

Fuzzy Product Configuration based on Market Segmentation to Form a Product Family

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Abstract

Product configuration is a key issue in the development of products which most closely conform to the expectations of customers, thereby enhancing customer satisfaction. It provides a means to customize products in such a way as to meet the requirements of different niches of the market. In this context, this paper proposes a fuzzy product configuration procedure to define product configurations based on the requirements of different market segments. A customer satisfaction metric is also proposed, which would be applied to each configuration. An illustrative example is provided to demonstrate the applicability and practicality of this procedure.

Keywords:

Product configuration, fuzzy logic, fuzzy clustering, market segmentation, product family

1 INTRODUCTION

Market segmentation is widely considered to be a principal means to achieve mass customization, because it permits the identification and fulfilment of individual customer wants and needs without sacrificing efficiency, effectiveness, and low cost [1]. It does so by identifying groups of customers with similar wants and needs. Various clustering techniques are then applied in the design of product platforms with a view to determining the values customers share, considering the changing nature of their requirements.

The use of fuzzy logic is thought to enrich the performance of clustering tools. It has been used, for example, to analyze the productivity of companies by identifying clusters in training productivity patterns, and fuzzy clustering has been combined with other tools, such as the similarity matrix, to reengineer product interfaces by identifying the relationships between them and attempting to reduce their redundancy.

Fuzzy clustering approaches have also been proposed to identify groups of customers having similar preferences in the principal segments of the market, the objective being to design the set of products to make up a product family by considering the engineering characteristics, and by establishing the relationship between customer preferences and product attributes. Also, fuzzy C-Means Clustering has been applied to classify the characteristics of customers during the first stage of product definition in order to design product families from a mass customization perspective.

This paper is organized as follows: Section 2 presents a literature review focusing on three topics: market segmentation, product configuration, and product configuration considering fuzzy logic. Section 3 describes a method for product configuration and presents an illustrative application to show its applicability. Section 4 concludes the paper and suggests some future research directions.

2 LITERATURE REVIEW

In this section, a number of recent works on market segmentation and product configuration are analyzed, beginning with market segmentation in the first part. The second and third parts analyze product configuration, with and without the application of fuzzy logic respectively.

2.1 Market segmentation

Market segmentation makes it possible to identify different customer groups with similar needs and wants with respect to goods and services, and with similar patterns of behaviour. In this context, a number of clustering techniques have been applied to aid in the development of product design. These techniques constitute an important data analysis tool with several applications in business areas like engineering, marketing, manufacturing, logistics, and so on. Some of these works are presented below.

In [2], clustering techniques have been applied to identify the optimal building blocks for formulating product family architectures by applying inductive learning software to identify clusters that match the design parameters and the product's functional requirements. Similarly, in [3], clustering analysis has been used to analyze the design matrix to identify modules by mapping the relationships between functional requirements and design parameters.

More recently, clustering analysis has been combined with other tools, such as fuzzy recognition in product design, to form standard structural trees of products according to the design requirements [4]. Cluster and sensitivity analysis have been used to design multiple-platform configurations in an attempt to improve the product family design [5]. In this way, cluster analysis has been applied to the design of product platforms by analyzing products designed individually and determining the optimal number of common values for each platform [6]. Clustering techniques have also been used to analyze the relationship between product features and customer requirements and to analyze the changing trends in those requirements [7].

Fuzzy logic has demonstrated how it contributes to the enrichment of several techniques in many different areas, and clustering techniques have been significantly developed to include it. Fuzzy clustering has been used to analyze company productivity using two methods, the fuzzy C-Means algorithm and the fuzzy K-NN algorithm, to identify clusters in training productivity patterns [8]. Also, fuzzy clustering has been combined with the similarity matrix to reengineer product interfaces by identifying the relationships between them and trying to reduce their redundancy [9].

In the context of the product family, a fuzzy clustering approach is proposed to identify groups of customers having similar preferences the principal segments of the

market, with the objective of designing the proper set of products for a product family by considering the engineering characteristics, and by establishing the relationship between customer preferences and product attributes [10]. Also, fuzzy C-Means Clustering is applied to classify the characteristics of customers during the first stage of a proposed product definition method, which is an essential issue in designing product families from a mass customization perspective [11].

