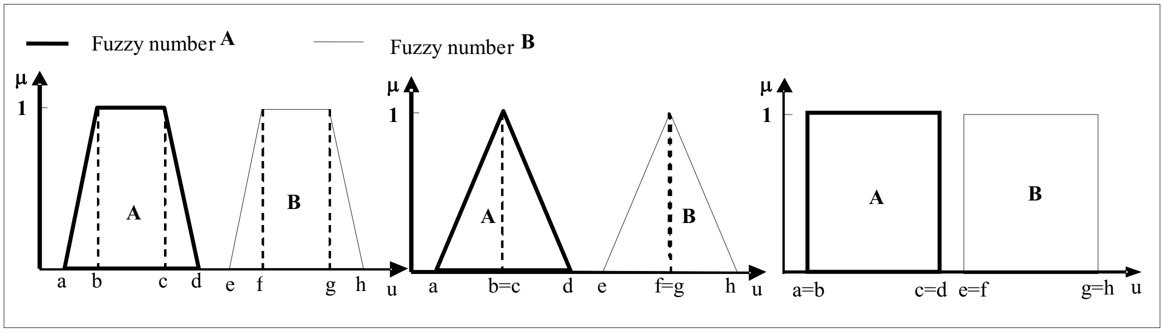


Figure 4.1 Triangular and rectangular fuzzy numbers as intrinsic cases of the trapezoidal form

Figure 4.2 shows that the extended illustration, based on trapezoidal fuzzy numbers, is able to rank any pairwise situation of trapezoidal, triangular, and rectangular fuzzy numbers.

4.4.2 Definitions

The proposed ranking procedure extends previous Tseng and Klein (1989) results. This extension is aimed at showing how it is possible to rank all possible pairwise situations of two normal fuzzy numbers (see Figure 4.1). To do this, some important concepts, such as indifference and dominance, overlap and non overlap areas, and the fuzzy preference relation must be defined.

4.4.2.1 Definition 1

If we let A and B be two normal and convex fuzzy numbers, then there exist the notions of indifference and dominance. These notions are defined as follows:

1) If there exists an area of overlap between fuzzy numbers A and B (A and B intersect), then the overlap area is defined as indifference; that is to say, A and B are indifferent relative to one another in this area.

2) If there exist one or more non overlap areas between fuzzy numbers A and B, then the non overlap areas represent the areas where either A dominates B or B dominates A.

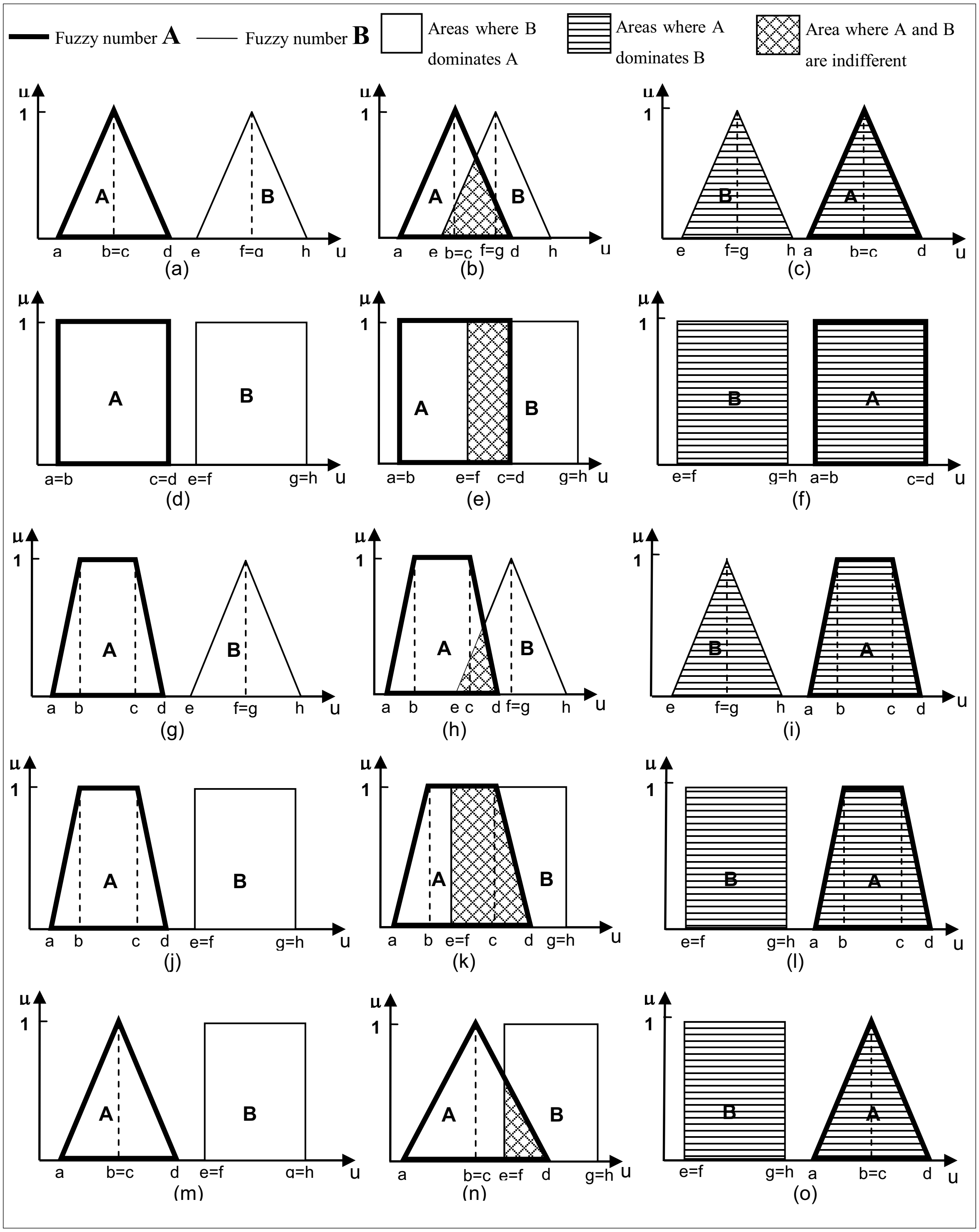


Figure 4.2 Possible pairwise situations of two normal fuzzy numbers

The above notions for the general trapezoidal fuzzy numbers A and B can be identified in Figure 4.3. Cases (a) and (c) show the notion of dominance. This means that, for case (a), B dominates A, and for case (c), A dominates B. Case (b) represents the notion of indifference represented by the area of intersection between fuzzy numbers A and B. The domination between fuzzy numbers is given by the directions of A and B. In Appendix 1, cases (1) and (2) represent the non overlap situations and cases (3) to (29) represent the overlap situations for the general form.

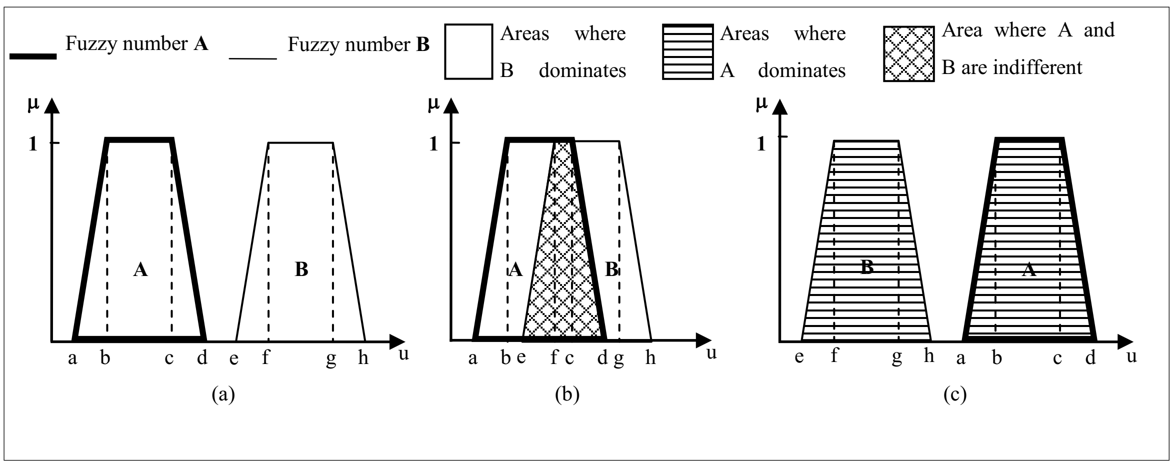


Figure 4.3 Depiction of notions. Dominance and indifference between two fuzzy numbers

4.4.2.2 Definition 2

If A and B are two fuzzy numbers, then R(A, B) and R(B, A) are two fuzzy preference relations and are defined as follows:

$$R(A, B)= \frac{\text{(areas where A dominates B) + (area where A and B are indifferent)}}{\text{(area of A)+(area of B)}}$$

$$R(B, A)= \frac{\text{(areas where B dominates A) + (area where A and B are indifferent)}}{\text{(area of A)+(area of B)}}$$

where R(A, B) and R(B, A) are interpreted as the degree to which A is preferred to or indifferent to B, and B is preferred to or indifferent to A respectively. R(A, B) and R(B, A) are reciprocal; that is to say, R(A, B) + R(B, A) = 1.

Based on the definitions of dominance and indifference, the following algorithm can be used to determine a preference relation (Tseng and Klein, 1989).

Algorithm:

Step 1) Find the area where A and B intersect

Step 2) Find the areas where A dominates B

Step 3) Find the areas where B dominates A

Step 4) Find the areas of A and B

Step 5) Compute the fuzzy preference relations R(A,B) and R(B,A).

4.4.2.3 Definition 3

From definition 2, the non overlap areas between two fuzzy numbers must be obtained. In our work here, we use the Hamming distance for this purpose, which makes it possible to determine the areas where A dominates B and the areas where B dominates A, as needed in steps 2 and 3 of the above algorithm. Here, we illustrate this concept considering normal trapezoidal, triangular, and rectangular fuzzy numbers. To determine the intervals of dominance on the real line for the two fuzzy numbers A and B, four cases must be considered. These cases depend on the number of intersections between the fuzzy numbers. There are five possibilities: four, three, two, one, and zero point(s) of intersection. Let the intersection points of the fuzzy numbers A and B be given by X_1, X_2, X_3, and X_4, where $X_1<X_2<X_3<X_4$ (see Appendix 1). Tables 1 to 5 show how the Hamming distance can be obtained for each general case.

From Table 4.1 to Table 4.5, twenty-nine general cases are defined, based on Appendix 1. These cases are capable of supporting any pairwise situation of normal trapezoidal, triangular, or rectangular fuzzy numbers. Table 4.1 illustrates the four cases where it is possible to have four points of intersection between two trapezoidal fuzzy numbers. Table 4.2 shows the thirteen cases where it is possible to have three points of intersection. Table 4.3 presents the eight cases where it is possible to have two points of intersection. Table 4.4 shows the two cases where it is possible to have one point of intersection. Finally, Table 4.5 presents the two cases where it is not possible to have any point of intersection. All the cases presented in Table 4.1 to Table 4.5 are depicted in Appendix 1.

Table 4.1 Cases where it is possible to have four points of intersection

Case	Four intersection points are only possible if either:	The Hamming distance $D(A,B)$ for each case can be obtained as follows:
10	$a \geq e, b < f, c < g, d \geq h, c > f$	$D(A,B) = \int_{e}^{x_1} \lvert\mu_A(u) - \mu_B(u)\rvert du + \int_{x_4}^{d} \lvert\mu_A(u) - \mu_B(u)\rvert du$
13	$a \geq e, b < f, c > g, d \leq h$	$D(A,B) = \int_{e}^{x_1} \lvert\mu_A(u) - \mu_B(u)\rvert du + \int_{x_3}^{x_4} \lvert\mu_A(u) - \mu_B(u)\rvert du$
23	$a \leq e, b > f, c > g, d \leq h, b < g$	$D(A,B) = \int_{x_1}^{x_2} \lvert\mu_A(u) - \mu_B(u)\rvert du + \int_{x_3}^{x_4} \lvert\mu_A(u) - \mu_B(u)\rvert du$
28	$a \leq e, f \leq b, c \leq g, h \leq d$	$D(A,B) = \int_{x_1}^{x_2} \lvert\mu_A(u) - \mu_B(u)\rvert du + \int_{x_4}^{d} \lvert\mu_A(u) - \mu_B(u)\rvert du$

Table 4.2 Cases where it is possible to have three points of intersection

Case	Three intersection points are only possible if either:	The Hamming distance $D(A,B)$ for each case can be obtained as follows:
6	$a \geq e, b < f, c < g, d \geq h, c < f$	$D(A,B) = \int_{e}^{x_1} \lvert\mu_A(u) - \mu_B(u)\rvert du + \int_{x_3}^{d} \lvert\mu_A(u) - \mu_B(u)\rvert du$
8	$a \geq e, b < f, c < g, d \leq h, c > f$	$D(A,B) = \int_{e}^{x_1} \lvert\mu_A(u) - \mu_B(u)\rvert du$

Table 4.2 (Contd.) Cases where it is possible to have three points of intersection

Case	Three intersection points are only possible if either:	The Hamming distance $D(A,B)$ for each case can be obtained as follows:
9	$a \le e, b < f, c < g, d \ge h, c > f$	$D(A,B) = \int_{x_3}^{d} \lvert\mu_A(u) - \mu_B(u)\rvert du$
12	$a \ge e, b < f, c > g, d \ge h, b < g$	$D(A,B) = \int_{e}^{x_1} \lvert\mu_A(u) - \mu_B(u)\rvert du + \int_{x_3}^{d} \lvert\mu_A(u) - \mu_B(u)\rvert du$
14	$a \le e, b < f, c > g, d \le h, c > f$	$D(A,B) = \int_{x_2}^{x_3} \lvert\mu_A(u) - \mu_B(u)\rvert du$
15	$a \ge e, b < f, c = g, d \ge h, b < g$	$D(A,B) = \int_{e}^{x_1} \lvert\mu_A(u) - \mu_B(u)\rvert du + \int_{x_3}^{d} \lvert\mu_A(u) - \mu_B(u)\rvert du$
16	$a \ge e, b < f, c = g, d \le h, b < g$	$D(A,B) = \int_{e}^{x_1} \lvert\mu_A(u) - \mu_B(u)\rvert du$
18	$e \le a, f = b, g < c, d \le h, b < g$	$D(A,B) = \int_{e}^{x_1} \lvert\mu_A(u) - \mu_B(u)\rvert du + \int_{x_2}^{x_3} \lvert\mu_A(u) - \mu_B(u)\rvert du$
20	$a \le e, b = f, c > g, d \le h, c > f$	$D(A,B) = \int_{x_2}^{x_3} \lvert\mu_A(u) - \mu_B(u)\rvert du$
21	$a \le e, b > f, c > g, d \le h, b > g$	$D(A,B) = \int_{x_1}^{x_2} \lvert\mu_A(u) - \mu_B(u)\rvert du + \int_{x_2}^{x_3} \lvert\mu_A(u) - \mu_B(u)\rvert du$
22	$a \le e, b > f, c > g, d \ge h, b < g$	$D(A,B) = \int_{x_1}^{x_2} \lvert\mu_A(u) - \mu_B(u)\rvert du + \int_{x_3}^{d} \lvert\mu_A(u) - \mu_B(u)\rvert du$
27	$a \le e, f \le b, c \le g, d \le h$	$D(A,B) = \int_{x_1}^{x_2} \lvert\mu_A(u) - \mu_B(u)\rvert du$
29	$e \le a, f \le b, c \le g, h \le d$	$D(A,B) = \int_{e}^{x_1} \lvert\mu_A(u) - \mu_B(u)\rvert du + \int_{x_3}^{d} \lvert\mu_A(u) - \mu_B(u)\rvert du$

Table 4.3 Cases where it is possible to have two points of intersection

Case	Two intersection points are only possible if either:	The Hamming distance $D(A,B)$ for each case can be obtained as follows:
4	$a \ge e, b < f, c < g, d \le h, c < f$	$D(A,B) = \int_{e}^{x_1} \lvert\mu_A(u) - \mu_B(u)\rvert du$

Table 4.3 (Contd.) Cases where it is possible to have two points of intersection

Case	Two intersection points are only possible if either:	The Hamming distance $D(A,B)$ for each case can be obtained as follows:
5	$a \le e, b < f, c < g, d \ge h, c < f$	$D(A,B) = \int_{x_2}^{d} \lvert \mu_A(u) - \mu_B(u) \rvert du$
7	$a \le e, b \le f, c \le g, d \le h, f \le c$	$D(A,B) = 0$
11	$a \le e, b \le f, g \le c, h \le d$	$D(A,B) = \int_{x_2}^{d} \lvert \mu_A(u) - \mu_B(u) \rvert du$
17	$e \le a, f = b, g = c, h \le d$	$D(A,B) = \int_{e}^{x_1} \lvert \mu_A(u) - \mu_B(u) \rvert du + \int_{x_2}^{d} \lvert \mu_A(u) - \mu_B(u) \rvert du$
19	$a \ge e, b = f, c = g, d \le h, b < g$	$D(A,B) = \int_{e}^{x_1} \lvert \mu_A(u) - \mu_B(u) \rvert du$
25	$a \le e, b > f, c > g, d \ge h, b > g$	$D(A,B) = \int_{x_1}^{x_2} \lvert \mu_A(u) - \mu_B(u) \rvert du + \int_{x_2}^{d} \lvert \mu_A(u) - \mu_B(u) \rvert du$
26	$a \ge e, b > f, c > g, d \le h, b > g$	$D(A,B) = \int_{e}^{x_1} \lvert \mu_A(u) - \mu_B(u) \rvert du + \int_{x_1}^{x_2} \lvert \mu_A(u) - \mu_B(u) \rvert du$

Table 4.4 Cases where it is possible to have one point of intersection

Case	One intersection point is only possible if either:	The Hamming distance $D(A,B)$ for each case can be obtained as follows:
3	$a \le e, b < f, c < g, d \ge e, c < f$	$D(A,B) = 0$
24	$a \ge e, b > f, c > g, d \ge h, a \le h, b > g$	$D(A,B) = \int_{e}^{x_1} \lvert \mu_A(u) - \mu_B(u) \rvert du + \int_{x_1}^{d} \lvert \mu_A(u) - \mu_B(u) \rvert du$

Table 4.5 Cases where it is not possible to have any point of intersection

Case	No intersection point is possible only if either:	The Hamming distance $D(A,B)$ for each case can be obtained as follows:
1	$a < e, b < f, c < g, d \leq e$	$D(A,B) = 0$
2	$a > e, b > f, c > g, a \geq h$	$D(A,B) = \int_e^h \lvert\mu_A(u) - \mu_B(u)\rvert du + \int_a^d \lvert\mu_A(u) - \mu_B(u)\rvert du$

4.4.2.4 Definition 4

Here, we apply a pseudo-order preference model for the fuzzy ranking procedure for two alternatives. This model has already been used in the literature several times (Roy and Vincke, 1984; Wang, 1997; Gungor and Arikan, 2000; Büyüközkan and Feyzioğlu, 2004a). Let the fuzzy preference relation between two ideas *a* and *b* for criterion *i* be obtained by the pairwise comparison of $g_i(a)$ and $g_i(b)$, which shows the linguistic performance of ideas a and b respectively. $g_i(a)$ and $g_i(b)$ are represented by fuzzy numbers. Three types of preference relation are defined in terms of the fuzzy preference relations between two alternatives $\forall a, b \in A$ and $i \in C$, as follows:

$$aP_ib \Leftrightarrow P(g_i(a), g_i(b)) - P(g_i(b), g_i(a)) > p_i,\ aQ_ib \Leftrightarrow P(g_i(a), g_i(b)) - P(g_i(b), g_i(a)) \leq p_i,$$
$$aI_ib \Leftrightarrow \lvert P(g_i(a), g_i(b)) - P(g_i(b), g_i(a))\rvert \leq q_i,$$

where P_i and Q_i depict strict and weak preference respectively, and I_i depicts indifference. The preference threshold p_i and the indifference threshold q_i (defined by common sense, Roy and Vincke, 1984) are used to discriminate between the indifference, strict preference, and weak preference of two alternatives for criterion *i*. The three possible types of preference should be read as follows:

aP_ib, where there is a strict preference between ideas *a* and *b* (idea *a* is strictly preferred to idea *b* for criterion *i*).

aQ_ib, where there is a weak preference between ideas *a* and *b* (idea *a* is weakly preferred to idea *b* for criterion *i*).

aI_ib, where there is no difference between ideas *a* and *b* (idea *a* is no different from idea *b* for criterion *i*).

