# Industrial Management & Data Systems

Integrating multi-criteria decision making and clustering for business customer segmentation

Hülya Güçdemir Hasan Selim

Received 26 January 2015
Revised 7 April 2015
19 April 2015
Accepted 21 April 2015

# Integrating multi-criteria decision making and clustering for business customer segmentation

Hülya Güçdemir
*Department of Industrial Engineering, Celal Bayar University, Manisa, Turkey, and*
Hasan Selim
*Department of Industrial Engineering, Dokuz Eylul University, Izmir, Turkey*



## Abstract
**Purpose** – The purpose of this paper is to develop a systematic approach for business customer segmentation.
**Design/methodology/approach** – This study proposes an approach for business customer segmentation that integrates clustering and multi-criteria decision making (MCDM). First, proper segmentation variables are identified and then customers are grouped by using hierarchical and partitional clustering algorithms. The approach extended the recency-frequency-monetary (RFM) model by proposing five novel segmentation variables for business markets. To confirm the viability of the proposed approach, a real-world application is presented. Three agglomerative hierarchical clustering algorithms namely "Ward's method," "single linkage" and "complete linkage," and a partitional clustering algorithm, "k-means," are used in segmentation. In the implementation, fuzzy analytic hierarchy process is employed to determine the importance of the segments.
**Findings** – Business customers of an international original equipment manufacturer (OEM) are segmented in the application. In this regard, 317 business customers of the OEM are segmented as "best," "valuable," "average," "potential valuable" and "potential invaluable" according to the cluster ranks obtained in this study. The results of the application reveal that the proposed approach can effectively be used in practice for business customer segmentation.
**Research limitations/implications** – The success of the proposed approach relies on the availability and quality of customers' data. Therefore, design of an extensive customer database management system is the foundation for any successful customer relationship management (CRM) solution offered by the proposed approach. Such a database management system may entail a noteworthy level of investment.
**Practical implications** – The results of the application reveal that the proposed approach can effectively be used in practice for business customer segmentation. By making customer segmentation decisions, the proposed approach can provides firms a basis for the development of effective loyalty programs and design of customized strategies for their customers.
**Social implications** – The proposed segmentation approach may contribute firms to gaining sustainable competitive advantage in the market by increasing the effectiveness of CRM strategies.
**Originality/value** – This study proposes an integrated approach for business customer segmentation. The proposed approach differentiates itself from its counterparts by combining MCDM and clustering in business customer segmentation. In addition, it extends the traditional RFM model by including five novel segmentation variables for business markets.

**Keywords** Fuzzy AHP, Multi-criteria decision making, Business customer segmentation, Data clustering
**Paper type** Case study

Industrial Management & Data Systems
Vol. 115 No. 6, 2015
pp. 1022-1040

0263-5577
DOI 10.1108/IMDS-01-2015-0027

## 1. Introduction
Customer segmentation can be defined as division of a customer base into distinct and internally consistent groups with similar characteristics. It allows companies to develop different marketing strategies according to customer characteristics.

To execute customer segmentation, various techniques and variables are proposed. Clustering, classification, self-organizing maps (SOM), evolutionary algorithms, interaction detection methods and artificial neural network techniques are some of the extensively used segmentation techniques. Among them, data clustering is the most commonly used technique and the components of the recency-frequency-monetary (RFM) model are the most commonly used variables for the customer segmentation (Punj and Stewart, 1983). Data clustering can be defined as the unsupervised classification of observations and it is based on grouping similar observations in the same cluster. RFM model is the numeric expression of customer behaviors and very effective for determining key customers. However, definition and computation of these variables can change depending on the problem (Miglautsch, 2000). For instance, these variables can be defined as: recency, period since the last purchase; frequency, number of purchases made within a certain period; and monetary, total money spent during a certain period.

Many researchers employed RFM model in their segmentation studies. Among them, Chan (2008) segments the customers of an automobile retailer by using genetic algorithm (GA). Chiu *et al.* (2009) proposed a decision support system for market segmentation that integrates conventional statistical analysis and two intelligent clustering methods; SOM and particle swarm optimization (PSO). Cheng and Chen (2009) joined the quantitative value of RFM variables and *k*-means clustering algorithm into rough set theory. Dhandayudam and Krishnamurthi (2012) suggested a clustering algorithm to overcome the difficulties of traditional clustering algorithms, and segmented the customers of a fertilizer manufacturing company. Wei *et al.* (2013) combined SOM and *k*-means clustering to segment customers of a hair salon in Taiwan. Deng (2013) proposed an algorithm which is based on *k*-means clustering, PSO and artificial bee colony to classify customers in e-commerce environment. The reader may refer to Wei *et al.* (2010) for the applications of RFM model.