2.2 Product configuration

Product configuration deals with the relative logical and spatial arrangements of the various parts/sub-assemblies of a product with respect to one another [12]. Product configuration is an important area of opportunity for developing products more strongly based on customer requirements and with the goal of mass customization, as well as for developing a large variety of products taking into account a company's constraints and limitations.

Several tools have been developed to address this important issue, among them the following two. One is an approach designed to find the perfect match between product configuration and industry requirements considering three principal steps: product configuration, bill of materials configuration, and routing configuration [13]. The other is designed to evaluate product configurations by applying a design structure matrix to show the interaction flow between configuration elements [14]. This latter approach was proposed to evaluate the product configuration from the sales point of view. Other works have attempted to optimize the product configuration process based on a multi-objective genetic algorithm [15].

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 [16]. Also, an interesting application of the case-based reasoning algorithm has been presented to reduce the design time and cost, and generate an accurate bill of materials at the beginning of the product design process [17].

In the same way, a methodology and 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 [18]. 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 [19]. Even though fuzzy logic has been applied in some of the above works, these applications remain only partial. In the next section, we look at works in which the application of fuzzy logic in the product configuration process figures more prominently.

2.3 Fuzzy logic in product configuration

Fuzzy logic has been increasingly applied during recent decades in other issues related to product configuration, such as concept evaluation, design requirements, company capabilities, and customer requirements. Some of these applications are explained below.

A fuzzy ranking methodology for concept evaluation has been developed to evaluate a conceptual design in the context of mass customization. This methodology evaluates and selects, from a set of alternatives, the one that can satisfy customer needs while also considering

the design requirements and the technical capabilities of the company [20]. In other words, it translates customer needs into applicable alternatives which will satisfy customer needs and wants by applying fuzzy inference to establish the relationship between those needs and wants and product alternatives [21].

An integrated approach to the design of configurable products has been developed based on multiple fuzzy models, such as fuzzy product specification, the fuzzy functional network, the fuzzy physical solution, and the fuzzy constraint model, to translate customer specifications into physical solutions dealing with various forms of uncertainty, such as imprecision, randomness, fuzziness, ambiguity, and incompleteness [22]. Another approach to product configuration [23] considers 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 [24].

The following section proposes an iterative method for product configuration applying fuzzy logic, in an attempt to contribute to the formation of a family of products which improves customer satisfaction by offering products which most closely meet to the expectations of different segments of the market.

3 FUZZY PRODUCT CONFIGURATION TO FORM A FAMILY OF PRODUCTS

In this section, we consider product configuration as a key issue in the process of obtaining different products from different segments of the market to form a family of products to satisfy customer wants and needs.

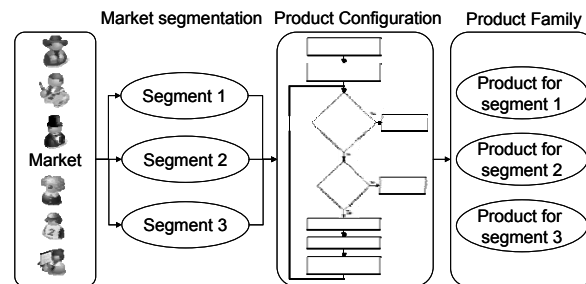


Figure 1: Product family formation through product configuration.

Figure 1 depicts the principal phases of this proposition as a framework consisting of three principal phases: market segmentation to identify the target niches of the market, product configuration to select the appropriate product configuration for each segment of the market, and product family formation, which is the result of the product configuration. All these phases are explained below.

3.1 Market segment identification

Various tools can be used to segment the market. In this work, we consider that fuzzy clustering can be applied to achieve this task. Let us suppose that a design team decided to use the Matlab fuzzy logic toolbox for this purpose. This toolbox contains two techniques, Fuzzy C-Means (FCM) Clustering and Subtractive Clustering. FCM is a data clustering technique wherein each data point belongs to a cluster to some degree that is specified by a membership grade. Subtractive Clustering is a very good

algorithm for estimating the number of clusters for a set of data. After the design team had completed this process, three principal clusters emerged. These are depicted in Figure 2.