4.4.2.5 Definition 5

To extend definition 4 for ranking more than two fuzzy numbers, the following four criteria procedure must be considered:

- Criterion 1. The largest number of strict preferences. The tie-breaker for this criterion is criterion 2.
- Criterion 2. The largest number of weak preferences. The tie-breaker for this criterion is criterion 3.
- Criterion 3. The smallest number of indifference situations. The tie-breaker for this criterion is criterion 4.
- Criterion 4. If the fuzzy preference belongs to the indifference situation, then there is no difference between these fuzzy numbers, and these can be ranked indifferently.

To apply these criteria, some priority rules must be followed. Criterion 1 has priority one, and it must be applied as long as possible until there is a conflict and a tie-breaker becomes necessary. Criteria 2 and 3 have priority two and three respectively, and these should be applied in the same way as criterion 1. Criterion 4 should be applied when the preference situation is a pairwise situation with indifference. Below we illustrate this procedure with an example.

4.5 Illustrative examples

4.5.1 Ranking of any pairwise situation of fuzzy numbers

The following example shows how the general form makes it possible to rank any pairwise situation (referred to hereafter as a "pairwise") of two normal fuzzy numbers. Let us consider the following fuzzy numbers:

A_1 is a trapezoidal fuzzy number [1.5, 3, 4, 6]

A_2 is a triangular fuzzy number [2, 5, 5, 7]

A_3 is a rectangular fuzzy number [1.5, 1.5, 6, 6]

B_1 is a trapezoidal fuzzy number [5, 7, 8, 9]

B_2 is a triangular fuzzy number [2, 6, 6, 8]

B_3 is a rectangular fuzzy number [5, 5, 9, 9]

By considering the preference threshold p_i=0.85 and the indifference threshold q_i=0.25, as used in (Wang, 1997), the ranking of A_1 with B_1, B_2, and B_3 is as follows:

4.5.1.1 Fuzzy ranking of A1 and B1

The pairwise A_1-B_1 belongs to case 3, as depicted in Appendix 1 and defined in Table 4.4. This general case deals with the fuzzy preference relation between two trapezoidal fuzzy numbers, as shown in Figure 4.4.

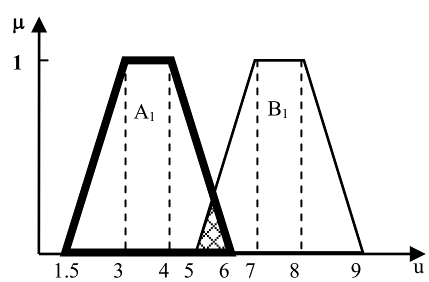


Figure 4.4 Pairwise of A_1-B_1

Based on definitions 1 to 3 in section 3, the fuzzy preference relation for A_1-B_1 can be obtained by applying the following notations:

Dom(A_1, B_1) is the area where A_1 dominates B_1,

Dom(B_1, A_1) is the area where B_1 dominates A_1,

$Ind(A_1\text{-}B_1)$ is the area where A_1 and B_1 are indifferent,

$Area(A_1)$ is the area of A_1,

$Area(B_1)$ is the area of B_1,

X_i are the points of intersection i.

Then,

$$R(A_1, B_1)= \frac{Dom(A_1, B_1) + Ind(A_1\text{-}B_1)}{Area(A_1)+Area(B_1)}$$

$$R(B_1, A_1)= \frac{Dom(B_1, A_1) + Ind(A_1\text{-}B_1)}{Area(A_1)+Area(B_1)}$$

$Dom(A_1,B_2)=0$, $Ind(A_1\text{-}B_1)=0.125$, $Area(A_1)=2.75$, $Area(B_1)=2.5$, and $X_1=5.5$.

Then, $R(A_1,B_1)=0.0238$ and $R(B_1,A_1)=0.9762$.

Since $R(B_1,A_1)=0.9762>q_i$, then B_1 is strictly preferred to A_1 and is denoted B_1PA_1 (see Table 4.6).

4.5.1.2 Fuzzy ranking of A1 and B2

The pairwise A_1-B_2 also belongs to case 3. This general case deals with the fuzzy preference relation between two trapezoidal fuzzy numbers, as shown in Figure 4.5.

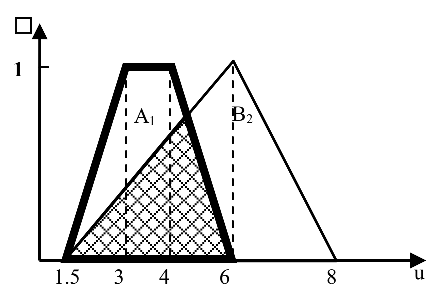


Figure 4.5 Pairwise of A_1-B_2

Dom(A_1,B_2)=0, Ind(A_1-B_2)=1.333, Area(A_1)=2.75, Area(B_2)=3, and X_1=4.6667.

Then, R(A_1,B_2)=0.2319 and R(B_2,A_1)=0.7681.

Since R(B_2,A_1)=0.7681<=q_i, then B_2 is weakly preferred to A_1 and is denoted B_2QA_1 (see Table 4.6).

4.5.1.3 Fuzzy ranking of A1 and B3

The pairwise A_1-B_3 also belongs to case 3. This general case deals with the fuzzy preference relation between two trapezoidal fuzzy numbers, as shown in Figure 4.6.

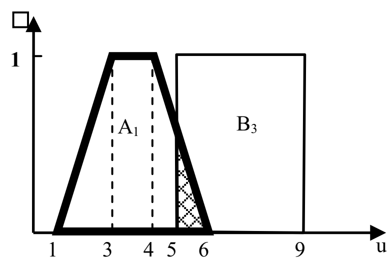


Figure 4.6 Pairwise of A_1-B_3

Dom(A_1,B_3)=0, Ind(A_1-B_3)=0.25, Area(A_1)=2.75, Area(B_3)=4, and X_1=5.

Then, R(A_1,B_3)=0.0370 and R(B_3,A_1)=0.9630.

Since R(B_3,A_1)=0.9630>q_i, then B_3 is strictly preferred to A_1 and is denoted B_3PA_1 (see Table 4.6).

4.5.1.4 Synthesis

Table 4.6 summarizes the values and types of fuzzy preference relations for some possible situations arising between predefined fuzzy numbers.

Table 4.6 Fuzzy preference relations between two normal fuzzy numbers

Fuzzy number	Trapezoidal A_1 [1.5 3 4 6]	Triangular A_2 [2 5 5 7]	Rectangular A_3 [1.5 1.5 6 6]
Trapezoidal B_1 [5 7 8 9]			
R(A,B)	0.0238	0.1	0.0357
R(B,A)	0.9762	0.9	0.9643
Preference	$B_1\boldsymbol{P}A_1$	$B_1\boldsymbol{Q}A_2$	$B_1\boldsymbol{P}A_3$
Triangular B_2 [2 6 6 8]			
R(A,B)	0.2319	0.3788	0.2667
R(B,A)	0.7681	0.6212	0.7333
Preference	$B_2\boldsymbol{Q}A_1$	$B_2\boldsymbol{I}A_2$	$B_2\boldsymbol{Q}A_3$
Rectangular B_3 [5 5 9 9]			
R(A,B)	0.037	0.1538	0.1176
R(B,A)	0.963	0.8462	0.8824
Preference	$B_3\boldsymbol{P}A_1$	$B_3\boldsymbol{Q}A_2$	$B_3\boldsymbol{Q}A_3$

Table 4.6 shows the three types of fuzzy preference relation defined for the pseudo-order preference model in section 3. These types are:

1. The strict preference relation belonging to the pairwise(s) A_1-B_1, A_1-B_3, and A_3-B_1;

2. The weak preference relation belonging to the pairwise(s) A_1-B_2, A_2-B_1, A_2-B_3, A_3-B_2, and A_3-B_3;

3. The indifference situation, which belongs to the pairwise A_2-B_2.

This example shows the advantage of using the general form proposed in this paper to rank any pairwise of normal fuzzy numbers, whether they are trapezoidal, triangular, or rectangular. This example also shows how the use of the pseudo-order preference model improves and simplifies the ranking procedure used by Tseng and Klein (1989).

4.5.2 Ranking more than two fuzzy numbers

The ranking of more than two fuzzy numbers can be achieved by applying the four-criterion procedure presented in definition 5 in section 3. Let us consider the six normal fuzzy numbers depicted in Figure 4.7 as different alternatives: A_1, A_2, A_3, A_4, A_5, and A_6, in a decision making process.

A_1 is a trapezoidal fuzzy number [1, 3, 4, 6.5];

A_2 is a rectangular fuzzy number [3, 3, 4, 4];

A_3 is a triangular fuzzy number [3, 5, 5, 7.5];

A_4 is a trapezoidal fuzzy number [4.5, 6, 7, 9.5];

A_5 is a triangular fuzzy number [5.5, 7.5, 7.5, 9];

A_6 is a rectangular fuzzy number [8, 8, 10, 10].

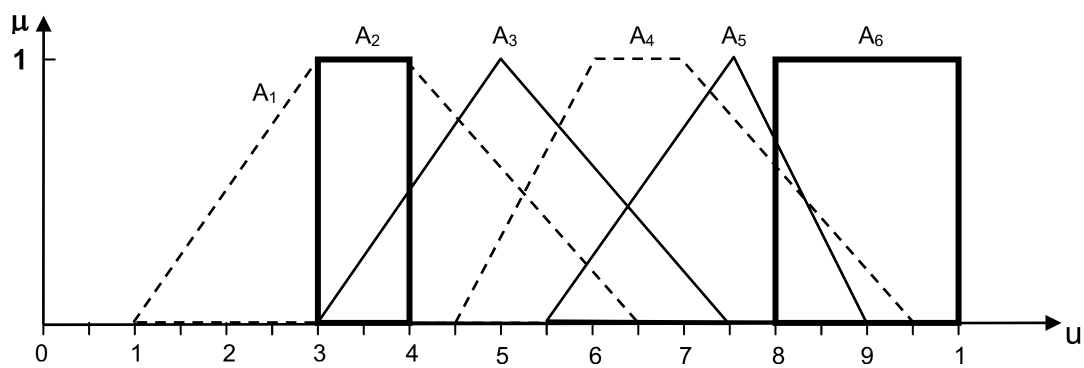


Figure 4.7 Ranking of multiple fuzzy numbers

To apply these criteria, the fuzzy preference relation for all the possible pairwises between them must be obtained. This information is presented in Table 4.7.

Also, the type of fuzzy preference must be considered for each pairwise. Table 4.8 presents the type of fuzzy preference relation for each pairwise among all the alternatives (the same preference threshold p_i=0.85 and indifference threshold q_i=0.25 are used).

Table 4.7 Fuzzy preference relation

Fuzzy number	A_1	A_2	A_3	A_4	A_5	A_6
A_1	0.5	0.5294	0.2475	0.08	0	0
A_2	0.4706	0.5	0.0769	0	0	0
A_3	0.7525	0.9231	0.5	0.2143	0.1111	0
A_4	0.92	1	0.7857	0.5	0.3743	0.09
A_5	1	1	0.8889	0.6257	0.5	0.0889
A_6	1	1	1	0.91	0.9111	0.5

Table 4.8 Type of fuzzy preference relation

Fuzzy number	A_1	A_2	A_3	A_4	A_5	A_6
A_1	-	$A_2\boldsymbol{I}A_1$	$A_3\boldsymbol{Q}A_1$	$A_4\boldsymbol{Q}A_1$	$A_5\boldsymbol{P}A_1$	$A_6\boldsymbol{P}A_1$
A_2	$A_2\boldsymbol{I}A_1$	-	$A_3\boldsymbol{Q}A_2$	$A_4\boldsymbol{P}A_2$	$A_5\boldsymbol{P}A_2$	$A_6\boldsymbol{P}A_2$
A_3	$A_3\boldsymbol{Q}A_1$	$A_3\boldsymbol{Q}A_2$	-	$A_4\boldsymbol{Q}A_3$	$A_5\boldsymbol{Q}A_3$	$A_6\boldsymbol{P}A_3$
A_4	$A_4\boldsymbol{Q}A_1$	$A_4\boldsymbol{P}A_2$	$A_4\boldsymbol{Q}A_3$	-	$A_5\boldsymbol{Q}A_4$	$A_6\boldsymbol{Q}A_4$
A_5	$A_5\boldsymbol{P}A_1$	$A_5\boldsymbol{P}A_2$	$A_5\boldsymbol{Q}A_3$	$A_5\boldsymbol{Q}A_4$	-	$A_6\boldsymbol{Q}A_5$
A_6	$A_6\boldsymbol{P}A_1$	$A_6\boldsymbol{P}A_2$	$A_6\boldsymbol{P}A_3$	$A_6\boldsymbol{Q}A_4$	$A_6\boldsymbol{Q}A_5$	-

To apply the proposed procedure, the frequency and type of fuzzy preference relation must be obtained for each pairwise of alternatives. This information is shown in Table 4.9.

Table 4.9 Frequency and type of fuzzy preference relation for each alternative

Alternative	Frequency		
	P	***Q***	***I***
A_1	0	0	1
A_2	0	0	1
A_3	0	2	0
A_4	1	2	0
A_5	2	2	0
A_6	3	2	0

Let us apply the proposed multi-ranking procedure:

1. Criterion 1. The largest number of strict preferences: By applying criterion 1 from the proposed procedure, the largest number of strict preferences belongs first to A_6, then to A_5, and finally to A_4. Now consider that (A>B) expresses that A is preferred to B. The first part of the multiple fuzzy ranking is: $A_6>A_5>A_4$ (tiebreaker not needed).

2. Criterion 2. The largest number of weak preferences: By applying criterion 2 to the rest of the numbers, the largest number of weak preferences belongs to A_3, and so the new ranking is: $A_6>A_5>A_4>A_3$ (tiebreaker not needed).

3. Criterion 3. The smallest number of indifference situations: By applying criterion 3 to the rest of the numbers, the smallest number of indifference situations belongs to A_1 and A_2. So, a tiebreaker is necessary. The tiebreaker for this criterion consists of the application of criterion 4.

4. Criterion 4. If the fuzzy preference belongs to the indifference situation, then there is no difference between the numbers. Finally, by applying criterion 4 to the rest of the numbers, if the fuzzy preference belongs to the indifference situation, then there is no difference between A_1 and A_2. Hence, the final fuzzy ranking can be as follows: $A_6>A_5>A_4>A_3>A_2>A_1$ or $A_6>A_5>A_4>A_3>A_1>A_2$, since A_1 and A_2 are indifferent.

This example shows how the pseudo-order preference model can be easily used to rank more than two fuzzy numbers by applying the four-criterion proposed procedure to a set of different alternatives.

4.6 Analysis and comparison

The ranking of fuzzy numbers has been a concern in many different areas, principally those related to decision making processes. Over recent decades, several fuzzy ranking methods and approaches have been proposed aimed at contributing to the improvement of the decision making process.

According to Lee and Chen (2008), various classifications of ranking methods have been published, which are listed below.

Tseng and Klein (1989), who classified the ranking methods based on:

- Hamming distance.
- Fuzzy boundaries.
- Centroid index.
- Possibility dominance.
- Probability proportions.

Chen and Hwang (1992), who grouped the methods into four major classes:

- Preference relation.
- Fuzzy mean and spread.
- Fuzzy scoring.
- Linguistic expression.

In the same context, Lee (2000) argued that ranking methods can be classified in two principal categories:

- Methods based on fuzzy preference relations.
- Methods based on defuzzification techniques.

Here, a comparison of fuzzy ranking methods is presented. This comparison is based primarily on Lee's (2000) classification (see Table 4.10).

Table 4.10 Comparison of fuzzy ranking methods

Method	Criteria									
	Type of MT			Type of MF			Size of FNS		Type of FN	
	1	2	3	4	5	6	7	8	9	10
Tseng and Klein 1989	*			*			*	*	*	
Yuan 1991	*			*		*	*	*	*	
Lee 2000	*			*		*	*		*	
Modarres and Sadi-Nezhad 2001	*			*			*		*	
Smith and Verma 2004		*		*			*		*	
Sun and Wu 2006			*	*	*		*		*	
Chen and Chen 2007		*		*	*		*	*	*	*
Ma and Li 2008			*	*			*		*	
Lee and Chen 2008		*		*	*	*	*	*	*	*
Chen and Wang 2009		*		*	*	*	*	*	*	*
Wu and Mendel 2009		*		*	*				*	*
Proposed method	*			*	*	*	*	*	*	

Table 4.10 presents a comparison of different fuzzy ranking methods considering ten criteria grouped into four principal categories: the type of mathematical tool (MT), the type of membership function (MF), the size of fuzzy number set (FNS), and the type of fuzzy number. The ten criteria considered are listed below.

(1). Fuzzy preference relation.

(2). Defuzzification.

(3). Other mathematical tools, such as: fuzzy simulation analysis (Sun and Wu 2006) and the range reduction technique with rank minimization (Ma and Li 2008).

(4). Triangular membership function.

(5). Trapezoidal membership function.

(6). Other membership functions, such as: the parabolic membership function (Yuan 1991, Lee 2000) and the rectangular membership function or crisp interval (Chen and Wang 2009).

(7). Set of two fuzzy numbers.

(8). Set of more than two fuzzy numbers.

(9). Normal fuzzy numbers.

(10). Non normal fuzzy numbers.

From Table 4.10, the fuzzy preference relation and defuzzification are two of the principal criteria (columns 1 and 2) that embrace different approaches and mathematical tools which make it possible to obtain the information needed to make decisions about how to order or rank variables considered as fuzzy numbers in this work. In column 3, some interesting ranking methods are considered that are not necessarily based on the fuzzy preference relation or on defuzzification. Other mathematical tools are applied in these methods, such as fuzzy simulation analysis (Sun and Wu 2006) and the range reduction technique with rank minimization (Ma and Li 2008).

Owing to their practicality and adaptability, the triangular and trapezoidal membership functions (columns 4 and 5) are two of the most widely used for representing linguistic information as fuzzy numbers. Most of the published fuzzy ranking methods consider one or both of these. Other membership functions (column 6) have been considered to represent fuzzy numbers. These include the parabolic membership function (Lee 2000), the rectangular membership function, and the crisp interval (Chen and Wang 2009).

Frequently, the decision making process involves the evaluation of several variables. For that, it is highly important to have the capability to manage multiple variables in the ranking methods. Column 8 shows which methods are capable of considering multiple variables instead of just pairs (column 7) of them.

As can be noted in Table 4.10 (columns 9-10), the proposed method in this paper is limited to normal fuzzy numbers. This limitation is also presented in all the ranking methods based on the fuzzy preference relation. Also, it is possible to note that, for all the methods based on defuzzification techniques, this limitation is not presented. But, according to Lee (2000), ranking methods based on defuzzification satisfy only one of the four criteria that a good ranking method should satisfy. These four criteria are: (1) fuzzy preference representation, (2) the rationality of preference ordering, (3) robustness, and (4) efficiency. Methods based on the preference relation satisfy criteria (1), (2), and (3), whereas methods based on defuzzification only satisfy criterion (4).

The efficiency of a ranking method is an important aspect which should be considered at the time of choosing a ranking method, but at the same time aspects such as fuzzy preference representation, rationality, and robustness are equally important. Nowadays, as a result of the development of quicker and more accessible computation methods, efficiency can be less important than robustness and accuracy.