There exist some other studies extending the RFM model by including additional variables. For instance, Li *et al.* (2011) added "relationship length" variable to traditional RFM model and segmented the customers of a textile manufacturing firm using a two-step clustering method; Ward with *k*-means. They defined the relationship length as the time between the last and first transaction. However, this definition does not give any information about the repetitiveness of the transactions of a particular customer. Therefore, strength of the relationship should be considered in addition to the relationship length. In addition, Hosseini *et al.* (2010) considered "loyalty" besides the RFM variables. They divided the database into equal quintiles. However, they do not apply any normalization method in their study. In addition, the details on how to obtain the loyalty value were not given. Furthermore, the researchers divided the customer base into 34 clusters, which is impracticable in most cases.

In some segmentation studies, problem-specific variables have been used instead of RFM. For instance, Kim *et al.* (2006) displayed the customers of a wireless telecommunication company with 3D space with axes denoting current value, potential value and customer loyalty and segmented the customers. Teichert *et al.* (2008) applied latent class modeling and segmented airline passengers based on behavioral and socio-demographic variables. Ahn and Sohn (2009) identified customer groups and propose suitable after sales services to these groups. They grouped customers by using fuzzy *c*-means clustering along with the indicators of customer satisfaction index. Gilboa (2009) segmented Israeli mall customers by using Ward with *k*-means. In another study, a soft clustering method that uses a latent mixed class membership clustering approach was developed by Wu and Chou (2011) to group the online consumers of an e-commerce market. Hosseni and Tarokh (2011) implemented a case study on an insurance database. They segmented the customers based on their current value and churn rate. Rajagopal (2011) clustered retail store customers based on variables such as recency, total profit, total revenue and top revenue department. Ho *et al.* (2012) proposed a GA-based *k*-means clustering algorithm to segment the customers of a window curtain manufacturer using the variables of volume, revenue and profit margin per order.

Clustering does not give any information about the importance of customer segments. However, customer value is essential for marketing decisions. Therefore, in some segmentation studies multi-criteria decision making (MCDM) approaches are utilized. In this regard, Liu and Shih (2005) combined group decision making and data mining techniques. They segmented customers based on weighted RFM by using *k*-means. Relative weights of the RFM variables are determined by using analytic hierarchy process (AHP) in the study. The clusters are ranked based on an integrated rating which equals to the weighted sum of RFM values of cluster centroids. In another study, Hosseini *et al.* (2010) segmented customers of a firm based on expanded RFM model. They weighted each variable by eigenvector technique and used *k*-means clustering algorithm to partition the customers into groups. They also obtained the ranking of clusters by considering the distance between center of each cluster with zero point and the integrated rate of each cluster (weighted sum of cluster centers). Table I summarizes the techniques and variables used for customer segmentation problem by the studies considered in our literature survey.

As reported in Table I, customer segmentation is widely studied in consumer markets. However, there is a huge need for systematic approaches for customer segmentation in business markets due to the following reasons. First, as companies have limited resources, they have to use their resources effectively by selecting the valuable customers and making efforts to keep them. In other words, companies should focus on their key customers instead of wasting resources for less profitable customers. Second, number of prospective customers is smaller in business markets and existing customer portfolio is an important reference to gain new customers in the future. Therefore, companies should maintain their market share against potential competitors by providing customized solutions. That is, they should satisfy distinct needs of distinct groups. Third, each and every business customer has special needs. Therefore, closer customer relationship is the key success factor for business markets. However, developing customer-specific strategies is complex and time consuming. Therefore, companies should first segment their customers and then determine the special offerings and priorities in order fulfilling and required degree of relationship for each segment.

As customer segmentation in business markets is quite different from consumer markets, it requires some significant modifications especially in terms of segmentation variables used (Doyle and Saunders, 1985). In consumer markets, customers can be segmented on the basis of their demographics, geography, e.g. country, zone, purchasing behaviors like recency of the last purchase, frequency and monetary value of the purchases, brand loyalty, readiness to buy or their psychographics, i.e. interests, values, attitudes, life styles (Kotler, 2003). Although many of these variables can be applied to business markets, some additional variables related to profit and customer relationship are needed in business market segmentation as today's companies expect an increasing profit stream and long-term partnership with their customers. Therefore, segmentation variables in business markets should be related to purchasing behavior