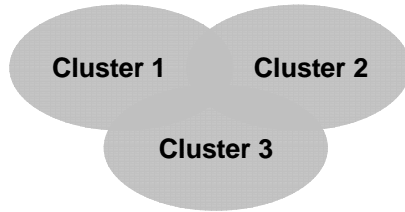


Figure 2: Market segmentation by fuzzy clustering.

3.2 Product configuration procedure

For the product configuration phase, we adapt the fuzzy product selection method proposed in [25], where the analysis of the fuzzy preference relation represents a fundamental means for evaluating the relationship between product features and customer preferences. To calculate the preference relation, a method presented by Tseng and Klein [26] and adapted by Barajas and Agard [27] is applied here.

The proposed configuration method consists of the following eight phases:

1. Definition of initial product configuration
2. Evaluation of initial product configuration
3. Evaluation of customer satisfaction
4. Analysis of replacement possibilities
5. Identification of features to change
6. Replacement of features
7. Evaluation of upgraded product configuration
8. Evaluation of final product configuration

This process starts with the definition of the initial product configuration that conforms to the set of the cheapest alternatives for each feature. To evaluate this configuration, which is an important step, the level of customer satisfaction must be determined. If the initial configuration does not satisfy the customer requirements, improvements must be made through an analysis of the replacement possibilities to determine which features should be changed. Then, if possible, all those features identified are replaced. The new configuration is evaluated and compared with the customer's preferences to confirm whether or not it satisfies their preferences. All these phases are explained in the example below.

We use a laptop configuration to illustrate the proposed method. A manufacturer aims to customize production according to the preferences of the end customer. Let us suppose that three principal segments of the market were identified from the clustering process in section 3.1 (see Figure 2). The individuals in Cluster 1 are highly interested in the entire product's features, those in Cluster 2 are more interested in storage capacity, and those in Cluster 3 are more concerned with performance speed (see Table 3). To achieve the manufacturer's objective, it is necessary to select a list of configurable key features in an attempt to increase the compatibility between the product and the customer preferences. These key features should be selected considering criteria such as manufacturability, modularity, commonality, compatibility, and functionality, among others.

After this process had been completed, the design team found that the most relevant features for a laptop configuration are: processor, operating system, display, memory, and hard drive. All these features and their various alternatives are illustrated in Figure 3, where it can be noted that there are three different alternatives for the processor (F_{11} , F_{12} , F_{13}), two for the operating system (F_{21} , F_{22}), six for the display (F_{31} , F_{32} , F_{33} , F_{34} , F_{35} , F_{36}), four for the memory (F_{41} , F_{42} , F_{43} , F_{44}), and six for the hard drive (F_{51} , F_{52} , F_{53} , F_{54} , F_{55} , F_{56}). Let us suppose that a cost/benefit analysis has been performed to list the different alternatives of each feature hierarchically, and the versions are such that F_{ij+1} outperform F_{ij} .

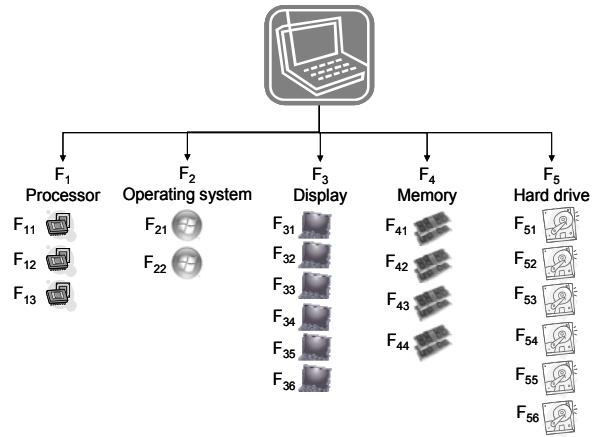


Figure 3: Key configurable features.

Let us now follow each phase of the method.

1. Definition of initial product configuration

As mentioned previously, the initial product configuration is made up of the lowest and cheapest alternative of each feature (see Figure 4).