Fuzzy ranking methods have been widely applied in a number of areas, principally in multiple-attribute decision making processes. Jiao and Tseng (1998) applied the fuzzy preference relation to a fuzzy ranking methodology for conceptual design evaluation. Liqing et al., (2008) applied a fuzzy ranking approach, also based on the fuzzy preference relation, to consider customer preferences and technical capabilities in the evaluation of design schemes. More recently, Ho et al., (2009) applied fuzzy ranking based on the fuzzy preference relation to compare and prioritize a Train Services Provider’s bid to produce a negotiation sequence. These three ranking methods use the Hamming distance to obtain the relations. According to Ho et al., (2009) the Hamming distance approach is suitable because a shorter computation time is required.

As mentioned previously, our proposed method also uses the Hamming distance approach to obtain the fuzzy preference relation, as proposed by Tseng and Klein (1989). For this reason, we consider it convenient here to note some important aspects of the two methods.

This work proposes an algorithm to rank any number of normal and convex fuzzy numbers. Tseng and Klein (1989) argue that their method is capable of managing non normal and non convex fuzzy numbers; however this is a contradiction, because their method is defined considering two normal and convex fuzzy numbers. They justify the ability to manage non normal and non convex fuzzy numbers through the application of human comparison as part of the algorithm in steps 2 and 3.

It is difficult to include human or manual comparison in an autonomous program or intelligent system. For this reason, human comparison is not considered pertinent for our method.

The Tseng and Klein (1989) algorithm was tested on a set of 13 cases of paired examples. For most of them, the fuzzy numbers are normal and convex. But, for the last two examples (L and M), some of the fuzzy numbers do not satisfy these characteristics. In example L, one of the fuzzy numbers is not normal, and, in example M, one is not convex. The evaluation of these numbers was made possible through the application of human comparison in the algorithm.

Our method avoids manual (human) comparison by visually controling the ranking procedure to permit proper application of the method in autonomous systems.

For normal and convex fuzzy numbers, the two methods are similar. The key here, though, is that our method is much easier to translate into a system because of the extended illustration of its general form.

The application of the pseudo-order preference model and the consideration of the preference type makes our method more accurate and easier to apply than that proposed by Tseng and Klein 1989 when ranking more than two fuzzy numbers.

In summary, our proposed method offers some interesting advantages over other proposed fuzzy ranking methods based on the fuzzy preference relation. The illustration and the mention of the twenty-nine cases can be considered to constitute a framework for the development of new decision making systems based on the application of fuzzy logic. Crisp values and crisp intervals must sometimes be represented through fuzzy numbers, because they can represent some variables such as schedule time, speed, and so on. The proposed method is able to manage this situation through the fuzzy line when a=b=c=d, or the triangular fuzzy numbers when a=b and c=d.

The depiction of the entire possible situation between two fuzzy numbers can be used as a framework for the development of statements to include other membership functions, such as Gaussian and parabolic, among others, and to include non normal fuzzy numbers as well.

4.7 Conclusions

In this paper, an improved fuzzy ranking method has been presented, which could be used to make important decisions around different processes such as product design. The calculation of the fuzzy preference relation and the application of the pseudo-order preference model constitute the basis for this proposition. The type of fuzzy preference relation is used to rank more than two alternatives in an easy and practical way by applying a four-criterion procedure. Two illustrative examples are presented, the first to show the capability of the improved procedure to rank rectangular, triangular, and trapezoidal fuzzy numbers, and the second to demonstrate the application of the proposed procedure to rank more than two normal fuzzy numbers in a practical way by exploiting the type of preference through the application of the ordering criteria. The comparison and analysis of the proposed method and others makes it possible to demonstrate the usefulness of our proposal. The application of fuzzy logic to the proposed method makes it possible for decision makers to profit from information expressed in linguistic terms which are frequently vague and imprecise.

CHAPITRE 5 : A METHODOLOGY TO FORM PRODUCT FAMILIES THROUGH FUZZY PRODUCT CONFIGURATION

5.1 Abstract

More and more companies are designing product families with the aim of making mass customization a reality, offering a wider variety of products while at the same time reducing product cost by standardizing components and processes. This paper proposes a global methodology to form product families taking advantage of fuzzy product configuration. In this methodology, fuzzy logic is considered as a way to improve the decision-making process because of its ability to manage information more accurately than binary logic. This methodology is presented in three principal parts: market consideration, product family formation through product configuration, and product variety consideration. To achieve these parts, seven steps are proposed and explained through an illustrative application to demonstrate the applicability and practicality of the methodology.

Keywords: product family, product configuration, fuzzy logic, market segmentation, mass customization.

5.2 Introduction

In recent decades, companies have applied various strategies in an attempt to be more competitive from a number of perspectives. Mass customization has played an important role in the improvement of product family design, allowing greater competitiveness with respect to product variety and cost by taking advantage of the benefits of product standardization. A powerful tool in product family design has been the product modularity; it makes possible the design of a variety of products using the same set of modules around a predefined platforms. In fact, according to Moon et al., (2006), a product family can be defined as a group of related products based on a product platform, which facilitates mass customization by providing a variety of products cost-effectively for different market segments.

The main objective of this paper is to propose a methodology for the design of product families, considering the customer preferences in different segments of the market from a fuzzy logic perspective. Fuzzy logic, principally fuzzy preference relation, has been applied in order to improve the decision making processes in most of the steps of the methodology. Product configuration is considered as one of the principal approaches for this methodology as well as other approaches and strategies such as mass customization, platforms, commonality and modularity are also significantly considered.

This paper differs from most prior studies, because they applied minimal and partially fuzzy logic tools in their processes. This research develops a global methodology with fuzzy logic-aided tools to design product families. These fuzzy logic-aided tools include: a procedure to perform the market segmentation, a procedure for the identification of modules, a procedure to identify alternatives of product configurations, and a procedure for the generic products configuration, all of them supported by fuzzy logic.

This paper is organized in the following sections. Section 2 presents a literature review of some interesting topics presented principally in three parts: market considerations, product considerations, and product family considerations, a summary and analysis part is presented as well. Section 3 presents a methodology for the formation of product families through product configuration by using fuzzy logic, and includes an illustrative application. Section 4 concludes the paper.

5.3 Literature review

This section is presented in three principal parts: market considerations, product considerations, and product family considerations. Market considerations include customer desires, and market segments. Product considerations such as: product development, and product configuration with fuzzy logic. Product development is divided in product definition, product design, process design, and product configuration. Product family considerations are classified in methodologies for product family design, and in some approaches and strategies for product family design. A summary and analysis part is presented at the end of this section as well.

5.3.1 Market considerations

5.3.1.1 Customer desires

Companies around the world generally aim to satisfy customer expectations. They try to avoid all the drawbacks inherent in failing to identify customer desires, such as the loss of a segment of the market and the shortening of the life cycle of a product.

During recent decades, Quality Function Development (QFD) has been a powerful tool used to translate customer needs and wants into product specifications. Lately, this tool has evolved through the application of fuzzy logic to its processes, and uses customer inputs to reveal the relative importance of their needs and to facilitate their implementation.

Several attempts have been made to simplify the application of QFD by using fuzzy logic. Such work considers: fuzzy inference techniques to accommodate possible imprecision and vagueness (Fung et al., 1999); fuzzy outranking to prioritize design requirements (Wang 1999); fuzzy numbers to represent the imprecise nature of judgments and to define the relationships between engineering characteristics and customer attributes (Vanegas and Labib 2001a); and fuzzy regression to identify the relational functions between, and among, engineering characteristics and customer requirements (Chen et al., 2004b).

5.3.1.2 Market segments

Market segmentation is a fundamental practice which makes possible the identification of different groups of customers with similar preferences and patterns of behavior with respect to some products and services. This aggregation allows the development of products and services that are closer to customer expectations and at the same time improve customer satisfaction. Interesting work on clustering techniques has been proposed with regard to market segmentation. In 1996, Tseng et al., applied clustering techniques to reveal optimal building blocks for the formulation of product family architectures by applying inductive learning software to identify clusters that may match the design parameters and the product's functional requirements. Also, clustering techniques have been used to analyze the relationship between product features and customer requirements and to analyze their changing trends (Chen and Wang 2008a).

Fuzzy logic has been applied in market segmentation. Chen et al., (1996) used fuzzy clustering to analyze company productivity, identifying clusters in training productivity patterns by using two methods, the fuzzy C-means algorithm and the fuzzy K-NN algorithm. Clustering analysis has been combined with fuzzy recognition to support product design, with a view to forming standard structural trees of products according to the design requirements (Lingling et al., 2006). Gao et al., (2008) combined similarity matrix fuzzy clustering to reengineer the product interfaces by identifying the relationships between them and attempting to reduce their redundancy. Also, fuzzy clustering approaches have been proposed in the context of product family design to identify groups of customers with similar preferences with the objective of designing the proper set of products in a product family by considering the engineering characteristics and by establishing the relationship between customer preferences and product attributes (Zhang et al., 2007). Also, fuzzy C-means clustering is applied to classify customer characteristics during the first stage of product definition, which is an essential issue in designing product families from a mass customization perspective (Yu and Wang 2007).

5.3.2 Product considerations

5.3.2.1 Product development

The product development process is an essential part of product family design. According to Jiao and Zhang (2005), it can be divided into three consecutive stages: product definition, product design, and process design. *Product definition* is characterized by the portfolio of products that represents the target of mass customization. *Product design* is an engineering process involving iterative and complex decision making. It usually starts with the definition of a need, proceeds through a sequence of activities to find an optimal solution to the problem, and ends with a detailed description of the product (Deciu et al., 2005). *Process design* is a very important issue to take into account during product development. A careful design of the product assembly sequence helps to create generic subassemblies which reduce subassembly proliferation and the cost of offering product variety (Gupta and Krishnan 1998). Also, *product configuration* is an important issue to product family design. It makes it possible to configure products more strongly closed to customer requirements and also it permits to develop a large variety of products taking into account company's constraints and limitations. A considerable number of tools have been developed to address the issue, among them an approach to find the perfect match between product configuration and industry requirements considering three principal steps: product configuration, bill of materials configuration, and routing configuration (Aldanondo et al., 1999). Another approach for evaluating product configurations from the sales point of view by applying a design structure matrix to show the interaction flow between configuration elements was designed by Helo (2006). Other attempts have been made to optimize the product configuration process based on a multi-objective genetic algorithm (Li et al., 2006). Moreover, some models, including a decision model, have been proposed to select concepts in a product configuration by considering the interactions of those concepts caused by their constraints and functional couplings (Chen et al., 2002). Also, an interesting application of the case-based reasoning algorithm has been presented to reduce design time and cost, and generate an accurate bill of materials at the beginning of the product design process (Tseng et al., 2005).

In the same way, a methodology and an architecture for requirement and engineering configurations in the configuration design process have been developed integrating data mining approaches, such as fuzzy clustering, and association rule mining to link customer groups with clusters of product specifications (Shao et al., 2006). Another work offers a method for product configuration based on a multi-layer evolution model considering the customer requirements and the product configuration design analysis performed in three layers: function, qualification, and structure, and also addresses fuzzy and incomplete customer requirements (Yi et al., 2006). Even though fuzzy logic has been applied in some of the above work, these applications remain only partial.

5.3.2.2 Product configuration with fuzzy logic

Fuzzy logic has been increasingly applied during recent decades to issues related to product configuration, such as concept evaluation, design requirements, company capabilities, and customer requirements. Some of these applications are the following: an integrated approach to the design of configurable products developed based on multiple fuzzy models, such as fuzzy product specification, fuzzy functional network, fuzzy physical solution, and the fuzzy constraint model, all of them designed to translate customer specifications into physical solutions dealing with various forms of uncertainty, such as imprecision, randomness, fuzziness, ambiguity, and incompleteness (Deciu et al., 2005). Another approach to product configuration (Zhu et al., 2007) considered uncertain and fuzzy customer requirements by applying fuzzy multi-attribute decision making. More recently, this approach has been presented as a method which can be used in a product data management system and on e-commerce websites. With it, the preferred product can be obtained for the customer according to the utility value with respect to the whole set of product attributes (Zhu et al., 2008).

5.3.3 Product family considerations

A product family can be defined as set of products that share identical internal interfaces which must be standardized in each of the functional, technological, and physical domains to allow the full exchange of components (Erens and Verhulst 1997).

5.3.3.1 Methodologies for product family design

Product family design is a powerful tool which makes it possible to take advantage of product similarities to reduce design and manufacturing costs. In the current literature, some methodologies for product family design have been published, including a methodology for designing product families in order to manage product diversity, proposed by Agard and Tollenaere (2003a, 2003b). This methodology consists of eight principal points: (1) management of product diversity, (2) selection of indicators, (3) analysis of functional requirements, (4) creation of a functional structure, (5) creation of a technical structure, (6) process selection, (7) search for a valid solution, and (8) selection of the final solution. In the same way, Hsiao and Liu (2005) proposed a methodology for the design of product families by managing the variety of products. This methodology comprises three stages: (1) market planning, (2) application of Quality Function Deployment (QFD), and (3) application of the Interpretative Structural Model (ISM). More recently, Kumar et al., (2009) proposed a methodology to design product families integrating market considerations to examine the impact of increasing the product variety offered to different market segments, and to explore the cost savings associated with the application of commonality decisions. This methodology consists of four steps: (1) creation of the market segmentation grid, (2) estimation of the demand, (3) construction of models for product performance, and (4) application of the profit maximization model. Also, some interesting tools have been applied to improve the design of product families. Agard and Kusiak (2004a) used data mining analysis to design families of products based on customer descriptions and requirements. This methodology consists of three steps: (1) analysis of functional requirements, (2) design of a functional structure, and (3) design of a technical structure.

5.3.3.2 Approaches and strategies for product family design

According to Simpson (2004), there are two approaches to product family design. The first is a top-down (proactive platform) approach, wherein the company’s strategy is to develop a family of products based on a product platform and its derivatives. The second is a bottom-up (reactive redesign) approach, wherein a company redesigns and/or consolidates a group of distinct products to standardize components and thus reduce costs.

The key to a successful product family is the common product platform around which the product family is derived (Messac et al., 2002). An important number of works has been published for developing platforms. These works include methods for identifying a platform using data mining techniques and fuzzy clustering (Moon et al., 2006), methods for the platform development applying preference aggregation, optimization (Dai and Scott, 2006), and cluster analysis (Dai, 2005). Also, clustering and sensitivity analysis have been used to design multiple-platform configurations in an attempt to improve product family design (Dai and Scott 2007). Cluster analysis has also been applied to the design of product platforms by analyzing products designed individually and determining the optimal number of common values for each platform (Chen and Wang 2008b). Ninan (2007) presented a platform cascading method for scale-based product family design. This method is presented in three stages: (1) the single platform stage; (2) the evaluation stage; and (3) the cascading stage, aimed at reducing the poor performance of the product family due to the consideration of a single platform by instead taking into account multiple platforms.

According to Huang et al., (2005) commonality and modularity are two strategies successfully applied in the development of product platforms. A brief summary of the work carried out related to these strategies follows.

1. *Commonality.* The proper balance between product platform commonality and individual product performance is very important to the success of a product family. Two sources of commonality have been identified by Jiao and Tseng (2000): the component part and the process part. To model the commonality of components, two models were presented by Mishra (1999): the multiple product/multiple common component method, and the multiple product/single common component method. In the same vein, Dai (2005) proposed a method for making an appropriate commonality decision in order to achieve a meaningful trade-off between the technical and monetary aspects of the product family, and Fellini (2003) and Fellini et al., (2005) presented a methodology for performing commonality optimization by choosing the components of the product that are to be shared without exceeding user-specified bounds on

performance and allowing the maximization of commonality at different levels of acceptable performance. In order to cluster the attributes of the product family in a platform and its associated differentiating modules, Ye and Gershenson (2008) presented a methodology for identifying the appropriate commonality and variety trade-off at the product attribute level using market analysis and conceptual engineering knowledge. Three matrices are used for this purpose: one for the product attributes, one for the specification ranges, and one for the changes of the specification ranges.

2. *Modularity.* Modularity has also been applied successfully in product platform development. In this context, clustering analysis has been used to analyze the design matrix to identify modules by mapping the relationships between functional requirements and design parameters (Tseng and Jiao 1997). In 1999, Kusiak proposed different points of view for the modular design of products, processes, and systems. Another method, based on the simulated annealing algorithm that permits development of a modular product family, was proposed by Wang et al., (2005). Then, Sered and Reich (2006) proposed a method for modularity standardization, focusing the engineering effort on the product platform components, and Meng, X., et al., (2007) presented a methodology to identify the component modules for product families which includes four principles: (1) identification and isolation of individualized components into modules; (2) identification and isolation of components with a strong possibility of replacement by one module; (3) improvement of the functional independence of the modules; and (4) improvement of the structural independence of the modules. Da Cunha et al., (2007) proposed various heuristic algorithms for the design of modular elements in a mass customization context, focusing on minimizing the manufacturing and transportation cost in the supply chain.

5.3.4 Summary and analysis

Product family design is a challenge that considers taking advantage of product similarities to reduce design and manufacturing costs. Many processes into in the design of product families can be improved in different ways by the application of fuzzy logic. Fuzzy logic allows input information to be provided in linguistic terms as colloquially expressed by people, for example to be moderately or highly interested to certain feature of a product such as the size or the weight, instead of crisp and non negotiable terms. This type of information permits to make better and more accurate decisions due to the wide range of possible answers that can be handled instead of just to be or not be interested to such product feature as permitted by traditional tools.

The publications considered in this paper were classified in different topics that include the market point of view (customer desires, market segments), the product point of view (product development, product definition, product design, process design, product configuration), and some methodologies and strategies for the product family design (platform, commonality, and modularity).

Fuzzy logic has not yet been applied to the entire process of design of product families, it has, however, been used in recent years to improve several specific tasks in that process. It is interesting to note that an important number of publications contain partial applications of fuzzy logic. Different fuzzy logic tools are used in one or more topics related to product family design. Customer desires, product definition, and product design are the topics the most frequently addressed. On the contrary, the topics that are less addressed with fuzzy logic applications are the design of processes, platforms, commonality, and modularity. Even if some works presented some application of fuzzy logic into the product family design process, these applications are very partial and still necessitate developing new tools for the entire product family design process.

This work aims at filling this lack and proposes to exploit the benefits of fuzzy logic to develop a global methodology to design families of products, it embrace all the related topics from a fuzzy logic perspective instead of partial applications to specific topics related to the design of product families.

5.4 Methodology for product family formation through product configuration using fuzzy logic and its application

Product family design can be improved in a wide range of areas by applying fuzzy logic, which allows opinions, knowledge, and expertise to be provided and managed in the linguistic terms commonly used by human beings. Fuzzy logic is increasingly used in decision aided systems, since it offers several advantages over other traditional decision making techniques. In this section, we propose a methodology for forming product families through product configuration applying fuzzy logic; in an attempt to improve customer satisfaction by offering the products that most closely meet to the expectations of different segments of the market (see Figure 5.1).