| Article | Customer type | Segmentation variables: RFM | Other variables | Variable weighting | Segmentation technique: Data clustering | Other techniques | Ranking of segments |
|---|---|---|---|---|---|---|---|
| Liu and Shih (2005) | Consumer | * | na | AHP | *k*-Means | na | Integrated rating |
| Kim *et al.* (2006) | Consumer | na | * | na | na | 3-D space analysis | Rule based |
| Teichert *et al.* (2008) | Consumer | na | * | na | na | Latent class modeling | na |
| Chan (2008) | Consumer | * | na | na | na | GA | na |
| Ahn and Sohn (2009) | Consumer | na | * | na | Fuzzy *c*-means | na | na |
| Chiu *et al.* (2009) | Consumer | * | na | na | *k*-Means | SOM and PSO | na |
| Gilboa (2009) | Consumer | na | * | na | Ward and *k*-means | na | na |
| Cheng and Chen (2009) | Business | * | na | na | *k*-Means | na | Rule based |
| Hosseini *et al.* (2010) | Business | * | * | Eigenvector | *k*-Means | na | Integrated rating |
| Wu and Chou (2011) | Consumer | na | * | na | Soft clustering | na | na |
| Hosseni and Tarokh (2011) | Consumer | na | * | na | na | Rule-based technique | na |
| Rajagopal (2011) | Consumer | na | * | na | IBM demographic clustering process | na | SQL queries |
| Li *et al.* (2011) | Consumer | * | * | na | Ward and *k*-means | na | na |
| Dhandayudam and Krishnamurthi (2012) | Consumer | * | na | na | Improved algorithm | na | na |
| Ho *et al.* (2012) | Business | na | * | na | *k*-Means | GA | na |
| Wei *et al.* (2013) | Consumer | * | na | na | *k*-Means | SOM | na |
| Deng (2013) | Consumer | * | na | na | *k*-Means | PSO and ABC | Rule based |
| This study | Business | * | * | Fuzzy AHP | *k*-Means, ward, single linkage, complete linkage | na | Integrated rating |

**Note:** * denotes the inclusion of the variables

**Table I.** The techniques and variables used for customer segmentation



characteristics, competitive characteristics and potential growth characteristics of customers. As the customer who purchases recently and frequently and spends a lot of money through purchases is much more likely to buy again, behavioral characteristics can include recency, frequency, monetary value and volume of purchases. In business markets, length of relationship (LoR) makes a positive impact on customers' loyalty (Reinartz and Kumar, 2000). Therefore, retaining customers over the long run will build a competitive advantage in the market and yield greater profits.

Accordingly, long-term relationship potential and loyalty level of a customer should be used as competitive characteristics in business market segmentation studies. In addition to the relationship length, customers are supposed to show an increasing trend in their purchases in terms of volume and monetary value during the relationship. In this concern, percentage changes in demand and sales revenue can be utilized to represent the potential growth characteristics of the customers.

As clustering achieves only the grouping of similar observations in the same cluster and does not give any information about the relative importance of clusters when multiple variables are of concern, multi-criteria analysis should be combined with clustering by the segmentation approaches to develop more effective customer relationship management (CRM) strategies.

Considering the above mentioned needs and the research gaps, this study proposes a two-step approach for business customer segmentation that integrates clustering and MCDM. The approach extended the traditional RFM model by proposing five additional novel segmentation variables related to business markets namely "loyalty," "average annual demand," "long term relationship potential," "average percentage change in annual sales revenue" and "average percentage change in annual demand." The proposed approach groups customers in a multi-dimensional way by using hierarchical and partitional clustering algorithms.

To confirm the viability of the proposed approach, a real-world application is presented in this study. In this regard, business customers of an international original equipment manufacturer (OEM) are segmented. Three agglomerative hierarchical clustering (AHC) algorithms namely "Ward's method," "single linkage" and "complete linkage," and a partitional clustering algorithm, "k-means," are used to segment the customers. To determine the importance levels of the customer segments fuzzy AHP is employed. More specifically, as the importance level of the segmentation variables depends on various factors related to the firms such as sector, competitive position, demand structure, etc., we utilized expert opinions in our application. However, expert judgments based on linguistic assessments and these assessments are often vague and imprecise. To overcome this and provide more realistic solution, we use fuzzy AHP in the application to determine the importance level of the segmentation variables. Finally, segment profiles of the firm are constructed and some CRM strategies are suggested.

The remainder of this study is organized as follows. Section 2 presents the methodological aspects of the study. In this concern, the proposed business customer segmentation approach is presented, and data clustering is briefly explained. Section 2 also explains fuzzy AHP since it is employed in the application of the proposed approach. In Section 3, computational experiments are provided. Finally, conclusions and future research directions are presented in Section 4.

## 2. The proposed approach and theoretical background

### *2.1 The proposed approach*

As illustrated in Figure 1, the proposed business customer segmentation approach includes three phases namely "preparing the data set," "segmenting the customers" and "ranking the customer segments." Phase 1 starts with understanding the business environment. Then, segmentation variables are defined and their values are computed for each customer. In the next step, data set is normalized. In phase 2, customers are segmented by using hierarchical and partitional clustering algorithms. Additionally, validity of the clusters is evaluated and the appropriate number of clusters is determined.