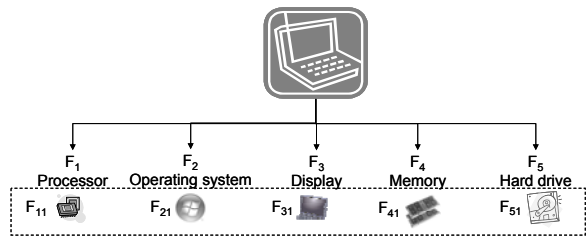


Figure 4: Initial product configuration.

2. Evaluation of initial product configuration

We evaluate this configuration by adapting the method proposed in [25], which consists of four steps: market and technical evaluation of products, general prioritization of features, customer preference consideration, and evaluation of final product configuration. These steps are applied as follows.

- *Market and technical evaluation of products.* Let us suppose that a group of experts evaluated each feature by evaluating the cost/benefit ratio for each of the selected product features, and they used fuzzy numbers to represent their results. These numbers are listed in Table 1. An example of how to represent them is shown in Figure 5. This corresponds to the alternatives for feature F_1 .

F1	F2	F3	F4	F5
[03510]	[04610]	[01210]	[02410]	[01210]
[05710]	[08910]	[02410]	[03610]	[02310]
[08910]	—	[04510]	[05710]	[03410]
—	—	[05610]	[081010]	[04610]
—	—	[05710]	—	[05710]
—	—	[08910]	—	[08910]

Table 1: Feature alternatives represented by fuzzy numbers.

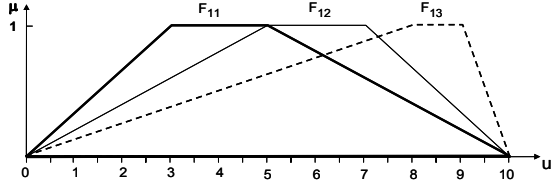


Figure 5: Fuzzy number depiction of feature F₁.

- **General prioritization of features.** In the same way, a general feature prioritization has been performed by using a customer survey to define their preferences about the product in question. These preferences have been expressed in colloquial terms, such as not important, somewhat important, moderately important, important, and highly important, as listed in Table 2 and depicted in Figure 6.

Level of prioritization	Fuzzy number representation
HI - 'Highly Important'	[1 9 10 10]
I - 'Important'	[1 6 7 9]
M - 'Moderately Important'	[1 5 5 9]
SI - 'Somewhat Important'	[1 3 4 9]
NI - 'Not Important'	[0 0 1 9]

Table 2: Feature prioritization represented by fuzzy numbers.

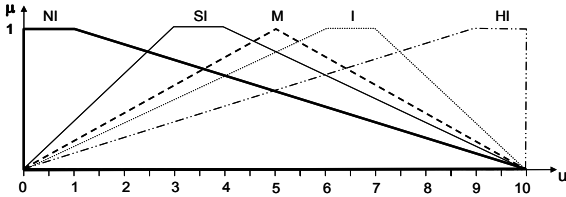


Figure 6: Depiction of feature prioritization

- **Customer preference consideration.** Three different clusters were identified previously. Table 3 presents the feature preferences for each segment of the market expressed in colloquial or linguistic terms, as listed in Table 2.

Product features	Customer preference		
	Cluster 1	Cluster 2	Cluster 3
F1. Processor	HI	M	HI
F2. Operating system	HI	SI	M
F3. Display	HI	I	I
F4. Memory	HI	M	HI
F5. Hard drive	HI	HI	SI

Table 3: Feature preference for each market segment.

- **Evaluation of product configuration.** Let $R(A,B)$ be the fuzzy preference relation and $\mu R(A, B)$ be the membership function representation of $R(A,B)$. According to [26], if the membership degree $\mu R(A,B)$ is equal to 0.5, then A and B are indifferent.