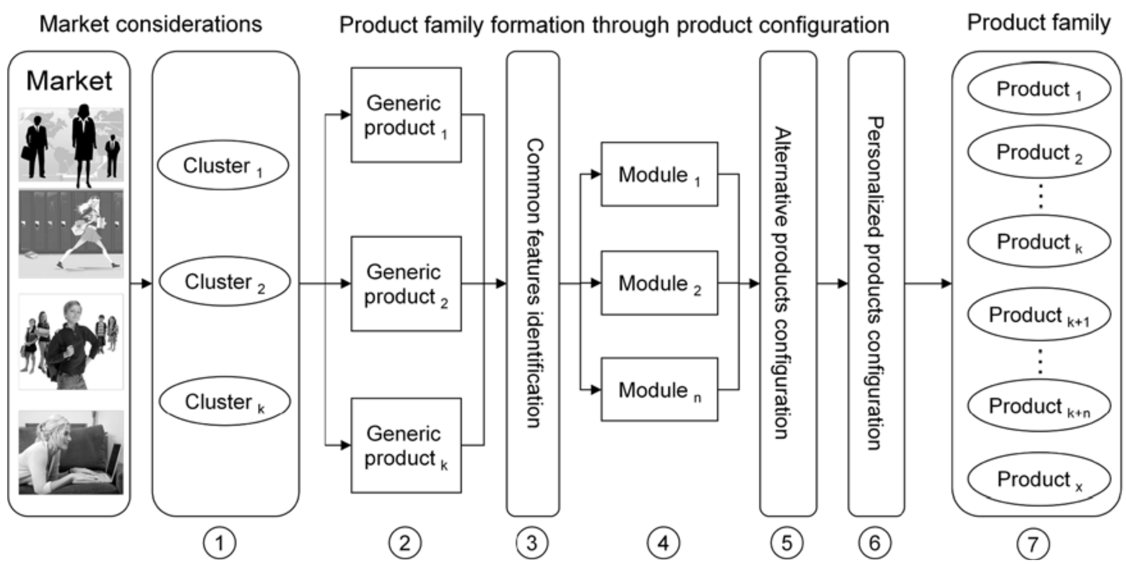


Figure 5.1 Product family formation methodology

The proposed methodology is presented in three principal parts: market considerations, product family formation through product configuration, and product variety consideration. These phases are achieved through the following seven steps: (1) market segmentation, (2) generic product configuration, (3) common features identification, (4) module identification, (5) alternative products configuration, (6) personalized products configuration, (7) listing of product variety (see Figure 5.1).

These steps are explained in greater detail through the following illustrative application.

Step 1. Market segmentation

First of all, we consider the application of fuzzy clustering techniques to identify groups of customers with similar needs and wants. According to Xu and Wunsch II (2005), fuzzy c-means (FCM) which was developed by Bezdek (1981), is one of the fuzzy clustering algorithms most often applied. The FCM function starts with an initial guess as to the cluster center, which is frequently incorrect. Then, the cluster centers are updated iteratively and the FCM moves the cluster centers, also iteratively, to the right location within the set of data. This iteration is based on minimizing an objective function, which represents the distance from any given data point to a cluster center. The output is a list of cluster centers and several membership grades for each data point that can be used to build a fuzzy inference system by creating membership functions to represent the fuzzy qualities of each cluster. There are other methods for estimating the number of clusters and their centers. According to Chiu (1996), the subtractive clustering method was first introduced by him in 1994 as a cluster estimation method to determine the number of clusters and their initial values that can be used to initialize other clustering algorithms such as FCM.

To perform the market segmentation, we propose the following five-phase procedure.

1. *Consider product features.* Let us assume that the design team found the most relevant features considered by customers in selecting a laptop. These include the processor (F_1), the operating system (F_2), the display (F_3), the memory (F_4), and the hard drive (F_5).

2. *Express customer preferences in linguistic terms.* In this application, we consider a case where a group of thirty customers has been surveyed about their preferences at the time of buying a laptop. The customer preferences for each feature are expressed in linguistic terms, such as: “highly important” (HI), “important” (I), “moderately important” (MI), “somewhat important” (SI), and “not important” (NI).

3. *Express customer preferences in numerical terms.* To represent these terms numerically, we use a five-level Liker scale with a range from 5 to 1, where 5 represents "highly important", 4 "important", and so on.

4. Table 5.1 lists a portion of the customer preferences for each feature. The complete list appears in Appendix 1.

Table 5.1 Customer feature preferences

Customer	Product Features				
	F_1	F_2	F_3	F_4	F_5
1	5	4	3	4	2
2	1	2	2	3	4
⋮	⋮	⋮	⋮	⋮	⋮
30	5	4	3	3	2

5. *Identify clusters using the FCM clustering method.* In this application, we apply the FCM clustering iterative method by using the Fuzzy Logic toolbox in Matlab to identify the clusters needed to represent different groups with similar preferences. Let us apply FCM to analyze the customer preferences listed in Appendix 1, evaluating three different scenarios: (a) four clusters, (b) three clusters, and (c) two clusters. Two interesting outputs of Matlab fuzzy clustering are: the membership matrix and the cluster centers. These are analyzed as follows.

   - *Membership matrix analysis.* A portion of the membership matrix obtained between clusters and customers for each scenario is presented in Figure 5.2. In this matrix, we may note that a customer can belong to different clusters with different membership degrees. For example, in case (a) with four clusters, customer 1 belongs 89% to cluster 4, 8% to cluster 3, 2% to cluster 2, and 1% to cluster 1.

Cluster	Customers			
	1	2	…	30
1	0.01	0.36	…	0.02
2	0.02	0.59	…	0.03
3	0.08	0.03	…	0.42
4	0.89	0.03	…	0.53

(a) Four clusters

Cluster	Customers			
	1	2	…	30
1	0.09	0.27	…	0.02
2	0.88	0.04	…	0.97
3	0.04	0.69	…	0.01

(b) Three clusters

Cluster	Customers			
	1	2	…	30
1	0.95	0.03	…	0.99
2	0.05	0.97	…	0.01

(c) Two clusters

Figure 5.2 Membership matrix for each scenario

Also, the entire membership matrix depicted in Figure 5.2 can be analyzed through some basic measures of a central tendency, such as: sum, average, and variance, where the highest sum and the highest average indicate that more customers belong to that cluster, and a low variance means that the customers are clustered more in the corresponding cluster than in the others. Figure 5.3 presents these measures for each cluster of all three scenarios, where the highest sum and highest average correspond to cluster 1 in scenario (c), with measures of 15.25 and 0.51 respectively, whereas that the lowest variance corresponds to cluster 1 in scenario (b).

Cluster	*Sum*	*Ave*	*Var*
1	7.83	0.26	0.10
2	7.37	0.25	0.08
3	7.17	0.24	0.08
4	7.63	0.25	0.09

(a) Four clusters

Cluster	*Sum*	*Ave*	*Var*
1	7.69	0.26	0.07
2	12.61	0.42	0.17
3	9.70	0.32	0.13

(b) Three clusters

Cluster	*Sum*	*Ave*	*Var*
1	15.25	0.51	0.18
2	14.75	0.49	0.18

(c) Two clusters

Figure 5.3 Comparison of the membership matrices for the three scenarios

- *Cluster center analysis.* Because there is no scenario that satisfies both the above criteria, the designer could analyze the center of the clusters with respect to the product features. Figure 5.4 and Figure 5.5 list and depict this information for each scenario respectively.

Clus	F_1	F_2	F_3	F_4	F_5
1	1.04	1.86	2.68	3.89	4.81
2	1.82	2.29	2.52	3.00	3.59
3	4.86	3.91	2.64	2.21	1.39
4	4.83	4.39	2.95	3.79	1.68

(a) Four clusters

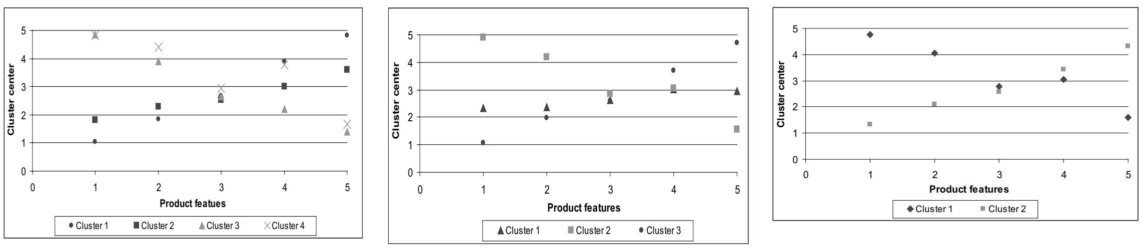
Clus	F_1	F_2	F_3	F_4	F_5
1	2.34	2.36	2.64	3.03	2.95
2	4.91	4.18	2.85	3.05	1.57
3	1.08	1.98	2.61	3.70	4.70

(b) Three clusters

Clus	F_1	F_2	F_3	F_4	F_5
1	4.76	4.06	2.79	3.05	1.61
2	1.33	2.09	2.57	3.43	4.31

(c) Two clusters

Figure 5.4 List of cluster center coordinates with respect to product features



(a) Four clusters (b) Three clusters (c) Two clusters

Figure 5.5 Depiction of the cluster centers with respect to product features

6. *Selection of the best clusters scenario.* In selecting the best number of clusters, the scenario with the lowest variance is preferred. These variances are obtained from the analysis of the membership matrix. The lowest scenario variance means that the customers are better segmented into these clusters. It is important to consider that while greater the number of clusters is within the scenario its variance tends to decrease. But, it is better to identify the scenario with the smallest number of clusters looking for representing the principal segments of the market. According to the information presented in Figure 5.3, the three cluster scenario (b) is the best option, since it satisfies the lowest variance criteria. Figure 5.5 in scenario (b) shows how cluster 1 includes customers moderately interested in almost all the laptop features, cluster 2 includes customers more interested in features such as the processor and the operating system, and cluster 3 includes customers more interested in storage capacity.

Step 2. Generic products configuration

To perform this step, we propose the following four-phase procedure, which is an adaptation from a method proposed by Barajas and Agard (2008b). This method has been restructured and simplified in order to achieve the objective of this step. In the first phase, consideration of customer preferences, a rule has been added to permit the introduction of information from the previous step. This rule consists in round the information from the cluster centers to the nearest integer to represent the customer preferences. In the last phase, selection of product features, a simple comparison between $R(F_{ij},C_{ki})$ and 0.5 has been considered in order to identify the best features for the product instead of the calculation of the fuzzy indifference degree.

1. *Consideration of customer preferences.* For this application, these customer preferences correspond to the customers in the target scenario. In this case, the information can be obtained from the cluster centers listed in Figure 5.4(b) that correspond to the three cluster scenario. This information needs to be rounded to the nearest integer to represent the customer preference for each feature in each cluster (see Table 5.2(a)). This information could also be expressed in linguistic terms, as explained in the previous step (see Table 5.2(b)).

Table 5.2 Customer preferences for the three cluster scenario

Cluster	F_1	F_2	F_3	F_4	F_5
1	2	2	3	3	3
2	5	4	3	3	2
3	1	2	3	4	5

(a) Numerical terms

Cluster	F_1	F_2	F_3	F_4	F_5
1	SI	SI	MI	MI	MI
2	HI	I	MI	MI	SI
3	NI	SI	MI	I	HI

(b) Linguistic terms

2. *General prioritization of customer preferences*. Let us suppose that a team of specialists defined a general scale based on a customer survey to prioritize the set of features (see Table 5.3). Figure 5.6 shows how this prioritization is represented using fuzzy numbers.

Table 5.3 General prioritization of customer preferences represented by fuzzy numbers

Linguistic terms	Fuzzy numbers
HI – “Highly Important”	[7 9 10 10]
I – “Important”	[5 6 8 9]
M – “Moderately Important”	[3 5 5 7]
SI – “Somewhat Important”	[1 2 4 5]
NI – “Not Important”	[0 0 1 3]

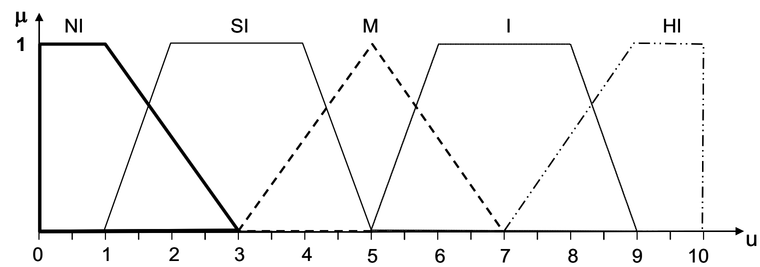


Figure 5.6 Fuzzy number depiction of product feature general prioritization

3. *Technical evaluation of product features.* Generally, this evaluation can be obtained from specialized sources in the industry in question. If this information is not available, a survey designed by experts can be used as well. Once this information is available, it must be represented by fuzzy numbers in order to be used in this phase. To do that, we considered a work proposed by (Jarventausta et al., 1994) which includes a detailed explanation about how to represent uncertain situations by using fuzzy numbers through the determination of a proper membership function. Also, these authors considered that in uncommon situations where no statistics are available, an expert may be able to express degrees of confidence in various hypotheses. In this work, we assume that this information is available, and it has been represented in fuzzy numbers by applying fuzzy set theory as listed in Table 5.4 where each alternative of the product features are represented with trapezoidal fuzzy numbers. It is important to consider that other membership functions could be considered. For this application trapezoidal membership function better fits to represent the evaluation of the alternatives for the product

features. More detailed information about fuzzy set theory can be found in Zimmermann, H.-J., (1991). Figure 5.7 presents a depiction of the available alternatives for feature 1 represented by fuzzy numbers

Table 5.4 Technical evaluation of product features represented by fuzzy numbers

F_1	F_2	F_3	F_4	F_5
[0 1 4 6]	[0 4 5 7]	[0 1 2 3]	[0 2 4 6]	[0 1 2 3]
[2 4 6 8]	[8 9 10 10]	[1 2 3 4]	[2 3 6 7]	[1 2 4 5]
[7 8 10 10]	-------	[3 4 5 7]	[4 6 7 9]	[2 3 5 6]
-------	-------	[4 5 6 8]	[7 8 10 10]	[3 4 6 7]
-------	-------	[6 7 8 9]	-------	[5 6 8 9]
-------	-------	[7 8 10 10]	-------	[7 8 10 10]

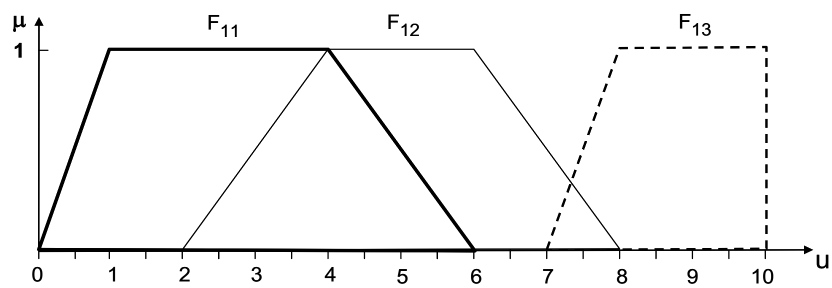


Figure 5.7 Fuzzy number depiction of the alternatives of feature 1

4. *Selection of product features.* As considered by Barajas and Agard (2008b), if the fuzzy preference relation R(A,B) is equal to 0.5, then A and B are indifferent, where A represents the feature evaluation and B represents the customer preference for that feature.

- *Fuzzy preference relation.* Let A and B be two normal and convex fuzzy numbers. Then, there exist two notions: dominance and indifference. If there exists an area of overlap between fuzzy numbers A and B (intersection between A and B), then the overlap area is defined as the indifference area. Also, if there exist one or more non-overlap areas between fuzzy numbers A and B, then, for each non-overlap area, either A dominates B or B dominates A (see Figure 5.8). R(A,B) could be obtained using the following equation:

$$R(A,B) = [D(A,B) + I(A,B)]/[A(A) + A(B)] \quad (1)$$

Where: D(A,B) is the area where A dominates B, I(A,B) is the area where A and B are indifferent, and A(A) and A(B) are the areas of A and B respectively.

In this work, the fuzzy preference relation R(A,B) is denoted as $R(F_{ij},C_{ki})$, where $F_{ij}=\{F_{11}, F_{12}, \ldots, F_{nm}\}$ is the set of the evaluations of the feature (i) for each feature alternative (j) for all i=1, 2,…, n, and for all j=1, 2,…, m, and $C_{ki}=\{C_1, C_2,\ldots,C_{pn}\}$ is the set of customer preferences of cluster (k) for each feature (i) for all k=1, 2,…, p.

- *Example of fuzzy preference calculation.* Let`s calculate the fuzzy preference relation $R(F_{11},C_{11})$ which corresponds to the first alternative of feature 1 (F_{11}), and to the customer preference of the cluster 1 to such feature alternative (C_{11}). The corresponding fuzzy numbers for F_{11} and for C_{11} are [0 1 4 6] and [1 2 4 5] respectively (see Figure 5.8). By adapting equation (1) to adapted notation in this work, the fuzzy preference relation can be calculated as follows. $D(F_{11},C_{11}) = 0.5$, $I(F_{11},C_{11}) = 3.0$, $A(F_{11}) = 4.5$, $A(C_{11}) = 3.0$. Then, $R(F_{11},C_{11})= 0.4667$.

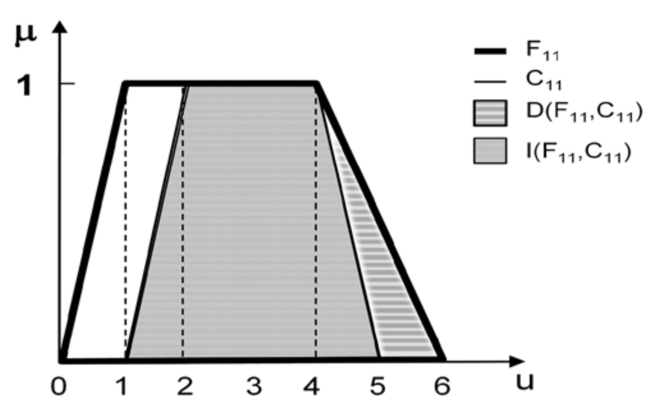


Figure 5.8 Fuzzy number depiction of F_{11} and C_{11}

Table 5.5 lists the fuzzy preference relation for all the relations in cluster 1. Appendices 2a and 2b present these preferences for cluster 2 and cluster 3 respectively.

Table 5.5 Fuzzy preference relation of Cluster 1

$F_{ij}\backslash C_{ki}$	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
	[1 2 4 5]	[1 2 4 5]	[3 5 5 7]	[3 5 5 7]	[3 5 5 7]
F_{11} [0 1 4 6]	0.4667				
F_{12} [2 4 6 8]	0.7857				
F_{13} [7 8 10 10]	1.0000				
F_{21} [0 4 5 7]		0.6429			
F_{22} [8 9 10 10]		1.0000			
F_{31} [0 1 2 3]			0.0000		
F_{32} [1 2 3 4]			0.0000		
F_{33} [3 4 5 7]			0.4444		
F_{34} [4 5 6 8]			0.6667		
F_{35} [6 7 8 9]			0.9670		
F_{36} [7 8 10 10]			1.0000		
F_{41} [0 2 4 6]				0.1875	
F_{42} [2 3 6 7]				0.4167	
F_{43} [4 6 7 9]				0.7750	
F_{44} [7 8 10 10]				1.0000	
F_{51} [0 1 2 3]					0.0000
F_{52} [1 2 4 5]					0.0000
F_{53} [2 3 5 6]					0.3000
F_{54} [3 4 6 7]					0.5000
F_{55} [5 6 8 9]					0.8666
F_{56} [7 8 10 10]					1.0000

To identify the best product features for each cluster in this application, we consider that the $R(F_{ij},C_{ki})$ nearest to 0.5 corresponds to the feature that should be part of the generic product for each cluster. To do this, it is necessary to compare the absolute value of the difference between 0.5 and $R(F_{ij},C_{ki})$ to identify the features with the smallest differences (see Table 5.6).

Table 5.6 Product features for each cluster

Features	**Clusters**		
	1	**2**	**3**
F_{11}	**0.0333**	0.5	**0.2692**
F_{12}	0.2857	0.4792	0.4792
F_{13}	0.5	**0.0556**	0.5
F_{21}	**0.1429**	0.4048	**0.1429**
F_{22}	0.5	**0.1667**	0.5
F_{31}	0.5	0.5	0.5
F_{32}	0.5	0.5	0.5
F_{33}	**0.0556**	**0.0556**	**0.0556**
F_{34}	0.1667	0.1667	0.1667
F_{35}	0.467	0.4167	0.4167
F_{36}	0.5	0.5	0.5
F_{41}	0.3125	0.3125	0.5
F_{42}	**0.0833**	**0.0833**	0.3571
F_{43}	0.275	0.2750	**0.0833**
F_{44}	0.5	0.5	0.3182
F_{51}	0.5	0.3	0.5
F_{52}	0.5	**0**	0.5
F_{53}	0.2	0.1667	0.5
F_{54}	**0**	0.3333	0.5
F_{55}	0.3666	0.5	0.3667
F_{56}	0.5	0.5	**0.0556**

Based on the previous statement and according to Table 5.6, the product configuration for each cluster is as follows: $F_{11} – F_{21} – F_{33} – F_{42} – F_{54}$ for cluster 1, $F_{13} – F_{22} – F_{33} – F_{42} – F_{52}$ for cluster 2, and $F_{11} – F_{21} – F_{33} – F_{43} – F_{56}$ for cluster 3.