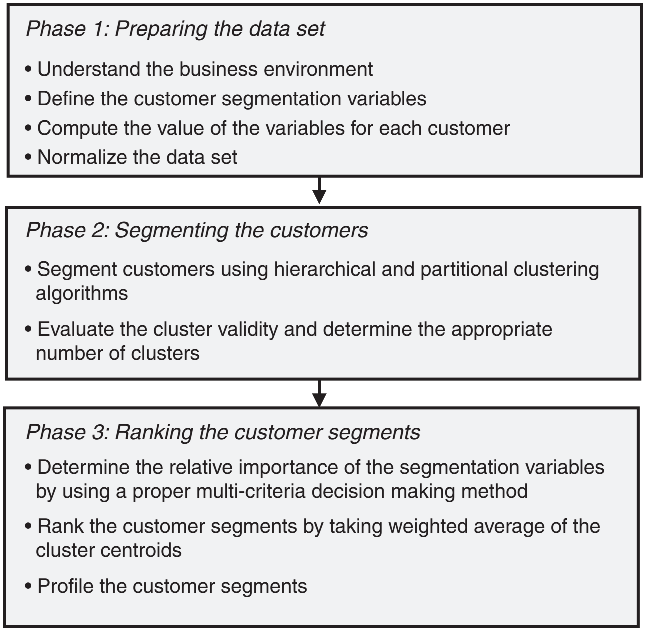


**Figure 1.** The proposed business customer segmentation approach

Finally, in phase 3, importance of the proposed segmentation variables are determined by using a proper multi-criteria decision-making method. Consequently, the customer segments are ranked by taking weighted average of the cluster centroids and then they are profiled.

### *2.2 Data clustering*

Clustering is an unsupervised learning technique and can be defined as division of a heterogeneous population into more homogenous groups. It has various applications including customer segmentation, image segmentation, information retrieval, web pages grouping and scientific and engineering analyses (Pham and Afify, 2007). Typical clustering activity involves the following steps:

- data representation;
- definition of a proximity measure appropriate to the data domain;
- grouping;
- data abstraction; and
- assessment of output.

Clustering algorithms can be classified as hierarchical and partitional. As stated previously, we employ both hierarchical and partitional algorithms in this study to divide the customer base. The hierarchical algorithms can be classified as agglomerative and divisive based on a bottom-up or top-down decomposition. In AHC, initially each data point is a distinct cluster then these clusters are merged until all data points combined in a single cluster. The most commonly used AHC algorithms are “single linkage,” “complete linkage,” “average linkage” and “Ward’s method” (Punj and Stewart, 1983). In single linkage clustering, two separate clusters that have the shortest distance are combined. Herein, distance between two clusters is the distance between the most similar members of the clusters. However, it can sometimes cause clustering some heterogeneous data points together. In addition, complete linkage clustering is sometimes called farthest neighbor approach. Like single linkage clustering, two separate clusters that have the shortest distance are combined by this algorithm. However, in complete linkage clustering, distance between two clusters is the distance between the most dissimilar members of the clusters. Moreover, Ward's method (Ward, 1963) combines the clusters based on the optimal objective function value. This algorithm considers the clustering problem as an analysis of variance problem and objective function is often defined as minimization of the sum of squared error.

Unlike AHC, in partitional clustering, initially all data points constitute a single cluster. Then this cluster is successively divided into clusters till one data point remains in each cluster. Partitional algorithms partition the database into a set of $k$ clusters so that it optimizes the chosen criterion. "k-means" is a well-known partitional clustering algorithm and finds a partition such that the squared error within clusters is minimized. The algorithm is based on assigning each data point to its nearest centroid, and it proceeds as follows:

Step 1. Determine the number of clusters ($k$).

Step 2. Randomly assign $k$ data points to be the initial cluster centroids.

Step 3. Assign each data point to a cluster that has the nearest centroid.

Step 4. Recalculate the cluster centroids.

Step 5. Repeat steps 3 to 5 until termination.

One of the major problems in cluster analysis is termination of the algorithm or in other words determining the number of clusters. The ideal number of clusters is the level of minimum variation within clusters and the maximum variation between clusters. However, the final decision on the number of clusters is left to decision maker (Dubes, 1993). Statistical approaches that use optimality of a specific criterion are often utilized for this purpose. The most commonly used cluster validity indices are *Dunn*, *Davies Bouldin*, *Silhouette*, *Sum of Squares within cluster (SSWC)*, *C*, *Calinski-Harabasz* (Rendon *et al.*, 2011).

In this study, *SSWC* is used as the cluster validity index. *SSWC* is a simple and the most widely used criterion to evaluate the validity of clustering results and determine the number of clusters. *SSWC* is formulated as follows:

$$SSWC = \sum_{k=1}^{K} \sum_{\forall x_i \in C_k} (x_i - \mu_k)^2 \tag{1}$$

where $K$ denotes the number of clusters; $C_k$ is the set of instances in cluster $k$; $\mu_k$ is the vector mean of cluster $k$. Smaller value of *SSWC* indicates a "better" clustering solution. *SSWC* and sum of squares between clusters (*SSBC*) is a constant that is equal to the total sum of squares (*TSS*), which is the sum of squares of the distance of each point to the overall mean of the data (see, Equations (2) and (3)). It means that minimizing *SSWC* is equivalent to maximizing *SSBC*:

$$TSS = SSWC + SSBC \tag{2}$$

$$TSS = \sum_{k=1}^{K} \sum_{\forall x_i \in C_k} (x_i - \mu_k)^2 \tag{3}$$

where $K$ denotes the number of clusters, $C_k$ is the set of instances in cluster $k$, and $\mu$ is the vector mean of data set.