3. Evaluation of customer satisfaction

We can apply Equation 1 to evaluate the level of customer satisfaction (CS) once a possible product configuration has been found.

$$CS_j = \left[\frac{\sum_{j=1}^m R(A_{ij}, B_{ki}) / m}{0.5} \right] \times 100 \quad (1)$$

where:

- $R(A_{ij}, B_{ki})$ is the fuzzy preference relation between A_{ij} and B_{ki}
- $A_{ij} = \{A_{11}, A_{21}, \dots, A_{nm}\}$ is the set of features (i) for each configuration (j) $\forall i \in [1, n]$, and $\forall j \in [1, m]$.
- $B_{ki} = \{B_{11}, B_{12}, \dots, B_{pn}\}$ is the set of customer preferences (k) for each feature (i) $\forall k \in [1, p]$, and $\forall i \in [1, n]$.

If the percentage of customer satisfaction is less than the fixed level of acceptance, then a feature replacement should be performed if one is available. For this application, six different evaluations were performed (see Table 4 and Figure 7).

4. Analysis of replacement possibilities

If the percentage of customer satisfaction falls short of the customer's expectations, it is necessary to check whether or not other features are available for replacement. To perform this evaluation, all the products' features should be listed in a hierarchical way, where the first option belongs to the lowest option for each feature. For example, if there exist five different options for F_1 (A_1), a hierarchical code can be expressed as (A_{ij}), where (i) identifies the feature, and (j) identifies the hierarchical precedence as $A_{11}, A_{12}, A_{13}, A_{14}, A_{15}$. This codification is depicted in Figure 3, where it can be noted that there exist five different options for F_1 , and their hierarchical codes are expressed as (F_{ij}), where (i) and (j) identify the feature and the hierarchical precedence respectively, as, for example, $F_{11}, F_{12}, F_{13}, F_{14}, F_{15}$. The same process applies for the rest of the features.

5. Identification of features to change

If the hierarchical precedence of the feature (A_{ij}) in the current product configuration is less than a maximum A_{ij} ($j < j_{max}$), there exists a replacement opportunity for that feature.

6. Replacement of features

Once all the replacement opportunities for each feature have been identified, they must all (A_{ij}) be replaced by the next feature (A_{ij+1}) on the hierarchical list.

7. Evaluation of upgraded product configuration

For each replacement iteration, the upgraded configuration must be evaluated by applying the procedure explained in phase 2.

8. Evaluation of final product configuration

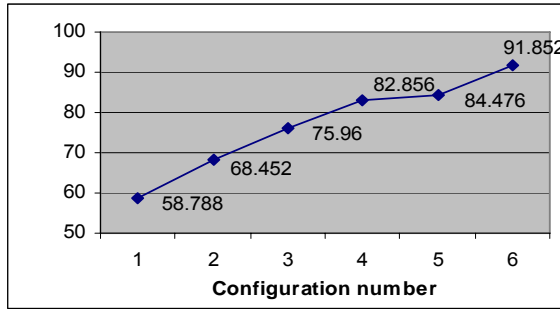
For each product configuration, it is possible to evaluate the level of customer satisfaction by applying Equation 1. If this percentage is greater than or equal to the acceptance percentage fixed by the customer, then the new product configuration satisfies the customer preferences. If not, an unsatisfactory product configuration is obtained. For this application, let us

consider a minimum level of customer satisfaction of 90%.

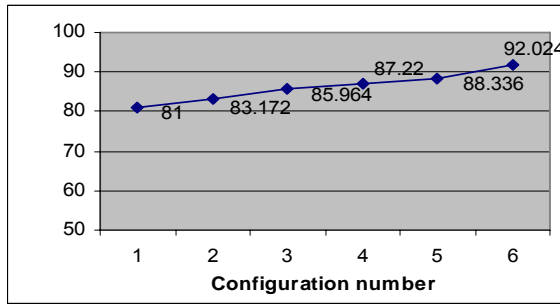
Iteration	Configuration Improvement by iteration		
	Cluster 1	Cluster 2	Cluster 3
1	58.788	81	73.536
2	68.452	83.172	78.332
3	75.96	85.964	85.728
4	82.856	87.22	90.368
5	84.476	88.336	
6	91.852	92.024	

Table 4: Customer satisfaction by iteration.