Step 3. Common features identification

This step consists of identifying if one or more features are common to all the product configurations identified in step 2 for all the clusters. By analyzing the previous product configurations, it is possible to note that F_{33} is common to all the generic products for all the clusters (see Table 5.7). This alternative corresponds to option 3 of feature 3. For this application, this can be translated as a medium-sized laptop display being preferred by most of the customers. This alternative will then be considered as fixed in future product mass customization. For this feature, other alternatives will also be considered, but for personalized configuration instead of mass customization.

Table 5.7 Product features for each cluster

Cluster	Product configuration
1	$F_{11} - F_{21} - \mathbf{F_{33}} - F_{42} - F_{54}$
2	$F_{13} - F_{22} - \mathbf{F_{33}} - F_{42} - F_{52}$
3	$F_{11} - F_{21} - \mathbf{F_{33}} - F_{43} - F_{56}$

Step 4. Modules identification

In this work, a module is defined as the integration of two or more product features. To identify possible modules we propose the following four-phase procedure.

1. *Ranking of features preferences.* This can be achieved by analyzing the cluster centers with respect to the product features. To do that, we calculate the variance among the cluster centers for each product feature. The feature with the smallest variance will be the first in the ranking. Based on the information in Table 5.8, the feature ranking is as follows: F_3, F_4, F_2, F_5, and F_1.

Table 5.8 Analysis of cluster centers with respect to product features

Feature	*Variance*
1	3.82
2	1.39
3	0.02
4	0.15
5	2.46

2. *Availability of features alternatives.* Considering the information depicted in Table 5.6, it is possible to identify if there are feature alternatives that are not used in the generic product. According to this table, the availability for each feature alternative is as follows: for feature 1 (F_{12}); for feature 3 (F_{31}, F_{32}, F_{34}, F_{35}, and F_{36}); for feature 4 (F_{41} and F_{44}); and (F_{51}, F_{53}, and F_{55}) for feature 5. As can be noted, there is no alternative available for feature 2.
3. *Common features alternative consideration.* If there is/are an alternative/alternatives which is/are common to all the generic products, then this/these should be included in the modules. According to step 3, F_{33} is common to all the generic products, and so this will be included in all the modules.
4. *Modules formation.* The module will be formed according to the ranking of the feature preference obtained previously (F_3, F_4, F_2, F_5, and F_1), considering the common features and the features that are not available. For this application, feature 2 cannot be considered to form a module, because there is no alternative available for it. On the other hand, F_{33} is the alternative that should be common to all the modules. Figure 5.1 depicts this procedure.

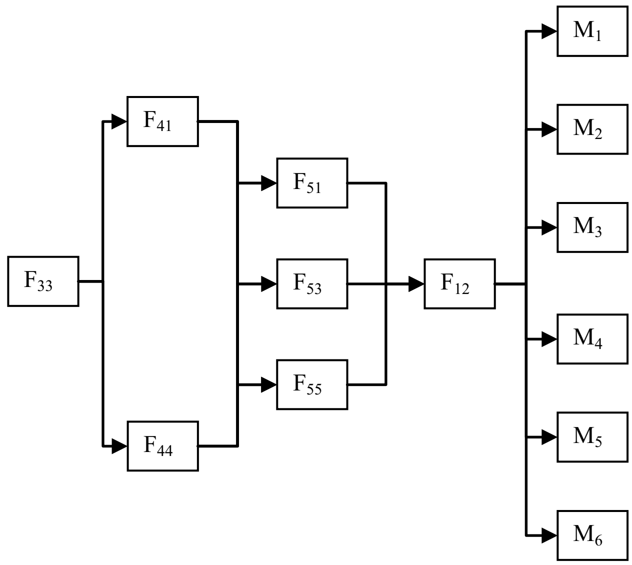


Figure 5.9 Modules identification

Step 5. Alternative products configuration

To identify possible product configuration alternatives, we propose the following two-phase procedure.

1. *Features with no alternative availability.* If there exist one or more features with no available alternatives, then all the alternatives for these features will be considered in the alternative product configuration. According to step 4, there is no alternative available for feature 2. That is, F_{21} and F_{22} will be part of the new product configuration (see Figure 5.10).
2. *Massive product configuration.* To form the alternative product configuration, the modules identified with feature alternatives which are not available must be combined. Table 5.9 lists the alternative product configuration for this application.

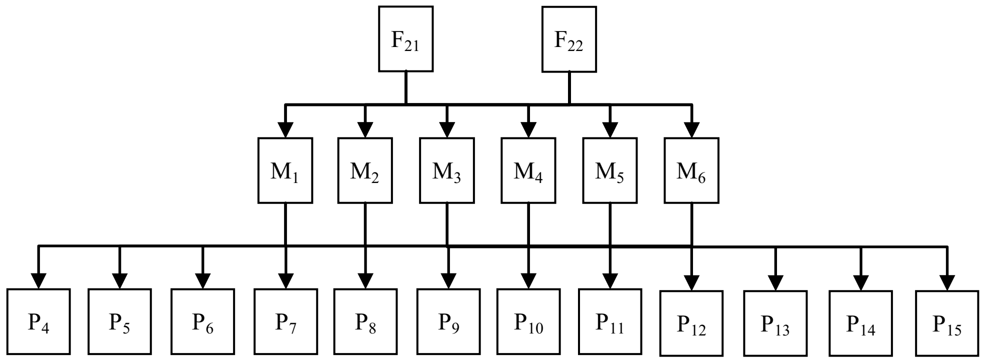


Figure 5.10 Alternative products configuration

Table 5.9 Features of the alternative product configuration.

Product alternative formation	Product configuration
$F_{21} + M_1 = P_4$	$F_{12} – F_{21} – F_{33} – F_{41} – F_{51}$
$F_{21} + M_2 = P_5$	$F_{12} – F_{21} – F_{33} – F_{41} – F_{53}$
$F_{21} + M_3 = P_6$	$F_{12} – F_{21} – F_{33} – F_{41} – F_{55}$
$F_{21} + M_4 = P_7$	$F_{12} – F_{21} – F_{33} – F_{44} – F_{51}$
$F_{21} + M_5 = P_8$	$F_{12} – F_{21} – F_{33} – F_{44} – F_{53}$
$F_{21} + M_6 = P_9$	$F_{12} – F_{21} – F_{33} – F_{44} – F_{55}$
$F_{22} + M_1 = P_{10}$	$F_{12} – F_{22} – F_{33} – F_{41} – F_{51}$
$F_{22} + M_2 = P_{11}$	$F_{12} – F_{22} – F_{33} – F_{41} – F_{53}$
$F_{22} + M_3 = P_{12}$	$F_{12} – F_{22} – F_{33} – F_{41} – F_{55}$
$F_{22} + M_4 = P_{13}$	$F_{12} – F_{22} – F_{33} – F_{44} – F_{51}$
$F_{22} + M_5 = P_{14}$	$F_{12} – F_{22} – F_{33} – F_{44} – F_{53}$
$F_{22} + M_6 = P_{15}$	$F_{12} – F_{22} – F_{33} – F_{44} – F_{55}$

Step 6. Personalized products configuration

Let us suppose that a customer X is not satisfied with the customized products offered. This customer wants his product to be personalized. For him, all the product features are “highly important” (HI). This configuration can be obtained by performing step 2 considering his feature preferences. Appendix 3 lists the complete fuzzy preference relation for this case. As can be inferred, the product configuration for this customer (Px) is formed with the highest ranking alternative for each feature (F_{13}– F_{22} – F_{36} – F_{44} – F_{56}).

Step 7. Product variety listing

There are three types of product configuration: a generic product for each cluster, modular customized products, and a personalized product configuration (see Figure 5.11).

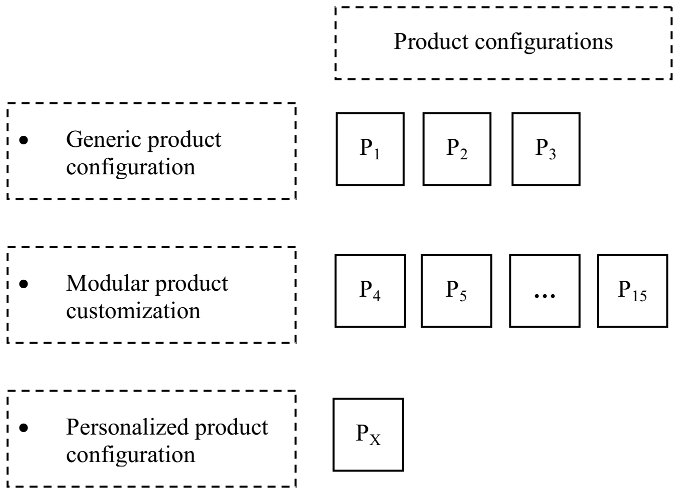


Figure 5.11 Product alternatives in the product family

Products 1 to 3 belong to clusters 1 to 3 respectively. But, it is important to identify which of the modular customized products are more closely associated with each cluster. From Table 5.2, it is possible to identify the most often preferred features for each cluster (see Table 5.10).

Table 5.10 Most often preferred features per cluster

Cluster	F_1	F_2	F_3	F_4	F_5
1	SI	SI	MI	MI	MI
2	HI	I	MI	MI	SI
3	NI	SI	MI	I	HI

According to the feature preferences for each cluster, we may note that P_4 to P_9 are more closely associated with cluster 1, P_{10} to P_{15} with cluster 2, and P_7 to P_9 and P_{13} to P_{15} with cluster 3 (see Figure 5.12 and Table 5.11).

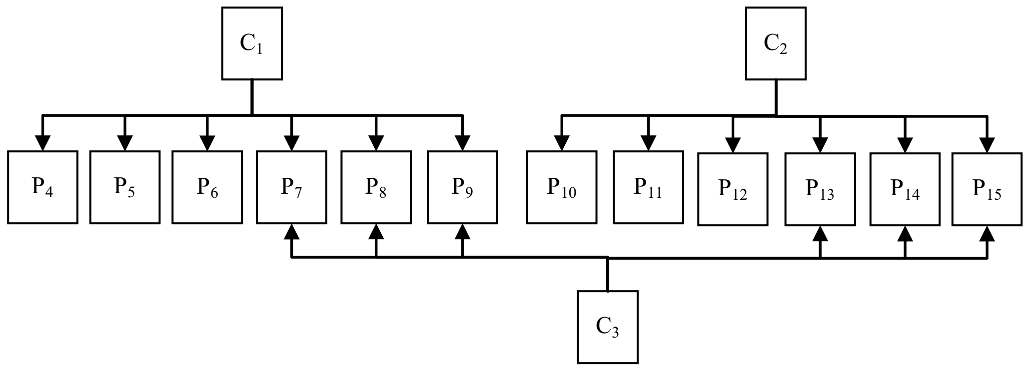


Figure 5.12 Alternative products for each cluster

Table 5.11 Identification of product configuration for each cluster

Product	Product configuration
4	$F_{12} - F_{21} - F_{33} - F_{41} - F_{51}$
5	$F_{12} - F_{21} - F_{33} - F_{41} - F_{53}$
6	$F_{12} - F_{21} - F_{33} - F_{41} - F_{55}$
7	$F_{12} - F_{21} - F_{33} - F_{44} - F_{51}$
8	$F_{12} - F_{21} - F_{33} - F_{44} - F_{53}$
9	$F_{12} - F_{21} - F_{33} - F_{44} - F_{55}$
10	$F_{12} - F_{22} - F_{33} - F_{41} - F_{51}$
11	$F_{12} - F_{22} - F_{33} - F_{41} - F_{53}$
12	$F_{12} - F_{22} - F_{33} - F_{41} - F_{55}$
13	$F_{12} - F_{22} - F_{33} - F_{44} - F_{51}$
14	$F_{12} - F_{22} - F_{33} - F_{44} - F_{53}$
15	$F_{12} - F_{22} - F_{33} - F_{44} - F_{55}$

5.5 Conclusions

A global methodology is proposed in this paper to form a product family through product configuration using fuzzy logic. It is aimed at contributing to increasing customer satisfaction by applying fuzzy preference relation in the various steps of the methodology to enrich the decision making process. This methodology unlike others published seeks to take advantage of fuzzy logic in all of its steps. The methodology is presented in three principal parts: market consideration, product family formation, and product variety consideration, and can be completed in seven steps. The output of the methodology is a family of products classified into three different types of products: a generic product for each segment of the market, a set of modular customized products associated with each segment of the market, and a personalized product for a specific customer. This methodology contributes to the possibility of offering both generic and standardized products for different segments of the market, and to reducing the costs of the product as a result of standardization of the components and the associated processes. It is also possible to form a personalized product, although at a higher cost, owing to the flexibility of using feature alternatives. Some future research directions could include study of a component-level instead of a feature-level methodology.

CHAPITRE 6 : DISCUSSION GÉNÉRALE

Les contributions présentées dans le cadre de cette thèse portent sur deux dimensions. D'une part, nous avons fait des avancées au niveau des outils de la logique floue en étendant les résultats actuels quand au classement de nombres flous. D'autre part, nous avons proposé une démarche structurée pour la conception des familles de produits; cette démarche utilise une modélisation plus fine des besoins des clients par rapport à ce qui se faisait actuellement.

6.1 Avancées au niveau de la logique floue.

Durant les dernières années, la logique floue a démontré son applicabilité à travers de multiples utilisations dans différents domaines, tels que les contrôleurs automatiques et les systèmes intelligents, entre autres. En partant de la bibliographie analysée dans le chapitre 2, nous avons remarqué qu'il existait une lacune entre l'application de la logique floue et le développement des familles de produits. C'est-à-dire, que les outils de la logique floue sont peu ou pas utilisés dans le contexte du développement des familles de produits. Une analyse plus approfondie a fait ressortir que cela était lié au fait que les outils disponibles n'étaient pas réellement adaptées. Tout d'abord il nous a semblé que les outils disponibles présentaient un faible pouvoir de modélisation utilisable pour la conception des familles de produits, ceci est cependant indispensable pour pourvoir convenablement comparer des alternatives dans le processus de conception.

Dans l'article présenté au chapitre 3, nous avons amélioré le classement de nombres flous en permettant de classer deux ou plusieurs nombres flous et aussi en permettant d'utiliser des nombres flous avec des fonctions d'appartenance différentes, comme trapézoïdale, triangulaire et rectangulaire. Une autre amélioration dans cet article a été la définition de vingt-neuf cas généraux qui permettent l'évaluation de toutes les relations possibles entre deux nombres flous normaux et convexes. Ces vingt-neuf cas ont été définis en utilisant des fonctions d'appartenance trapézoïdales comme modèle général pour supporter également les fonctions triangulaires et rectangulaires. Ces cas ont été classés selon le nombre de points d'intersection entre les nombres à comparer. Il ressort: quatre, trois, deux, un ou aucun point d'intersection. Ces contributions sont significatives, car la majorité des méthodes de classement proposées dans la catégorie des méthodes basées sur l'analyse des relations de préférences floues, sont limitées au classement des paires de nombres flous avec des fonctions d'appartenance triangulaires ou rectangulaires.

Par rapport à d'autres travaux publiés, cet article présente l'illustration et la déclaration de toutes les interactions possibles entre deux nombres flous normaux et convexes. Cette illustration et déclaration permet d'avoir un cadre de référence pour faciliter l'inclusion d'autres fonctions d'appartenance comme gaussienne ou parabolique ainsi que la considération de nombres flous non normaux et non convexes. La majorité des méthodes de classement disponibles présentent l'illustration et la déclaration des cas les plus typiques comme les cas : 1, 2, 3, 4, et 5 illustrés dans l'annexe A. Également, cette déclaration inclut la définition de tous les calculs nécessaires pour obtenir les relations de préférences floues lesquelles sont la base de cette méthode. Pour effectuer le classement de deux nombres flous, un modèle de préférence de pseudo-ordre a été adapté et simplifié. Ce modèle est basé sur la considération et l'évaluation du type de relation de préférence floue (stricte, faible, et d'indifférence) entre les nombres comparés. Pour effectuer le classement de plusieurs nombres flous, une procédure de quatre critères d'ordre a été proposée. L'application de cette procédure est faite à travers la combinaison avec le modèle de préférence de pseudo-ordre précité.

La méthode de classement proposée dans le chapitre 3 est limitée au classement de nombres flous normaux et convexes. Cette limitation est également présente dans toutes les méthodes basées sur l'analyse des relations de préférence floues. En revanche, les méthodes basées sur les techniques de clarification «defuzzification» ne présentent pas cette limitation, mais, selon Lee (2000) ces méthodes présentent une autre limitation hautement importante, comme satisfaire seulement un des quatre critères qu'une bonne méthode de classement doit satisfaire. Ces quatre critères sont : (1) la représentation de préférences floues, (2) la rationalité de l'ordre de préférences, (3) la robustesse, et (4) l'efficience. Les méthodes basées sur l'analyse de relations de préférences floues satisfont les critères : 1, 2 et 3 tandis que les méthodes basées sur les techniques de clarification satisfont seulement le critère 4.

L'efficience est un aspect important qui doit être considéré au moment de choisir une méthode de classement. Il est aussi important que les autres aspects tels que: la représentation de préférences floues, la rationalité de l'ordre de préférences, et la robustesse qui doivent être également considérés. Actuellement, grâce au développement de méthodes computationnelles plus rapides et plus accessibles, l'efficience peut être moins importante par rapport à la robustesse et la précision pour ce type de méthodes.

Dans la méthode présentée par Tseng et Klein (1989), les auteurs font valoir que leur méthode est capable de manier des nombres flous non normaux et non convexes. Toutefois cela représente une contradiction à la définition initiale de la méthode, parce qu'elle a été définie en considérant deux nombres flous normaux et convexes. Ils justifient que la méthode peut être capable de manier des nombres flous non normaux et non convexes à travers une comparaison visuelle comme une partie de son algorithme dans les pas 2 et 3. Nous considérons qu'il n'est pas pertinent d'inclure des comparaisons humaines ou manuelles qui compliquent l'autonomie des systèmes intelligents. Pour cette raison, ce type de comparaisons n'est pas considéré comme pertinent dans notre méthode.

En résumé, la méthode présentée dans le chapitre 3 offre des avantages intéressants par rapport à d'autres méthodes basées sur l'analyse des relations de préférence floues. L'illustration et la déclaration de toutes les situations possibles entre deux nombres flous peuvent être prises comme un cadre de référence pour le développement de nouveaux systèmes de prise de décisions basés sur l'application de la logique floue.

6.2 Avancées au niveau de la conception des familles de produits.

De plus en plus les compagnies conçoivent des familles de produit pour profiter des avantages qu'offre la personnalisation de masse, offrant une plus grande variété de produits tout en réduisant le coûts de produits par la standardisation des composants et des processus. La conception des familles de produits permet aussi le développement de produits différents pour satisfaire les besoins des différents types de clients dans chaque marché.

Le processus décisionnel joue un rôle important dans le succès de toute entreprise, et pratiquement tous les processus d'ingénierie impliquent différentes activités itératives et complexes de prise de décision. La base du processus de décision est le classement des nombres flous. La logique floue est de plus en plus utilisée dans les systèmes de décision assistée par ordinateur, puisqu'elle offre plusieurs avantages par rapport à d'autres techniques traditionnelles de prise de décision. L'application de la logique floue à plusieurs outils de prise de décision permet la considération d'une information imprécise comme variables d'entrée. Les méthodes de classement floues ont été largement appliquées dans un certain nombre de secteurs appliquant la relation de préférence floue dans l'évaluation de dessins de produits.