*2.3 Fuzzy AHP*

Today, decision makers confront with many complex decision problems and they often use multiple criteria to handle these problems. AHP is one of the most widely used MCDM tools and has been applied in a wide variety of areas. Sipahi and Timor (2010) presented a literature review of recent applications of AHP, and categorized the studies according to the application area such as manufacturing, environmental management and agriculture, general decision problem, power and energy industry, transportation industry, construction industry, health and others. Some review studies focussed on the application of AHP in specific fields such as marketing (Mark, 2001), energy (Pohekar and Ramachandran, 2004), medical and healthcare decision making (Liberatore and Nydick, 2008). The reader may refer to Subramanian and Ramanathan (2012) for a review of the applications of AHP in operations management.

In AHP, decision maker's knowledge is represented with crisp values. However, human judgments are usually based on unclear linguistic assessments and it is not realistic to represent them with crisp values. In addition, people may have difficulties arranging competing alternatives consistently if two or more criteria have to be taken into account (Fiarni *et al.*, 2013).

To deal with uncertainty of human thought, Zadeh (1965) first introduced the fuzzy set theory, which was oriented to the rationality of uncertainty due to imprecision or vagueness. A fuzzy set is a class of objects with a continuum of grades of membership. Such a set is characterized by a membership function, which assigns to each object a grade of membership ranging between zero and one. Triangular fuzzy numbers (TFNs) are the most commonly used fuzzy numbers and a TFN, $\tilde{M}$, is denoted as $M = (l, m, u)$ as illustrated in Figure 2. The parameters $l$, $m$, and $u$, respectively denote the smallest possible value, the most promising value and the largest possible value that describe a fuzzy event (Kahraman *et al.*, 2004).

Fuzzy AHP is an effective tool for solving MCDM problems. It has been extensively used in various fields such as location selection (Kuo *et al.*, 2002), supplier selection (Kahraman *et al.*, 2003; Chan *et al.*, 2008), project selection (Enea and Piazza, 2004; Huang *et al.*, 2008), machine tool selection (Ayağ and Özdemir, 2006; Duran and Aguilo, 2008) and personnel selection (Güngör *et al.*, 2009). The main advantage of this method is that it reflects the human reasoning and thinking style by making allowances for the vagueness and imprecision of human judgments. Different from classical AHP, pair-wise comparisons are represented by fuzzy numbers in fuzzy AHP. There exist several fuzzy comparison methods proposed by researchers. For instance, Van Laarhoven and

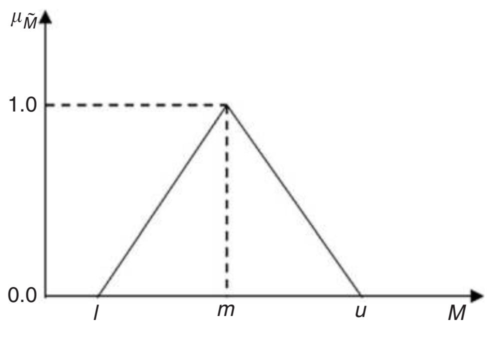


**Figure 2.**
A triangular fuzzy number

Pedrycz (1983) proposed a fuzzy logarithmic least squares method to obtain triangular fuzzy weights from a fuzzy comparison matrix. Buckley (1985) used geometric mean method to calculate the fuzzy weights. Csutora and Buckley (2001) proposed $\lambda$-max method, which is the direct fuzzification of the $\lambda$-max method. Mikhailov (2003) proposed a fuzzy preference programming method that computes crisp weights from fuzzy comparison matrices. Chang (1992) introduced an extent analysis method that derives crisp weights from fuzzy pair-wise comparison matrices.

In this study, Chang's (1992) extent analysis method is used for weighting the customer segmentation variables. According to this method, each object is taken from an object set $X = \{x_1, x_2, \ldots, x_n\}$ and extent analysis for each goal, $g_i$, in a goal set $U = \{u_1, u_2, \ldots, u_m\}$ is performed. Computational procedure of Chang's (1992) extended fuzzy AHP is described as follows:

Step 1. The value of fuzzy synthetic extent value with respect to the $i$th criterion is defined by the following equation:

$$S_i = \sum_{j=1}^{m} M_{gi}^{j} \otimes \left[ \sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right]^{-1} \tag{4}$$

where all $M_{gi}^{j} (j = 1, 2, \ldots, m)$ are TFNs.