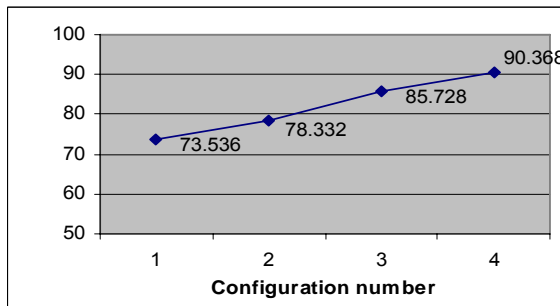
Table 4 displays the changes in the customer satisfaction percentage for all possible iterations to obtain a new product configuration.



(a)



(b)



(c)

Figure 7: Percentage of customer satisfaction for each segment of the market.

Figure 7 shows that the best configuration for segment or cluster 1 corresponds to the configuration during iteration 6, letter (a), for segment 2 during iteration 6, letter (b), and for segment 3 during iteration 4, letter (c). Appendix 1 presents the fuzzy preference relations for all possible

iterations used to obtain these customer satisfaction percentages.

3.3 Product family formation

The features required to make up the best configuration for each segment of the market are listed in Table 5 and depicted in Figure 8 by adapting Figure 3.

Market segment	Product configuration
1	$F_{13} - F_{22} - F_{36} - F_{44} - F_{56}$
2	$F_{11} - F_{21} - F_{33} - F_{41} - F_{56}$
3	$F_{13} - F_{21} - F_{33} - F_{44} - F_{51}$

Table 5: Set of features for each product configuration.

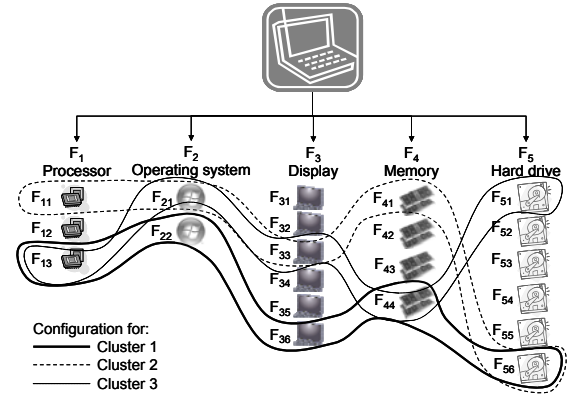


Figure 8: Feature identification for each product configuration.

4 CONCLUSIONS

Product configuration has demonstrated its major contribution to developing better products aimed at increasing customer satisfaction. In our work here, fuzzy logic has been applied to enrich this ability. We are proposing a method to configure suitable products for different segments of the market, which consists basically in the selection of an initial product configuration, iterative evaluation of the product configuration, evaluation of customer satisfaction for each configuration, analysis of feature replacement possibilities, identification of features to change, replacement of selected features, and reevaluation of the new product configuration. The fuzzy preference relation and an adapted pseudo-order preference model have been applied as principal tools to perform the proposed iterative method, and a way to evaluate customer satisfaction for each product configuration has been proposed. If the percentage of customer satisfaction reaches a predetermined threshold, the iterative process of feature replacement stops. The application presented in section 3 reveals the practical applicability of fuzzy logic in the various areas, like the formation of a family of modular and scalable products to satisfy the needs and wants of different types of customers grouped in clusters. Some future research directions could include the integration of tools to include fuzzy logic in a general methodology to optimize the design of product families.

ACKNOWLEDGMENTS

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APPENDIX 1A: FUZZY PREFERENCE RELATION PER CLUSTER 1

$F_j C_k$	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
	[091010]	[091010]	[091010]	[091010]	[091010]
$F_{11}[03510]$	0.3106				
$F_{12}[04610]$		0.3344			
$F_{13}[01210]$			0.2674		
$F_{14}[02410]$				0.2899	
$F_{15}[01210]$					0.2674
$F_{11}[05710]$	0.3623				
$F_{12}[08910]$		0.4545			
$F_{13}[02410]$			0.2899		
$F_{14}[03610]$				0.3205	
$F_{15}[02310]$					0.2841
$F_{11}[08910]$	0.4545				
————		0.4545			
$F_{13}[04510]$			0.3247		
$F_{14}[05710]$				0.3623	
$F_{15}[03410]$					0.303
————	0.4545				
————		0.4545			
$F_{13}[05610]$			0.3497		
$F_{14}[081010]$				0.4783	
$F_{15}[04610]$					0.3344
————	0.4545				
————		0.4545			
$F_{13}[05710]$			0.3623		
————				0.4783	
$F_{15}[05710]$					0.3623
————	0.4545				
————		0.4545			
$F_{13}[08910]$			0.4545		
————				0.4783	
$F_{15}[08910]$					0.4545