Dans ce contexte, l'application de la logique floue permet de prendre de décisions meilleures et plus précises en raison de la large gamme de réponses possibles qui peuvent être traitées au lieu de simplement d'être ou ne pas être intéressés à une caractéristique du produit comme permise par les outils traditionnels. Plusieurs tentatives ont été faites pour appliquer la logique floue, comme l'application de techniques d'inférence floue pour adapter l'imprécision des variables, le surclassement «outranking» flou pour prioriser les exigences de conception, les nombres flous pour représenter la nature imprécise des jugements, la régression floue pour déterminer identifier les relations fonctionnelles entre les caractéristiques d'ingénierie et les demandes du client.

Dans l'article présenté au chapitre 5 se retrouvent tous les outils développés dans cette recherche. Ces outils appuyés sur l'application de la logique floue sont intégrés dans une méthodologie globale pour la formation de familles de produits. Ces outils sont : une procédure pour effectuer la segmentation du marché, une procédure pour l'identification des modules interchangeables entre les produits, une procédure pour l'identification des configurations de produit alternatives et une procédure pour identifier une configuration générique de produit.

La segmentation du marché est largement considérée comme un des principaux moyens pour réaliser la personnalisation de masse. La logique floue a démontré comment elle pouvait contribuer à l'enrichissement de plusieurs techniques dans différents domaines. Le groupement «clustering» flou a été appliqué pour classifier les caractéristiques des clients pendant la première phase de la définition de produits. Cette définition est un aspect essentiel dans la conception des familles de produits sous une perspective de la personnalisation de masse. Une procédure en cinq étapes a été proposée dans la méthodologie. Ces étapes ont été : la considération de caractéristiques du produit, la représentation des préférences des clients en termes linguistiques, la représentation des préférences des clients en termes numériques, l'identification de groupes en appliquant la méthode de groupement flou «FCM, fuzzy c-means» et la sélection d'un scénario avec le meilleur ensemble de groupes. L'application du groupement flou représente une amélioration en comparaison avec l'application des techniques de groupement non flou, car il permet d'introduire des informations plus proches de celles exprimées par les consommateurs concernant leurs préférences. Pour identifier une configuration générique de produit dans la méthodologie, une procédure de quatre étapes a été proposée. Ces étapes ont été : la considération des préférences des clients, la fixation des priorités générale des préférences des clients, l'évaluation technique des caractéristiques du produit et la sélection des caractéristiques pour le produit. L'application de l'analyse des relations de préférence floues est employée pour évaluer et pour sélectionner les diverses caractéristiques pour la configuration de produits. Cela s'appuie sur l'utilisation de nombres flous pour représenter des préférences des clients et aussi pour caractériser les caractéristiques du produit.

L'identification des alternatives de caractéristiques communes, consiste à déterminer s'il existe des alternatives communes à toutes les configurations de produits. La liste des configurations génériques, identifiées pour chacun des groupes et présentées dans la Table 5.7, permet d'identifier une ou plusieurs alternatives communes à toutes les configurations. L'identification de ces alternatives communes peut être traduite ou interprétée comme les alternatives de caractéristiques qui sont préférées par tous les différents types de clients. Du point de vue de la personnalisation de masse, ces caractéristiques communes doivent être considérées comme fixes pour être partagées par toutes les différentes conceptions du produit.

Dans cette recherche, un module est défini comme l'intégration de deux ou plusieurs alternatives de caractéristiques du produit. Pour l'identification des modules possibles, une procédure en quatre phases a été proposée, ces phases sont : le classement des préférences de chaque caractéristique, l'analyse de la disponibilité d'alternatives pour chaque caractéristique, l'analyse des alternatives de caractéristiques communes entre les configurations de produits et finalement la formation de modules. Pour effectuer le classement des préférences des caractéristiques des produits, une analyse de la variance entre les centres des groupes «cluster centers» a été effectuée. La caractéristique avec la variance la plus petite est classée comme première dans la liste, suivie des caractéristiques dans l'ordre croissant de la variance. Grâce à l'analyse des préférences floues et au calcul des variances entre les centres des groupes il est possible d'identifier si après avoir choisi les configurations génériques des produits, il reste encore des alternatives qui permettent d'améliorer les configurations des produits selon les préférences de clients spécifiques si cela est nécessaire.

La configuration d'autres alternatives de produits a été effectuée en appliquant une procédure en deux phases. Ces phases ont été : (1) l'identification des caractéristiques qui ne présentent aucune alternative disponible et (2) la configuration du produit. Les alternatives disponibles sont celles qui n'ont pas été considérées dans aucune configuration comme c'est le cas pour : F_{12}, F_{31}, F_{32}, F_{34}, F_{35}, F_{36}, F_{41}, F_{44}, F_{51}, F_{53} et F_{55}, dans la Table 5.6 du chapitre 5. Au contraire, dans ce même tableau, il est montré que pour la caractéristique 2 (F_2) il n'existe aucune alternative disponible, ce qui signifie que ces deux alternatives F_{21} et F_{22} doivent être incluses dans les configurations alternatives du produit comme il est montré dans la Figure 5.10 du même chapitre. La configuration de masse des produits est obtenue à travers la combinaison des modules identifiés avec les caractéristiques des produits qui n'ont pas présenté d'alternatives disponibles comme illustré dans la Figure 5.10. Cette combinaison permet d'obtenir une liste de configurations alternatives de produits. La Table 5.9 montre la liste de caractéristiques pour chaque configuration du produit.

La configuration de produits personnalisés a été rendue possible grâce à l'application de la procédure présentée dans le pas 2 de cette méthodologie. Dans ce pas une procédure pour identifier une configuration générique de produit a été expliquée en détail, laquelle peut être appliquée pour obtenir des configurations personnalisées pour des clients spécifiques quand on utilisera comme variables d'entrée les préférences de ces clients.

Toute cette variété de configurations de produits, permet d'obtenir une gamme de différents types de produits en cherchant à satisfaire les différents types de consommateurs dans un marché cible. La famille de produits est le résultat des différents types de produits formés, comme : produits génériques pour les différents groupes identifiés, produits standardisés de manière modulaire et produits personnalisés pour des clients spécifiques. La Figure 5.11 montre les différents types de produits dans la famille. En considérant les préférences des groupes pour chaque caractéristique du produit, il est possible d'identifier quels sont les produits dans la famille qui sont plus connexes à chaque groupe comme montré dans la Figure 5.12 et la Table 5.11.

En conclusion, la formation de familles de produits a été améliorée par l'application et le développement de différents outils assistés par la logique floue. Ces améliorations contribuent à augmenter les niveaux de satisfaction des clients en enrichissant les processus de prise de décisions à travers l'analyse des relations des préférences floues des clients en ce qui concerne les caractéristiques du produit.

CHAPITRE 7 : CONCLUSIONS ET PERSPECTIVES

7.1 Conclusions

Cette recherche part de la nécessité de définir des familles de produits à travers des procédures plus précises qui permettent une meilleure interprétation de l'information utilisée dans le processus de définition de ces familles. Dans les marchés globalisés, toujours plus compétitifs, les clients peuvent opter pour des produits et des services qui satisfont au mieux leurs besoins, à partir de n'importe quel point de la planète. Cette situation a rendu les consommateurs plus exigeants. Pour faire face à cette situation, nous avons considéré l'application de la logique floue pour aider à la définition des familles de produits, à travers le développement et l'amélioration de plusieurs outils. Le choix de la logique floue comme outil pour l'amélioration des différents processus est basée sur une vaste analyse de la littérature présentée dans le chapitre 2, en analysant les différents sujets en rapport au développement des familles de produits, ainsi que l'application de la logique floue dans différents sujets en rapport à la conception des familles de produits.

Dans ce contexte, nous avons proposé d'aider les entreprises et les consommateurs à configurer les produits qui couvrent mieux les demandes et les besoins de chacun. Nous proposons différents outils appuyés sur l'application de la logique floue pour améliorer la conception des familles de produits. La logique floue permet de manier des informations imprécises en termes linguistiques comme : « beaucoup », « un peu » et ainsi de suite, et non seulement manier des informations en termes binaires comme : « oui » ou « non ». L'intégration de tous ces outils a permis le développement d'une méthodologie globale pour la formation des familles de produits à partir d'une nouvelle approche, l'utilisation de la logique floue, qui permet la considération d'informations plus proches de celles exprimées par les consommateurs. Le tout permet la conception de produits plus conformes à ceux attendus par les clients.

Ce travail de recherche présente des avancées à deux niveaux. D'une part, à l'égard de la logique floue et l'autre par rapport à la conception des familles de produits.

Au niveau de la logique floue, une amélioration de la méthode de classement de nombres flous a été présentée dans le chapitre 3. Cette amélioration a consisté à permettre de classer deux ou plusieurs nombres flous normaux et convexes, avec différentes fonctions d'appartenance, comme trapézoïdal, triangulaire ou rectangulaire. Aussi, une autre amélioration dans ce chapitre a été la définition de vingt-neuf cas généraux pour évaluer toutes les situations possibles entre deux nombres flous normaux et convexes. Ces cas ont été définis en utilisant des fonctions d'appartenance trapézoïdales comme modèle général pour supporter des fonctions triangulaires et rectangulaires aussi. Cette définition présente l'illustration et la déclaration de toutes les interactions possibles entre deux nombres flous, elle permet de fournir un cadre de référence pour faciliter l'inclusion d'autres fonctions d'appartenance ainsi que la considération de nombres flous non normaux et non convexes permettant la caractérisation d'autres variables avec des comportements différents. Ces améliorations sont significatives puisque la majorité des méthodes de classement dans la catégorie des méthodes basées sur l'analyse des relations de préférences floues, sont limitées au classement des paires de nombres flous avec des fonctions d'appartenance triangulaires ou rectangulaires.

Au niveau de la conception des familles de produits, différents outils ont été développés et intégrés dans une méthodologie globale pour la formation de familles de produits. Ces outils aidés par la logique floue correspondent à différentes méthodes et procédures conçues pour s'occuper de différentes situations comme : la segmentation du marché, l'identification de modules interchangeables et la configuration de produits. L'application du groupement flou a permis de classer les caractéristiques des clients pendant la définition de produits, ce qui représente une amélioration par rapport aux autres techniques de groupement non flou. Grâce au groupement flou il est possible d'avoir certains clients qui appartiennent à différents groupes avec différents degrés d'appartenance. À la fin, selon les variables considérées dans l'analyse, il est possible de trouver les meilleurs ensembles de groupes qui représentent adéquatement les différents segments du marché. L'identification de caractéristiques communes et l'identification des modules sont des procédures qui ont été aussi améliorées à travers l'application de la logique floue : par exemple, l'analyse de la variance entre les centres des groupes pour le classement des préférences des caractéristiques des produits. La configuration de produits est une procédure qui a été améliorée à travers l'application de l'analyse des relations de préférence floues pour évaluer et sélectionner les diverses caractéristiques des produits pour former une configuration du produit plus adéquate selon les préférences des consommateurs.

Il est important de remarquer que la méthode de classement proposée au chapitre 3 est limitée au classement de nombres flous normaux et convexes. Cette limitation est également présente dans toutes les méthodes basées sur l'analyse des relations de préférence floues. Ceci répond tout de même à trois des quatre critères que doit satisfaire une bonne méthode de classement flou.

Les résultats de cette recherche sont utiles pour tous ceux qui ont besoin de comparer différentes options de produits à travers l'application de la procédure classement flou développée pour améliorer le processus de prise de décisions dans le processus de conception de produits. Pour tous ceux qui ont besoin de sélectionner des alternatives de produits au moyen de l'application de la procédure développée pour cette fin considérant les préférences floues des clients. Pour tous ceux qui souhaitent former des produits plus conformes aux désirs et aux nécessités des consommateurs considérant ses préférences floues en ce qui concerne à certaines caractéristiques des produits et les services et aussi considérant les préférences floues des différents segments du marché à travers l'application des méthodes développées pour cette fin, lesquels considère, la configuration du produit comme un aspect clé pour la formation d'une famille de produits, afin de satisfaire les demandes des principaux segments du marché.

Et finalement, pour tous ceux qui considèrent important et nécessaire le développement de familles de produits à travers des outils plus précis qui permettent un meilleur maniement de l'information dans tout ce processus.

7.2 Perspectives

Ce travail de recherche exploratoire fait le lien entre deux domaines assez indépendants. Même s'il propose des contributions dans les deux directions, il reste encore de nombreuses voies à explorer.

Une perspective à considérer au niveau de la logique floue, est l'inclusion d'autres fonctions d'appartenance continues comme : fonctions gaussiennes normalisées, fonctions sigmoïdales, fonctions Bell entre autres. Les fonctions linéaires comme les triangulaires et les trapézoïdales sont préférées grâce à leur simplicité et efficience, mais quelques applications peuvent requérir des courbes continues comme celles précédemment mentionnées, cela pourrait améliorer la modélisation des préférences des clients. Bien que les fonctions d'appartenance gaussienne et Bell atteignent une grande finesse, elles sont incapables de modéliser les fonctions d'appartenance asymétriques, qui sont importantes dans certaines applications, ce qu'il faudra considérer.

Autre perspective à considérer au niveau de la logique floue, est de prouver la possibilité ou la non possibilité de classer des nombres non normaux et non convexes à travers des méthodes basées sur l'analyse des relations de préférence floues. Il est possible de remarquer dans la comparaison des méthodes de classement flou présenté dans la Table 4.10, que seules les méthodes basées sur les techniques de clarification ont la capacité de classer des nombres non normaux, ce qui paraît logique étant donné la nature de ce type de méthodes. De notre point de vue, ces méthodes sont moins précises, puisque leur processus de classement est fait sur une information clarifiée « deffuzified » laquelle ne représente pas les termes linguistiques avec la même précision.

Au niveau de la conception des familles de produits, il est important de remarquer que la méthodologie proposée dans le chapitre 5, considère la configuration de produits à travers la sélection de caractéristiques du produit. Pour cette raison, une perspective est l'étude et l'analyse au niveau des composants du produit, pour identifier les composants communs entre tous les designs de produits différents dans une famille de produits, ainsi qu'évaluer la possibilité de former des modules interchangeables en intégrant les composants communs selon les restrictions physiques, techniques et fonctionnelles des produits et des entreprises.

Même si chaque procédure et chaque méthode proposées ont été validées à travers des applications académiques à caractère industriel, une autre perspective au niveau des familles de produits, est la validation des procédures et des méthodes ainsi que de la méthodologie sur une famille de produits réelle. En raison de la nature de la méthodologie, basée sur la sélection de caractéristiques du produit «product features», certaines applications pertinentes peuvent être sur les produits configurables comme : les ordinateurs personnels, les ordinateurs portables, les voitures, certains types de maisons, et même la sélection du cours dans un plan de formation pour une entreprise avec certains besoins.

Une autre perspective est l'inclusion de certaines procédures proposées dans les processus en ligne de quelques entreprises, pour la configuration automatisée de produits selon les préférences des clients. Cette application représente une amélioration considérable au processus de sélection des caractéristiques du produit, puisque ce processus peut être simplifié en diminuant la quantité de questions nécessaires pour connaître les préférences du client et aussi en permettant que les réponses puissent être exprimées dans termes plus familiaux aux consommateurs.

La nature générale des outils proposés dans cette recherche, permet son application dans différents domaines très divers. Par exemple, en marketing, certaines méthodes et procédures peuvent être appliquées pour identifier les caractéristiques des produits et des services qui doivent être exploitées dans une campagne de publicité. Une compagnie de téléphonie cellulaire peut profiter de certaines procédures proposées, pour former les différents plans qu'il offrira pour ses différents types de clients.

BIBLIOGRAPHIE

Agard, B. (2004). Conception et fabrication des familles de produits : Etat de l'art. *Journal Européen des Systèmes Automatisés, 38*(1-2), 59-84.

Agard, B., & Kusiak, A. (2004a). Data-mining-based methodology for the design of product families. *International Journal of Production Research, 42*(15), 2955-2969.

Agard, B., & Kusiak, A. (2004b). Standardization of components, products and processes with data mining. *Proceeding of the International Conference on Production Research Americas, Santiago, Chile* (pp. 1-9).

Agard, B., & Tollenaere, M. (2003a). Méthodologie de conception des familles de produits. *Journal Européen des Systèmes Automatisés, 37*(6), 755-777.

Agard, B., & Tollenaere, M. (2003b). Design of product families: methodology and application. *Proceeding of the 14th International Conference on Engineering Design – ICED'03, Stockholm, Sweden.*

Aldanondo, M., Veron, M., & Fargier, H. (1999). Configuration in manufacturing industry requirements, problems and definitions. *Proceeding of the IEEE International Conference on Systems, Man and Cybernetics* (Vol. 6, pp. 1009-1014). IEEE.

Anderson, D.M. (1997). *Agile product development for mass customization* (1e éd.). Chicago, IL, USA: Irwin Professional Publishing.

Baas, S. M., & Kwakernaak, H. (1977). Rating and ranking of multiple-aspect alternatives using fuzzy sets. *Automatica, 13*(1), 47-58.

Barajas, M., & Agard, B. (2009a). Improved fuzzy ranking procedure for decision making in product design. *International Journal of Production Research,* accepté.

Barajas, M., & Agard, B. (2009b). A methodology to form product families through fuzzy product configuration, *Rapport de recherche du CIRRELT-2009-30,* soumis à *International Journal of Engineering Design,* en revue.

Barajas, M., & Agard, B. (2009c). The use of fuzzy logic in product family development: literature review and opportunities. *Rapport de recherche du CIRRELT-2009-31,* soumis à *Journal of Intelligent Manufacturing,* en revue.

Barajas, M., & Agard, B. (2009d). Fuzzy product configuration based on market segmentation to form a family of products. *Proceeding of the 42nd CIRP Conference on Manufacturing Systems, Grenoble, France.*

Barajas, M., & Agard, B. (2009e). Iterative product configuration with fuzzy logic. *Proceeding of the International Conference on Industrial Engineering and Systems Management - IESM' 2009, Montréal, Canada*.

Barajas, M., & Agard, B. (2008a). A ranking procedure for fuzzy decision-making in product design. *Proceeding of the IDMME - Virtual Concept 2008 International Conference, Beijing, China.*

Barajas, M., & Agard, B. (2008b). Selection of products based on customers preferences applying fuzzy logic. *Proceeding of the IDMME - Virtual Concept 2008 International Conference, Beijing, China*.

Biao, Y., Burns, N.D., & Backhouse, C.J. (2004). Postponement: a review and an integrated framework. *International Journal of Operations and Production Management, 24*(5), 468-487.

Burgess, R.H. (1997). Mass customization and process improvement: competitive dynamic model. *Proceedings of the Annual Meeting of Decision Sciences Institute, San Diego, CA, USA.*

Büyüközkan, G., & Feyzioğlu, O. (2005). Group decision making to better respond customer needs in software development, *Computers & Industrial Engineering, 48*(2), 427-441.

Büyüközkan, G., & Feyzioğlu, O. (2004a). A fuzzy-logic-based decision-making approach for new product development. *International Journal of Production Economics, 90*(1), 27-45.

Büyüközkan, G., & Feyzioğlu, O. (2004b). A new approach based on soft computing to accelerate the selection of new product ideas. *Computers and Industry, 54*(2), 151-167.

Callahan, S. (2006). Extended generic product structure: An information model for representing product families. *Journal of Computing and Information Science in Engineering, 6*(3), 263-275.

Chang, W. (1981). Ranking of fuzzy utilities with triangular membership functions. *Proceedings of the International Conference on Policy Analysis and Information Systems*, (pp. 263-272).

Chen C.-B., & Klein C. M. (1994). Fuzzy Ranking Methods for Multi-Attribute Decision Making. *Proceeding of the International Conference on Systems, Man, Cybernetics* (Vol. 1, pp. 475-480). IEEE.