Step 2. As $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$ are TFNs, the degree of possibility of $M1 \geqslant M2$ is defined as:

$$V(M_1 \geqslant M_2) = \begin{cases} 1, & \text{if } m_1 \geqslant m_2 \\ 0, & \text{if } l_2 \geqslant u_1 \\ \frac{l_2 - u_1}{(m_1 - u_1) - (m_2 - l_2)}, & \text{otherwise} \end{cases} \tag{5}$$

Step 3. To compare $M_1$ and $M_2$, we need both the values of $V(M_1 \geqslant M_2)$ and $V(M_2 \geqslant M_1)$. The degree of possibility for a convex fuzzy number to be greater than $k$ convex fuzzy numbers $M_i (i = 1, 2, \ldots, k)$ can be defined as follows:

$$\begin{aligned} V(M \geqslant M_1 M_2 M_3, \ldots, M_k) &= V[(M \geqslant M_1) \textit{ and } (M \geqslant M_2 \textit{ and } .. \textit{ and } (M \geqslant M_k))] \\ &= \min V(M \geqslant M_i), \quad i = 1, 2, \ldots, k. \end{aligned} \tag{6}$$

Assume that $d'(A_i) = \min V(S_i \geqslant S_k)$ for $k = 1, 2, \ldots, n$; $k \neq i$ then the weight vector is given by Equation (7):

$$W' = \left(d'(A_1), d'(A_2), \ldots, d'(A_n)\right)^T \tag{7}$$

where $A_i (i = 1, 2, \ldots, n)$ are $n$ elements.

Step 4. Via normalization, the normalized weight vectors are presented in Equation (8) where $W$ is a non-fuzzy number:

$$W = (d(A_1), d(A_2), \ldots, d(A_n))^T \tag{8}$$

## 3. Application of the proposed approach

### *3.1 The case company and data set*

In business markets, most of the leading brands take the advantage of the economies of scale by collaborating with OEMs. In today's highly competitive markets, becoming a successful OEM necessitates deeper understanding of customers and satisfying their needs. Therefore, OEMs should segment their customers to make better operational, tactical and strategic decisions.

The case company is one of the successful OEMs over the world and it has an integrated TV production process extending from the production of electronic cards to the final assembly. The company has a wide export network and it produces TVs both for its own brand and also for many other worldwide electronic companies. In this study, we focus on the business customers of the company and divide the business customer base into discrete customer groups and find the relative importance of them. Customer transaction data are extracted from the enterprise resource planning system of the company. In this regard, 28,840 records of 317 customers between January 2002 and December 2011 are analyzed.

### *3.2 Definition of the segmentation variables*

Customers of a company should be evaluated according to their special characteristics. Types of data held about customers vary across industries and even across companies. For instance, industries like fast moving consumer goods, retail, financial services and telecommunication have a rich customer database that can be utilized in making effective CRM policies. On the other hand, companies in business markets generally have relatively limited information about their customers. Therefore, business customer assessments differ from one industry to another. At this point, both business understanding and market analysis become vital for customer segmentation.

In this study, we propose five novel segmentation variables for business markets namely "loyalty," "average annual demand," "long term relationship potential," "average percentage change in annual demand" and "average percentage change in annual sales revenue." In our application, these five variables and the RFM variables are used for business customer segmentation. Definitions of these variables are presented in the following.

*V1: recency*. Recency can be described as the date of last transaction of a specific customer within the observation period. Recent order indicates that the relationship is live. The value of recency is scaled from 1 to 7 and it equals to 1 for 2005 and 7 for 2011.

*V2: loyalty*. The term customer loyalty is the behavior of repeat customers. Customers can be said "loyal" when they consistently purchase a certain product or brand over a long period of time. In this study, loyalty value is calculated by Equation 9, where active years corresponds to total number of years that transactions were conducted by a specific customer during its LoR. LoR is the number of years between the first transaction of a specific customer and the end of the observation period (2011). The reason for multiplying the ratio of active years to LoR by active years is to distinguish between loyalty values of customers whose active years equal to their LoR:

$$Loyalty = \frac{(Active\ years)^2}{LoR} \tag{9}$$

*V3: average annual demand (AAD)*. The value of this variable is calculated by averaging demand of a customer during its LoR with the company. In other words, it is the ratio of total demand to LoR. The reason to use this variable is to calculate comparable values for each customer with respect to total demand.

*V4: average annual sales revenue (AASR) (monetary value)*. This variable can be defined as the average expenditure of a customer made during its LoR. It is the ratio of total sales revenue to LoR.

*V5: frequency*. Frequency indicates the average number of transactions conducted per year. It is computed by multiplying the ratio of total number of months in which at least a transaction was conducted to total number of months between the first transaction and the end of observation period by 12.