APPENDIX 1B: FUZZY PREFERENCE RELATION PER CLUSTER 2

$F_j C_k$	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}
	[05510]	[03410]	[06710]	[05510]	[091010]
$F_{11}[03510]$	0.4545				
$F_{12}[04610]$		0.5652			
$F_{13}[01210]$			0.3247		
$F_{14}[02410]$				0.4132	
$F_{15}[01210]$					0.2674
$F_{11}[05710]$	0.4545				
$F_{12}[08910]$		0.5652			
$F_{13}[02410]$			0.3623		
$F_{14}[03610]$				0.4132	
$F_{15}[02310]$					0.2841
$F_{11}[08910]$	0.4545				
————		0.5652			
$F_{13}[04510]$			0.4132		
$F_{14}[05710]$				0.4132	
$F_{15}[03410]$					0.303
————	0.4545				
————		0.5652			
$F_{13}[05610]$			0.4132		
$F_{14}[081010]$				0.4132	
$F_{15}[04610]$					0.3344
————	0.4545				
————		0.5652			
$F_{13}[05710]$			0.4132		
————				0.4132	
$F_{15}[05710]$					0.3623
————	0.4545				
————		0.4545			
$F_{13}[08910]$			0.4545		
————				0.4783	
$F_{15}[08910]$					0.4545

APPENDIX 1C: FUZZY PREFERENCE RELATION PER CLUSTER 3

F_{C_i}	C_{g1}	C_{g2}	C_{g3}	C_{g4}	C_{g5}
	[091010]	[05510]	[06710]	[091010]	[03410]
$F_{11}[03510]$	0.3106				
$F_{12}[04610]$		0.5			
$F_{13}[01210]$			0.3247		
$F_{14}[02410]$				0.2899	
$F_{15}[01210]$					0.4132
$F_{16}[05710]$	0.3623				
$F_{17}[08910]$		0.5			
$F_{18}[02410]$			0.3623		
$F_{19}[03610]$				0.3205	
$F_{20}[02310]$					0.4132
$F_{21}[08910]$	0.4545				
————		0.5			
$F_{22}[04510]$			0.4132		
$F_{23}[05710]$				0.3623	
$F_{24}[03410]$					0.4132
————	0.4545				
————		0.5			
$F_{25}[05610]$			0.4132		
$F_{26}[081010]$				0.4783	
$F_{27}[04610]$					0.4132

REFERENCES

[1] Pine II, J. (1993). Mass customization: The new frontier in business competition, Boston, Massachusetts: Harvard Business School Press. Boston, MA.

[2] Tseng, M.M, Jiao, J., and Merchant M.E. (1996). Design for mass customization. CIRP Annals – Manufacturing Technology, vol. 45, no. 1, pp. 153-156.

[3] Tseng, M.M. and Jianxin, J. (1997). A module identification approach to the electrical design of electronic products by clustering analysis of the design matrix. Computers & Industrial Engineering, vol. 33, no. 1-2, pp. 229-233.

[4] Lingling, L., Quanming, Z., Zhigang, Li, and Huijuan, Z. (2006). Product design based on clustering analyzing and fuzzy recognition. 2006 IEEE Conference on Cybernetics and Intelligent Systems.

[5] Dai, Z. and Scott, M.J. (2007). Product platform design through sensitivity analysis and cluster analysis. Journal of Intelligent Manufacturing, vol. 18, no. 1, pp. 97-113.