Chen S.-J., & Chen S.-M. (2007). Fuzzy risk analysis based on the ranking of generalized trapezoidal fuzzy numbers. *Applied Intelligence: The International Journal of Artificial Intelligence, Neural Networks, and Complex Problem-Solving Technologies, 26*(1), 1-11.

Chen Y-S. (1999). Fuzzy Ranking and Quadratic Fuzzy Regression. *Computers and Mathematics with Applications, 38*(11-12), 265-279.

Chen, C., & Wang, L. (2008a). Integrating rough set clustering and grey model to analyse dynamic customer requirements. *Journal of Engineering Manufacture, 222*(2), 319-332.

Chen, C., & Wang, L. (2008b). Product platform design through clustering analysis and information theoretical approach. *International Journal of Production Research, 46*(15), 4259-4284.

Chen, C.Y., Chen, L.C., & Lin, L. (2004a). Methods for processing and prioritizing customer demands in variant product design. *IIE Transactions (Institute of Industrial Engineers), 36*(3), 203-219.

Chen, L. -Ch., & Lin, L. (2002). Optimization of product configuration design using functional requirements and constraints. *Research in Engineering Design, 13*(3), 167-182.

Chen, L. -H., Kao, C., Kuo, S., Wang, T. -Y, and Jang, Y.-C. (1996). Productivity diagnosis via fuzzy clustering and classification: an application to machinery industry. *Omega, 24*(3), 309-319.

Chen, L.H., & Weng, M.C. (2006). An evaluation approach to engineering design in QFD processes using fuzzy goal programming models. *European Journal of Operational Research, 172*(1), 230-248.

Chen, S.-H, (1985). Ranking fuzzy numbers with maximizing set and minimizing set. *Fuzzy Sets and Systems, 17*(2), 113-129.

Chen, S.J., & Hwang, C.L. (1992). *Fuzzy multiple attribute decision making methods and applications.* Lecture notes in economics and mathematical systems. New York: Springer.

Chen, S.-M., & Wang, C.-H. (2009). Fuzzy risk analysis based on ranking fuzzy numbers using α-cuts, belief features and signal/noise ratios. *Expert Systems with Applications, 36*(3-1), 5576-5581.

Chen, Y., Fung, R.Y.K., & Tang, J. (2006). Rating technical attributes in fuzzy QFD by integrating fuzzy weighted average method and fuzzy expected value operator. *European Journal of Operational Research, 174*(3), 1553-1566.

Chen, Y., Fung, R.Y.K., & Tang, J. (2005). Fuzzy expected value modelling approach for determining target values of engineering characteristics in QFD. *International Journal of Production Research, 43*(17), 3583-3604.

Chen, Y., Tang, J., Fung, R.Y.K., & Ren, Z. (2004b). Fuzzy regression-based mathematical programming model for quality function deployment. *International Journal of Production Research, 42*(5), 1009-1027.

Chiu, S. (1996). Method and software for extracting fuzzy classification rules by subtractive clustering. *Proceeding of the Annual Conference of the North American Fuzzy Information Processing Society - NAFIPS, New Frontiers in Fuzzy Logic and Soft Computing* (pp. 461-465). IEEE.

Da Cunha, C., & Agard, B. (2005). Composition of modules' stock using simulated annealing. *Proceeding of the IEEE International Symposium on Assembly and Task Planning (ISATP),* Montreal, QC, Canada.

Da Cunha, C., Agard, B., & Kusiak, A. (2007). Design for cost: Module-Based Mass Customization. *IEEE Transactions on Automation Science and Engineering, 4*(3), 350-359.

Dahmus, J.B., Gonzalez-Zugasti, J.P., & Otto, K.N. (2001). Modular product architecture. *Design Studies, 22*(5), 409-424.

Dai, Z. (2005). *Robust product family design.* Ph.D. University of Illinois, Chicago, Illinois, USA.

Dai, Z., & Scott, M. J. (2007). Product platform design through sensitivity analysis and cluster analysis. *Journal of Intelligent Manufacturing, 18*(1), 97-113.

Dai, Z., & Scott, M.J. (2006). Effective product family design using preference aggregation. *Transactions of the ASME. Journal of Mechanical Design, 128*(4), 659-667.

Deciu, E.R., Ostrosi, E., Ferney, M., & Gheorghe, M. (2005). Configurable product design using multiple fuzzy models. *Journal of Engineering Design, 16*, 209-235.

Delgado, M., Verdegay, J. L., & Vila, M. A. (1988). A procedure for ranking fuzzy numbers using fuzzy relations. *Fuzzy Sets and Systems, 26*(1), 49-62.

Dong J., Xiao T., & Qiao G. (2001). Study on a configuration framework for product family. *High Technology Letters, 7*(4), 58-62.

Du, X. (2000). *Architecture of product family for mass customization.* Ph.D. Hong Kong University of Science and Technology, Hong Kong.

Erens, F., & Verhulst, K. (1997). Architectures for product families. *Computers in Industry, 33*(2-3), 165-178.

Ertay, T., & Kahraman, C. (2007). Evaluation of design requirements using fuzzy outranking methods. *International Journal of Intelligent Systems, 22*(12), 1229-1250.

Fan, Z.-P., Ma, J., & Zhang, Q. (2002). An approach to multiple attribute decision making based on fuzzy preference information on alternatives. *Fuzzy Sets and Systems, 131*(1), 101-106.

Feitzinger, E., & Lee, H.L. (1997). Mass Customization at Hewlett-Packard: the Power of Postponement. *Harvard Business Review, 75*, 116-120.

Fellini, R. A. (2003). *A model-based methodology for product family design.* Ph.D. University of Michigan, Michigan, USA.

Fellini, R., Kokkolaras, M., Papalambros, P., & Perez-Duarte, A. (2005). Platform selection under performance bounds in optimal design of product families. *Journal of Mechanical Design, Transactions of the ASME, 127*(4), 524-535.

Feyzioğlu, O., & Büyüközkan, G. (2006). Evaluation of New Product Development Projects using Artificial Intelligence and Fuzzy Logic. *Proceeding of the World Academy Of Science, Engineering And Technology, 11*(February), 183-189.

Fung, R.Y.K., Law, D.S.T., & Ip, W.H. (1999). Design targets determination for inter-dependent product attributes in QFD using fuzzy inference. *Integrated Manufacturing Systems, 10*(6), 376-383.

Fung, R.Y.K., Tang, J., Tu, Y., & Wang, D. (2002). Product design resources optimization using a non-linear fuzzy quality function deployment model. *International Journal of Production Research, 40*(3), 585-599.

Gao, F., Xiao, G., & Chen, J. -J. (2008). Product interface reengineering using fuzzy clustering. *CAD Computer Aided Design, 40*(4), 439-446.

Gonzalez-Zugasti, J.P., Otto, K.N., & Baker, J.D. (2001). Assessing value in platformed product family design. *Research in Engineering Design - Theory, Applications, and Concurrent Engineering, 13*, 30-41.

Gonzalez-Zugasti, J.P., Otto, K.N., & Baker, J.D. (2000). Method for architecting product platforms. *Research in Engineering Design - Theory, Applications, and Concurrent Engineering, 12*(2), 61-72.

Gungor, Z., & Arikan, F. (2000). A fuzzy outranking method in energy policy planning. *Fuzzy Sets and Systems, 114*(1), 115-122.

Gupta, S., & Krishnan, V. (1998). Product family-based assembly sequence design methodology. *IIE Transactions (Institute of Industrial Engineers), 30*(10), 933-945.

Hanumaiah, N., Ravi, B., & Mukherjee, N.P. (2006). Rapid hard tooling process selection using QFD-AHP methodology. *Journal of Manufacturing Technology Management, 17*(3), 332-350.

He, D.W., & Kusiak, A. (1997). Design of assembly systems for modular products. *IEEE Transactions on Robotics and Automation, 13*, 646-655.

Helo, P. T. (2006). Product configuration analysis with design structure matrix. *Industrial Management + Data Systems, 106*(7), 997-1011.

Ho, T. K., Ip, K. H., & Tsang, C. W. (2009). Service bid comparisons by fuzzy ranking in open railway market timetabling. *Expert Systems with Applications, 36*(7), 10334-10343.

Hsiao, S. -W., & Liu, E. (2005). A structural component-based approach for designing product family. *Computers in Industry, 56*(1), 13-28.

Huang, G.Q., Simpson, T.W., & Pine II, B.J. (2005). The power of product platforms in mass customisation. *International Journal of Mass Customisation, 1*(1), 1-13.

Işıklar G., & Büyüközkan, G. (2007). Using a multi-criteria decision making approach to evaluate mobile phone alternatives. *Computer Standards & Interfaces, 29*(2), 265-274.

Jarventausta, P., Verho, P., & Partanen, J. (1994). Using fuzzy sets to model the uncertainty in the fault location process of distribution networks. *IEEE Transactions on Power Delivery, 9*(2), 954-960.

Jiang, B. C., & Chi-Hsing H. (2001). Fuzzy decision modeling for manufacturability evaluation under the concurrent engineering environment. *Proceedings of the Joint 9th IFSA World Congress and 20th NAFIPS International Conference, Vancouver, BC, Canada,* (Vol. 5 pp. 1511-16). IEEE.

Jiang, Z. H., & Yan, J.Q. (2003). Research and development on constraint-based product family design and assembly simulation. *Proceeding of the 9th International Manufacturing Conference, Journal of Material Processing Technology Hong Kong, China,* (Vol. 139, pp. 257-62). Elsevier.

Jiao, J. (1998). *Design for mass customization by developing product family architecture*. Ph.D. Hong Kong University, Pokfulam, Hong Kong.

Jiao, J., & Tseng, M. M. (2000). Understanding product family for mass customization by developing commonality indices. *Journal of Engineering Design, 11*(3), 225-243.

Jiao, J., & Tseng, M.M. (1999). A methodology of developing product family architecture for mass customization. *Journal of Intelligent Manufacturing, 10*(1), 3-20.

Jiao, J., & Tseng, M. M. (1998). Fuzzy Ranking for Concept Evaluation in Configuration Design for Mass Customization. *Concurrent Engineering: Research and applications, 6*(3), 189-206.

Jiao, J., & Zhang, Y. (2005). Product portfolio identification based on association rule mining. *CAD Computer Aided Design, 37*(2), 149-172.

Jiao, J., Tseng, M.M., Duffy, V.G., & Fuhua L. (1998). Product family modeling for mass *customization. Proceeding of the 22nd International Conference on Computers and Industrial Engineering, Cairo, Egypt* (Vol. 35, pp. 495-498). Elsevier Sci Ltd, Exeter, United Kingdom.

Jose, A., & Tollenaere, M. (2005). Modular and platform methods for product family design: Literature analysis. *Journal of Intelligent Manufacturing, 16*(3), 371-390.

Kalargeros, N., & Gao, J.X. (1998). QFD: Focusing on its simplification and easy computerization using fuzzy logic principles. *International Journal of Vehicle Design, 19*(3), 315-325.

Kim, K. (1998). *Commonality and product design*. Ph.D. University of Illinois, Urbana-Champaign, Illinois, USA.

Kim, K.J., Moskowitz, H., Dhingra, A., & Evans, G. (2000). Fuzzy multicriteria models for quality function deployment. *European Journal of Operational Research, 121*(3), 504–518.

Koga, T., & Ohta, H. (2005). A new method of operating on fuzzy sets in quality function deployment. *Journal of Japan Industrial Management Association, 56*(3), 191-199.

Krishnan, V., Singh, R., & Tirupati, D. (1999). A model-based approach for planning and developing a family of technology-based products. *Manufacturing & Service Operations Management, 1*(2), 132-156.

Kumar, D., Chen, W., and Simpson, T. W. (2009). A market-driven approach to product family design. *International Journal of Production Research, 47*(1), 71-104.

Kuo, T. C., Chang, S.-H., & Huang, S. H. (2006). Environmentally conscious design by using fuzzy multi-attribute decision-making. *International Journal of Advanced Manufacturing Technology, 29*(3-4), 209-215.

Kusiak, A. (1999). *Engineering Design: Products, Processes, and Systems* (1e éd.). San Diego, CA, USA: Academic Press.

Lee, H. S. (2000). A new fuzzy ranking method based on fuzzy preference Relation. *Proceeding of the International Conference on Systems,* (Vol. 5, pp. 3416-3420). IEEE.

Lee, H.L., & Tang, C.S. (1997). Modelling the costs and benefits of delayed product differentiation. *Management Science, 43*(1)*,* 40-53.

Lee, J.-H., & You, K-H. (2003). A fuzzy Ranking Method for Fuzzy Numbers. *IEICE Transactions, Fundamentals,* E86-A, 2650-2658.

Lee, L.-W., & Chen, S.-M. (2008). Fuzzy risk analysis based on fuzzy numbers with different shapes and different deviations. *Expert Systems with Applications, 34*(4), 2763-2771.

Li, B., Chen, L., Huang, Z., & Zhong, Y. (2006). Product configuration optimization using a multiobjective genetic algorithm. *International Journal of Advanced Manufacturing Technology, 30*(1-2), 20-29.

Lin, Ch-T., & Chen, Ch-T. (2004). A Fuzzy-Logic-Based Approach for New Product Go/NoGo Decision at the Front End. *IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans, 34*(1), 132-142.

Lingling, L., Quanming, Z., Zhigang, L., & Huijuan, Z. (2006). Product design based on clustering analyzing and fuzzy recognition. *Proceeding of the Conference on Cybernetics and Intelligent Systems*. IEEE.

Liqing, G., Li, Z., Shan, H., & Hongwei, Li. (2008). Fuzzy ranking approach for conceptual design evaluation. *Proceedings of the 27th Chinese Control Conference, CCC,* (pp. 379-383). Inst. of Elec. and Elec. Eng. Computer Society.

Ma, L.-Ch., & Li, H.-L. (2008). A fuzzy ranking method with range reduction techniques. *European Journal of Operational Research, 184*(3), 1032-1043.

Meng, X., Jiang, Z., & Huang, G. Q. (2007). On the module identification for product family development. *International Journal of Advanced Manufacturing Technology, 35*(1-2), 1-2, 26-40.

Messac, A., Martinez, M. P., & Simpson, T. W. (2002). Introduction of a product family penalty function using physical programming. *Journal of Mechanical Design, Transactions of the ASME 124*(2), 164-172.

Meyer, M.H., Tertzakian, P., & Utterback, J.M. (1997). Metrics for managing research and development in the context of the product family. *Management Science, 43*(1), 88-111.

Mishra, A. K. (1999). *Optimization models for component commonality in assemble-to-order systems*. Ph.D. University of Pittsburgh, Pennsylvania, USA.

Modarres, M., & Sadi-Nezhad, S. (2001). Ranking fuzzy numbers by preference ratio. *Fuzzy Sets and Systems, 118*(3), 429-436.

Moon, S.K., Kumara, S.R.T., & Simpson, T.W. (2006). Data mining and fuzzy clustering to support product family design. *Proceeding of the 2006 ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, DETC2006, Philadelphia, PA, USA*. American Society of Mechanical Engineers.

Nanda, J., Thevenot, H.J., & Simpson, T.W. (2005). Product family representation and redesign: Increasing commonality using formal concept analysis. *Proceeding of the ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, DETC2005, Long Beach, CA, USA* (Vol. 2, pp. 969-978). American Society of Mechanical Engineers.

Nepal, B.P. (2005). *An integrated framework for modular product architecture.* Ph.D. Wayne State University, Michigan, USA.

Ninan, J. A. (2007). A platform cascading method for scale based product family design. *Ph.D. dissertation,* University of Oklahoma.

Park, J., & Simpson T.W. (2005). AN activity-based costing method for product family design in the early of development. *Proceeding of the ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, DETC2005, Long Beach, CA, USA* (Vol. 2, pp. 959-968). American Society of Mechanical Engineers.

Pine II, J. (1993). *Mass customization: The new frontier in business competition* (1e éd.). Boston, Massachisetts: Harvard Business School Press.

Rai, R., & Allada, V. (2003). Modular Product Family Design: Agent-Based Pareto-Optimization and Quality Loss Function-Based Post-Optimal Analysis. *International Journal of Production Research, 41*(17), 4075-4098.

Ramasamy, N.R., & Selladurai, V. (2004). Fuzzy logic approach to prioritise engineering characteristics in quality function deployment (FL-QFD). *International Journal of Quality Reliability Management, 21*(9), 1012-1023.

Roy, B., & Vincke, P. (1984). Relational Systems of Preferences with One or More Pseudo-Criteria: Some New Concepts and Results. *Management Science, 30*(11), 1323-1335.

Salvador, F., Forza, C., & Rungtusanatham, M. (2002). Modularity, product variety, production volume, and component sourcing: Theorizing beyond generic prescriptions. *Journal of Operations Management, 20*(5), 549-575.

Sered, Y., & Reich, Y. (2006). Standardization and modularization driven by minimizing overall process effort. *CAD Computer Aided Design, 38*(5), 405-416.

Shao, X. -Y., Wang, Z.-H., Li, P.-G., & Feng, C.-X. J. (2006). Integrating data mining and rough set for customer group-based discovery of product configuration rules. *International Journal of Production Research, 44*(14), 2789-2811.

Shaowei, G. (2006). Discussion of the design philosophy and modified non-expert fuzzy set model for better product design. *Journal of Engineering Design, 17*(6), 533-548.

Shen, L., Zhou, Z., Li, M., Zhao, W., Li, Y., Wu, M., & Zheng, J.J. (2005). Costumer oriented virtual cooperative product design. *Proceeding of the 9th International Conference on Computer Supported Cooperative Work in Design, Coventry, UK* (Vol. 1, pp. 164-169). Institute of Electrical and Electronics Engineers Computer Society.

Shipley, M.F., de Korvin, A., & Yoon, J.M. (2004). Fuzzy quality function deployment: determining the distributions of effort dedicated to technical change. *International Transactions in Operational Research, 11*(3), 293-307.

Siddique, Z., & Adupala, R. (2005). Product family architecture reasoning. *Proceeding of the ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, DETC2005, Long Beach, CA, USA* (Vol. 5, pp. 413-421). American Society of Mechanical Engineers.

Siddique, Z., & Ninan, J.A. (2005). A grammatical approach to support real-time design of customized products. *Proceeding of the ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, DETC2005, Long Beach, CA, USA* (Vol. 3, pp. 971-981). American Society of Mechanical Engineers.

Simpson, T. W. (2004). Product platform design and customization: Status and promise. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AIEDAM, 18*(1), 3-20.

Simpson, T.W., & Mistree, F. (1999). A Concept Exploration Method for Product Platform and Product Family Design. *Proceeding of the Optimization in Industry II Conference - 1999, Banff, AB, Canada,* (Vol. 2, pp. 371-386). American Society of Mechanical Engineers.

Simpson, T.W., Seepersad, C.C., & Mistree, F. (2001). Balancing commonality and performance within the concurrent design of multiple products in a product family. *Concurrent Engineering Research and Applications, 9*(3), 177-190.

Sivard, G. (2001). *A generic information platform for product families*. Ph.D. Kungliga Tekniska Hogskolan, Sweden.

Smith, C. and Verma, D., (2004). Conceptual system design evaluation: rating and ranking versus compliance analysis. *Systems Engineering, 7*(4), 338-351.

Sopadang, A., Cho, B.R., & Leonard, M.S. (2001-2002). Development of a scaling factor identification method using design of experiments for product-family-based product and process design. *Quality Engineering, 14*(2), 319-29.

Su, J.C.P., Chang, Y.L., & Ferguson, M. (2005). Evaluation of postponement structures to accommodate mass customization. *Coordinating Product Design, Process Design and Supply Chain Design Decisions: Journal of Operations Management, 23*(3-4), 305-318.

Sun, H., & Wu, J. (2006). A new approach for ranking fuzzy numbers based on fuzzy simulation analysis method. *Applied Mathematics and Computation, 174*(1), 755-767.