*V6: long-term relationship potential (LTRP)*. Long-term relationship simply means building customer loyalty for the company. It is thought that if a customer works with the company for a long time or in other words its loyalty is high and at the same time has a recent order we may assume that this customer will keep working with this company in the future. Long-term relationship potential is calculated as a score by the following equation:

$$LTRP = Loyalty \times \mathrm{Rec}ency \tag{10}$$

*V7: average percentage change in annual demand (APCIAD)*. Not only the amount of but also the variation in annual demand of a specific customer is important for companies. Therefore, a variable that indicates the average percentage change in annual demand is necessary. With this variable, we can see whether the annual customer demand increases or decreases. If we consider demand values in two consecutive years, respectively $a$ and $b$, APCIAD is calculated as $(b-a)/a$. This variable equals to zero for customers whose first transaction was conducted in 2011.

*V8: average percentage change in annual sales revenue (APCIASR)*. This variable is the measure of change in annual sales revenue. By evaluating the value of APCIASR, we can see whether the annual sales revenue obtained from a particular customer increases or decreases. If we consider sales revenues of two consecutive years, respectively, $c$ and $d$, APCIASR is calculated by $(d-c)/c$ for each customer.

After computing values of these eight variables for each customer, initial data set is obtained and then normalized by using min-max normalization (standardization) between 0 and 1 to create a common scale for the variables and make them commensurate. The summary statistics are presented in Table II.

### *3.3 Segmenting the customers*

In our application, we used Euclidean distance as dissimilarity metric and employed three AHC algorithms, which are "Ward's method," "single linkage" and "complete linkage," and a partitional clustering algorithm, "k-means," to segment the customers. As recalled,

| Variable | Observations | Min. | Max. | Mean | SD |
|---|---|---|---|---|---|
| V1 | 317 | 0.000 | 1.000 | 0.812 | 0.236 |
| V2 | 317 | 0.000 | 1.000 | 0.220 | 0.233 |
| V3 | 317 | 0.000 | 1.000 | 0.023 | 0.100 |
| V4 | 317 | 0.000 | 1.000 | 0.026 | 0.103 |
| V5 | 317 | 0.000 | 1.000 | 0.298 | 0.302 |
| V6 | 317 | 0.000 | 1.000 | 0.216 | 0.232 |
| V7 | 317 | 0.000 | 1.000 | 0.064 | 0.099 |
| V8 | 317 | 0.000 | 1.000 | 0.018 | 0.061 |

**Table II.**
Summary statistics of the data set

the aim of this study is to divide customer base into manageable number of groups. Determining the number of clusters is important for the management of these groups. Increasing the number of clusters makes the management more difficult. As known, number of customers is smaller in business markets compared to consumer markets and business customers' behaviors vary less than consumers' behaviors. Therefore, we determine the number of clusters as three, five and seven in our application.

Application results of the clustering algorithms are presented in Table III. The results reveal that "k-means" provides superior results in terms of *SSWC* than those of the other methods. After determining the best method, we should also determine the number of clusters. It is obvious that when the number of clusters increases, *SSWC* decreases. The clustering with small number of clusters and low value of *SSWC* is treated as adequate. Figure 3 visualizes *SSWC* values for the clustering algorithms for different number of clusters. The results indicate that *SSWC* value of *k*-means algorithm is subject to small changes for the number of clusters bigger than five. Accordingly, we conclude that segmenting the customers into five clusters is proper.

| Clustering algorithm | No. of clusters | SSWC | SSBC | TSS | SSWC/TSS |
|---|---|---|---|---|---|
| Ward's method | 3 | 37.111 | 54.295 | 91.406 | 0.406 |
| Ward's method | 5 | 23.777 | 67.628 | 91.406 | 0.260 |
| Ward's method | 7 | 17.389 | 74.017 | 91.406 | 0.190 |
| Single linkage | 3 | 87.226 | 4.180 | 91.406 | 0.954 |
| Single linkage | 5 | 81.470 | 9.936 | 91.406 | 0.891 |
| Single linkage | 7 | 80.076 | 11.329 | 91.406 | 0.876 |
| Complete linkage | 3 | 61.218 | 30.188 | 91.406 | 0.670 |
| Complete linkage | 5 | 32.055 | 59.351 | 91.406 | 0.351 |
| Complete linkage | 7 | 29.783 | 61.623 | 91.406 | 0.326 |
| *k*-Means | 3 | 35.303 | 56.103 | 91.406 | 0.386 |
| *k*-Means | 5 | 22.996 | 68.410 | 91.406 | 0.252 |
| *k*-Means | 7 | 17.212 | 74.194 | 91.406 | 0.188 |