[6] Chen, C. and Wang, L. (2008). Product platform design through clustering analysis and information theoretical approach. International Journal of Production Research, vol. 46, no. 15, pp. 4259-4284.

[7] Chen, C. and Wang, L. (2008). Integrating rough set clustering and grey model to analyze dynamic customer requirements. Journal of Engineering Manufacture, vol. 222, no. 2, pp. 319-332.

[8] 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, vol. 24, no. 3, pp. 309-319.

[9] Gao, F., Xiao, G., and Chen, J.-J. (2008). Product interface reengineering using fuzzy clustering. CAD Computer Aided Design, vol. 40, no. 4, pp. 439-446.

[10] Zhang, Y., Jiao, J., and Ma, Y. (2007). Market segmentation for product family positioning based on

fuzzy clustering. Journal of Engineering Design, vol. 18, no. 3, pp. 227-41.

[11] Yu, L. and Wang, L. (2007). Two-stage product definition for mass customization. 5th IEEE International Conference on Industrial Informatics, pp. 699-704.

[12] Viswanathan, S. and Allada, V. (2006). Product configuration optimization for disassembly planning: A differential approach. Omega: The International Journal of Management Science, vol. 34, pp. 599-616.

[13] Aldanondo, M., Veron, M., and Fargier, H. (1999). Configuration in manufacturing industry requirements, problems and definitions. Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, vol. 6, VI-1009-VI-1014.

[14] Helo, P.T. (2006). Product configuration analysis with design structure matrix, Industrial Management + Data Systems, vol. 106, pp. 997-1011.

[15] Li, B., Chen, L., Huang, Z., and Zhong, Y. (2006). Product configuration optimization using a multiobjective genetic algorithm, International Journal of Advanced Manufacturing Technology, vol. 30, pp. 20-29.

[16] Chen, L.-Ch. and Lin, L. (2002). Optimization of product configuration design using functional requirements and constraints, Research in Engineering Design, vol. 13, pp. 167-182.

[17] Tseng, H.-E., Chang, Ch.-Ch., and Chang, Sh.-H. (2005). Applying case-based reasoning for product configuration in mass customization environments, Expert Systems with Applications, vol. 29, no. 4, pp. 913-925.

[18] Shao, X.Y., Wang, Z.-H., Li, P.-G., and 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, vol. 44, no. 14, pp. 2789-2811.

[19] Yi, G., Zhang, S., and Tan, J. (2006). Product configuration design based on multi-layer evolution, 2006 IEEE/ASME International Conference on Mechatronics and Embedded Systems and Applications.

[20] Jiao, J. and Tseng, M.M. (1998). Fuzzy ranking for concept evaluation in configuration design for mass customization, Concurrent Engineering: Research and Applications, vol. 6, n 3, pp. 189-206.

[21] Tsai, H.-Ch., and Hsiao, S.W. (2004). Evaluation of alternatives for product customization using fuzzy logic, Information Sciences, vol. 158, pp. 233-262.

[22] Deciu, E.R., Ostrosi, E., Ferney, M., and Gheorghe, M. (2005). Configurable product design using multiple fuzzy models, Journal of Engineering Design, vol. 16, no. 2, pp. 209-235.

[23] Zhu, B., Wang, Z., Yang, H., and Li, H. (2007). Study on approach to fuzzy product configuration based on vague customer requirements, Materials Science Forum, vol. 532-533, pp. 1068-1071.

[24] Zhu, B., Wang, Z., Yang, H., Mo, R., and Zhao, Y. (2008). Applying fuzzy multiple attribute decision making for product configuration. Journal of Intelligent Manufacturing, vol. 19, no. 5, pp. 591-598.

[25] Barajas, M. and Agard, B. (2008). Selection of products based on customer preferences applying fuzzy logic, IDMME – Virtual Concept 2008.

[26] Tseng, T.Y. and Klein, C.M. (1989). New algorithm for the ranking procedure in fuzzy decision making, IEEE Transaction Systems, Man and Cybernetics, vol.19, no. 5, pp. 1289-1296.

[27] Barajas, M. and Agard, B. (2008). A ranking procedure for fuzzy decision-making in product design, IDMME-Virtual Concept 2008.