Thevenot, H.J. (2006). *A method for product family redesign based on component commonality analysis.* Ph.D. Pennsylvania State University, Pennsylvania, USA.

Thevenot, H.J., & Simpson, T.W. (2006). A comprehensive metric for evaluating component commonality in a product family. *Proceeding of the 2006 ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, DETC2006, Philadelphia, PA, USA.* American Society of Mechanical Engineers.

Thevenot, H.J., & Simpson, T.W. (2004). A comparison of commonality indices for product family design. *Proceeding of the 2004 ASME Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Salt Lake City, UT, USA* (Vol. 1, pp. 169-178). American Society of Mechanical Engineers.

Thevenot, H.J., Nanda, J., & Simpson, T.W. (2007). Redesigning product families using heuristics and shared ontological component information. *Proceedings of the 2006 IEEE International Conference on Information Reuse and Integration, Waikoloa Village, HI* (pp. 330-335). Inst. of Elec. and Elec. Eng. Computer Society.

Thevenot, H.J., Nanda, J., & Simpson, T.W. (2005). A methodology to support product family redesign using a genetic algorithm and commonality indices. *Proceeding of the ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, DETC2005, Long Beach, CA, USA* (Vol. 2, pp. 1009-1018). American Society of Mechanical Engineers.

Tseng, H. -E., Chang, Ch. -Ch., & Chang, Sh. -H. (2005). Applying case-based reasoning for product configuration in mass customization environments. *Expert Systems with Applications, 29*(4), 913-925.

Tseng, M. M, Jiao, J., & Merchant M. E. (1996). Design for mass customization. *CIRP Annals – Manufacturing Technology, 45*(1), 153-156.

Tseng, M. M., & Jiao, J. (1997). A module identification approach to the electrical design of electronic products by clustering analysis of the design matrix. *Computers & Industrial Engineering, 33*(1-2), 229-233.

Tseng, T. Y., & Klein, C. M. (1989). New algorithm for the ranking procedure in fuzzy decision making. *IEEE Transaction Systems, Man and Cybernetics, 19*(5), 1289-1296.

Tseng, T. Y., & Klein, C. M. (1988). A survey and comparative study of ranking procedures in fuzzy decision making. *Dept. Ind. Eng., Univ. Missouri-Columbia, Working Paper*, 881210.

Van Hoek, R.I. (2001). The rediscovery of postponement a literature review and directions for research. *Journal of Operations Management, 19*(2), 161-184.

Vanegas, L.V., & Labib, A.W. (2005). Fuzzy approaches to evaluation in engineering design. *Journal of Mechanical Design, Transactions of the ASME 127*, 24-33.

Vanegas, L.V., & Labib, A.W. (2001a). A fuzzy quality function deployment (FQFD) model for deriving optimum targets. *International Journal of Production Research, 39*(1), 99-120.

Vanegas, L.V., & Labib, A.W. (2001b). Application of new fuzzy-weighted average (NFWA) method to engineering design evaluation. *International Journal of Production Research, 39*(6), 1147-1172.

Wang, H.J., Zhang, Q., & Zhao, T.T. (2005). A SA-based method for developing modular product family. *Proceeding of the International Conference on Machine Learning and Cybernetics, ICMLC 2005, Guangzhou, China* (pp. 2483-2488). Institute of Electrical and Electronics Engineers Computer Society.

Wang, J. (1997). A fuzzy outranking method for conceptual design evaluation. *International Journal of Production Research, 35*(4), 995-1010.

Wang, J. (1999). Fuzzy outranking approach to prioritize design requirements in quality function deployment*. International Journal of Production Research, 37*(4), 899-916.

Wang, Y.-M., & Parkan, C. (2005). Multiple attribute decision making based on fuzzy preference information on alternatives: Ranking and weighting. *Fuzzy Sets and Systems, 153*(3), 331-346.

Wijnstra, J.G. (2005). Classifying product families using platform coverage and variation mechanisms. *Software - Practice and Experience, 35*(5), 413-444.

Wu, D., & Mendel, J., (2009). A comparative study of ranking methods, similarity measures and uncertainty measures for interval type-2 fuzzy sets. *Information Sciences, 179*(8), 1169-1192.

Xianghui, M., Zuhua, J., & Gq, H. (2007). On the module identification for product family development. *International Journal of Advanced Manufacturing Technology, 35*(1-2), 1-2, 26-40.

Xu, R., & Wunsch II, D. (2005). Survey of clustering algorithms. *IEEE Transactions on Neural Networks, 16*(3), 3, 645-678.

Ye, X., & Gershenson, J. K. (2008). Attribute-based clustering methodology for product family design. *Journal of Engineering Design, 19*(6), 571-586.

Yi, G., Zhang, S., & Tan, J. (2006). Product configuration design based on multi-layer evolution. *Proceeding of the ASME International Conference on Mechatronics and Embedded Systems and Applications, Beijing, China.* IEEE.

Yu, L., & Wang, L. (2007). Two-stage product definition for mass customization. *Proceeding of the 5th International Conference on Industrial Informatics, Vienna, Austria* (Vol. 2, pp. 699-704). IEEE.

Yuan, Y. (1991). Criteria for evaluating fuzzy ranking methods. *Fuzzy Sets and Systems, 43*(2), 139-157.

Zha, X.F., Sriram, R.D., & Lu, W.F. (2004). Evaluation and selection in product design for mass customization: A knowledge decision support approach. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AIEDAM, 18*(1), 87-109.

Zhang, K. (2006). System analysis of new product family development selection. *Wuhan Ligong Daxue Xuebao/Journal of Wuhan University of Technology, 28*, 177-180.

Zhang, Q., Wang, Y., & Yang, Y. (2007). Fuzzy multiple attribute decision making with eight types of preference information on alternatives. *Proceeding of the Symposium on Computational Intelligence in Multicriteria Decision Making, MCDM 2007*, (pp288-293). IEEE.

Zhang, W.Y., Tor, S.Y., & Britton, G.A. (2006). Managing modularity in product family design with functional modeling. *International Journal of Advanced Manufacturing Technology 30*(7-8), 579-588.

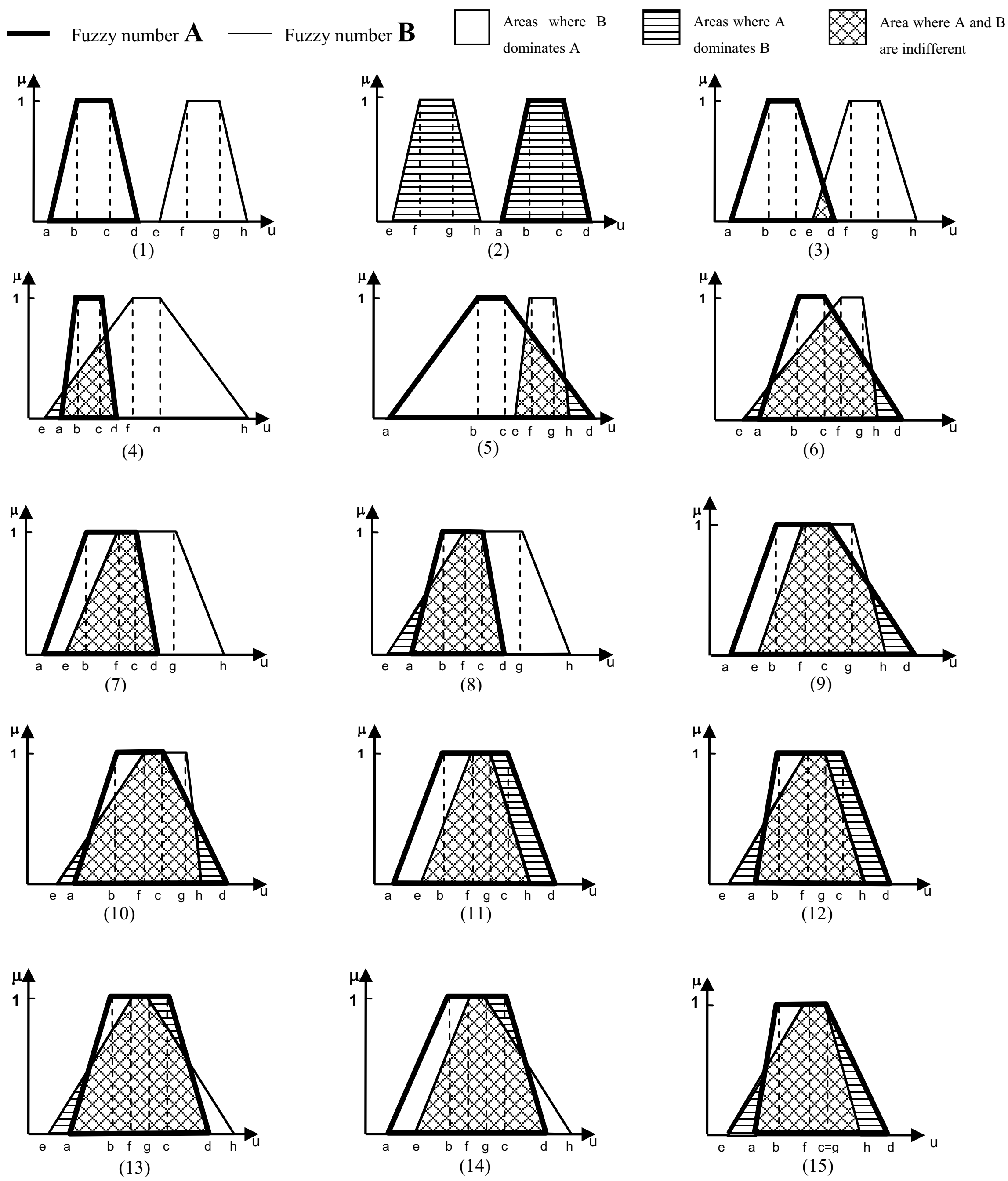
Zhang, Y., Jiao, J., & Ma, Y. (2007). Market segmentation for product family positioning based on fuzzy clustering. *Journal of Engineering Design, 18*(3), 227-41.

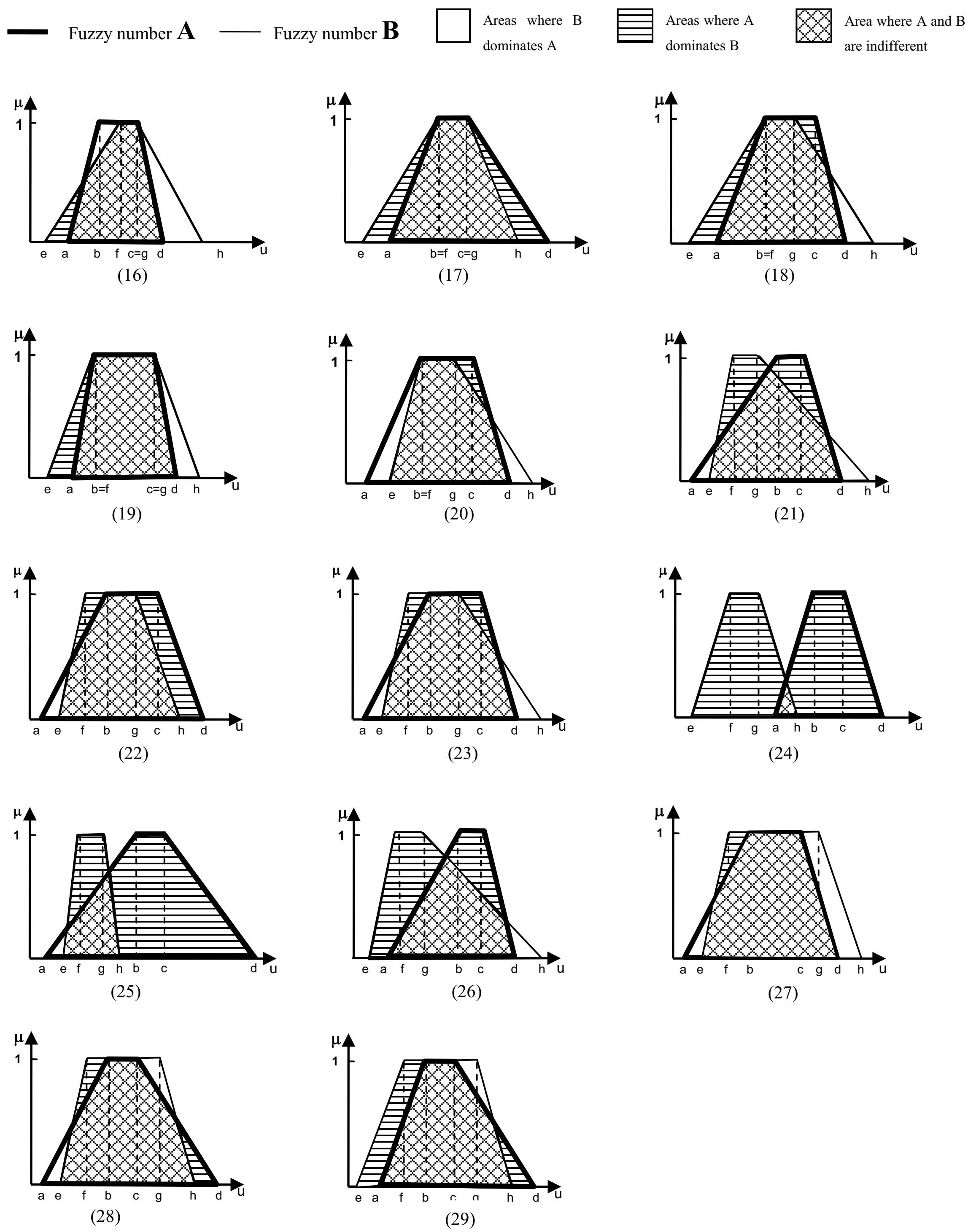
Zhu, B., Wang, Z., Yang, H., & Li, H. (2006). Study on approach to fuzzy product configuration based on vague customer requirements. *Materials Science Forum 532-533*, 1068-1071.

Zhu, B., Wang, Z., Yang, H., Mo, R., & Zhao, Y. (2008). Applying fuzzy multiple attribute decision making for product configuration. *Journal of Intelligent Manufacturing, 19*(5), 591-598.

Zimmermann H.-J. (1991). *Fuzzy set theory and its applications* (2e éd.). Boston, Massachusetts, USA: Kluwer Academic Publishers.

ANNEXE A: Twenty-nine cases of the general trapezoidal pairwise of fuzzy numbers (nommé comme Appendix 1 dans le chapitre 4)




Fuzzy number A
Fuzzy number B
Areas where B dominates A
Areas where A dominates B
Area where A and B are indifferent
(16)
(17)
(18)
(19)
(20)
(21)
(22)
(23)
(24)
(25)
(26)
(27)
(28)
(29)

ANNEXE B: Customer preferences for each product feature (nommé comme Appendix 1 dans le chapitre 5)

Customer	Product Features				
	F_1	F_2	F_3	F_4	F_5
1	5	4	3	4	2
2	1	2	2	3	4
3	4	3	2	3	2
4	1	2	3	4	5
5	5	5	3	4	1
6	5	4	3	3	2
7	4	4	3	5	2
8	2	2	2	3	4
9	5	4	3	2	1
10	5	4	2	2	2
11	1	3	3	3	4
12	2	2	3	3	3
13	1	1	3	4	5
14	2	3	2	3	4
15	1	3	3	3	5
16	5	4	3	2	1
17	5	4	3	3	2
18	1	2	3	4	4
19	2	2	3	3	3
20	5	4	3	3	1
21	3	3	2	3	2
22	5	5	3	4	1
23	1	2	2	2	5
24	5	5	3	4	2
25	1	2	2	4	5
26	1	1	2	5	5
27	3	2	3	3	2
28	5	4	2	1	1
29	1	2	3	4	5
30	5	4	3	3	2

ANNEXE C: Fuzzy preference relation of cluster 2 (nommé comme Appendix 2a dans le chapitre 5)

$F_{ij}\backslash C_{ki}$	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}
	[7 9 10 10]	[5 6 8 9]	[3 5 5 7]	[3 5 5 7]	[1 2 4 5]
F_{11} [0 1 4 6]	0.0000				
F_{12} [2 4 6 8]	0.0208				
F_{13} [7 8 10 10]	0.4444				
F_{21} [0 4 5 7]		0.0952			
F_{22} [8 9 10 10]		0.9444			
F_{31} [0 1 2 3]			0.0000		
F_{32} [1 2 3 4]			0.0000		
F_{33} [3 4 5 7]			0.4444		
F_{34} [4 5 6 8]			0.6667		
F_{35} [6 7 8 9]			0.9167		
F_{36} [7 8 10 10]			1.0000		
F_{41} [0 2 4 6]				0.1875	
F_{42} [2 3 6 7]				0.4167	
F_{43} [4 6 7 9]				0.7750	
F_{44} [7 8 10 10]				1.0000	
F_{51} [0 1 2 3]					0.2000
F_{52} [1 2 4 5]					0.5000
F_{53} [2 3 5 6]					0.6667
F_{54} [3 4 6 7]					0.8333
F_{55} [5 6 8 9]					1.0000
F_{56} [7 8 10 10]					1.0000

ANNEXE D: Fuzzy preference relation of cluster 3 (nommé comme Appendix 2b dans le chapitre 5)

$F_{ij}\backslash C_{ki}$	C_{31}	C_{32}	C_{33}	C_{34}	C_{35}
	[0 0 1 3]	[1 2 4 5]	[3 5 5 7]	[5 6 8 9]	[7 9 10 10]
F_{11} [0 1 4 6]	0.7692				
F_{12} [2 4 6 8]	0.9792				
F_{13} [7 8 10 10]	1.0000				
F_{21} [0 4 5 7]		0.6429			
F_{22} [8 9 10 10]		1.0000			
F_{31} [0 1 2 3]			0.0000		
F_{32} [1 2 3 4]			0.0000		
F_{33} [3 4 5 7]			0.4444		
F_{34} [4 5 6 8]			0.6667		
F_{35} [6 7 8 9]			0.9167		
F_{36} [7 8 10 10]			1.0000		
F_{41} [0 2 4 6]				0.0000	
F_{42} [2 3 6 7]				0.1429	
F_{43} [4 6 7 9]				0.4167	
F_{44} [7 8 10 10]				0.8182	
F_{51} [0 1 2 3]					0.0000
F_{52} [1 2 4 5]					0.0000
F_{53} [2 3 5 6]					0.0000
F_{54} [3 4 6 7]					0.0000
F_{55} [5 6 8 9]					0.1333
F_{56} [7 8 10 10]					0.4444

ANNEXE E: Fuzzy preference relation of customer X (nommé comme Appendix 3 dans le chapitre 5)

$F_{ij}\backslash C_{ki}$	C_{x1}	C_{x2}	C_{x3}	C_{x4}	C_{x5}
	[7 9 10 10]	[7 9 10 10]	[7 9 10 10]	[7 9 10 10]	[7 9 10 10]
F_{11} [0 1 4 6]	0.0000				
F_{12} [2 4 6 8]	0.0208				
F_{13} [7 8 10 10]	0.4444				
F_{21} [0 4 5 7]		0.0000			
F_{22} [8 9 10 10]		0.5714			
F_{31} [0 1 2 3]			0.0000		
F_{32} [1 2 3 4]			0.0000		
F_{33} [3 4 5 7]			0.0000		
F_{34} [4 5 6 8]			0.0000		
F_{35} [6 7 8 9]			0.1667		
F_{36} [7 8 10 10]			0.4444		
F_{41} [0 2 4 6]				0.0000	
F_{42} [2 3 6 7]				0.0000	
F_{43} [4 6 7 9]				0.1000	
F_{44} [7 8 10 10]				0.4444	
F_{51} [0 1 2 3]					0.0000
F_{52} [1 2 4 5]					0.0000
F_{53} [2 3 5 6]					0.0000
F_{54} [3 4 6 7]					0.0000
F_{55} [5 6 8 9]					0.1333
F_{56} [7 8 10 10]					0.4444