**Table III.** Application results of the clustering algorithms

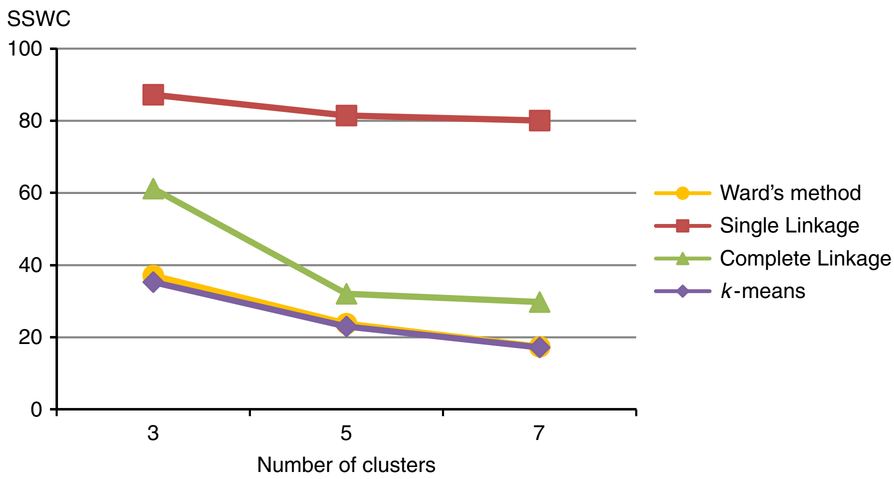


**Figure 3.** SSWC values of the clustering algorithms

Table IV presents the centroid, rank and size of each cluster that is generated by *k*-means method. Further, Figure 4 visualizes the group averages for each variable.

*3.4 Determining the importance of the segmentation variables*

In our application, fuzzy AHP approach is employed to determine the importance of the segmentation variables. Each variable is evaluated by the sales supervisor through stating the importance of the variables using linguistic variables and filling the pair-wise comparison matrix $L$ (see Table V) that is defined as a set of linguistic values. $L = \{VHI, HI, SHI, M, SLI, LI, VLI\}$, where VHI = very high important, HI = high important, SHI = somewhat high important, M = medium, SLI = somewhat

**Table IV.**
Results of *k*-means algorithm corresponding to five clusters

| Cluster | V1 | V2 | V3 | V4 | V5 | V6 | V7 | V8 | Number of customers |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.995 | 0.174 | 0.036 | 0.037 | 0.627 | 0.184 | 0.083 | 0.017 | 61 |
| 2 | 0.83 | 0.114 | 0.001 | 0.001 | 0.097 | 0.11 | 0.035 | 0.008 | 109 |
| 3 | 0.98 | 0.49 | 0.014 | 0.018 | 0.492 | 0.488 | 0.101 | 0.037 | 67 |
| 4 | 0.424 | 0.04 | 0.001 | 0.001 | 0.045 | 0.024 | 0.033 | 0.008 | 68 |
| 5 | 0.986 | 0.935 | 0.342 | 0.372 | 0.811 | 0.925 | 0.21 | 0.056 | 12 |

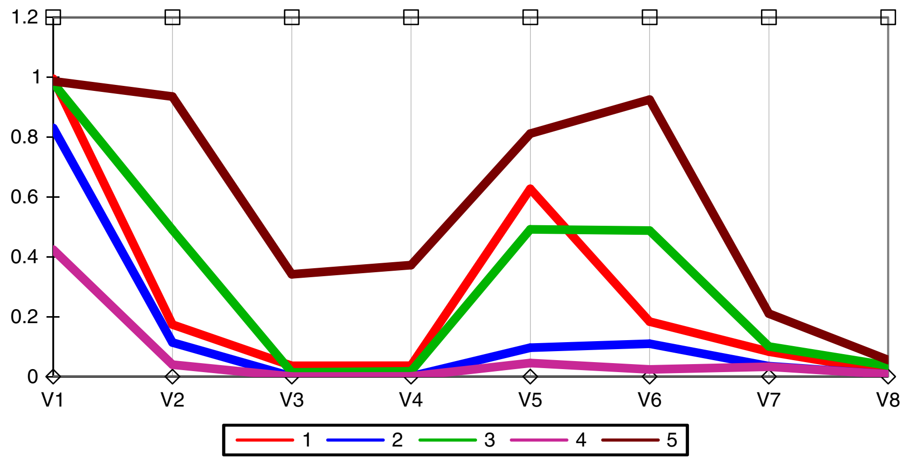


**Figure 4.**
Profile plot of clusters obtained by *k*-means method

**Table V.**
Pair-wise comparison matrix

| | V1 | V2 | V3 | V4 | V5 | V6 | V7 | V8 |
|---|---|---|---|---|---|---|---|---|
| V1 | M | SLI | LI | LI | SHI | SLI | SHI | M |
| V2 | SHI | M | SLI | LI | SHI | SLI | SHI | M |
| V3 | HI | SHI | M | SLI | HI | SHI | SHI | SHI |
| V4 | HI | HI | SHI | M | HI | SHI | HI | SHI |
| V5 | SLI | SLI | LI | LI | M | M | SLI | M |
| V6 | SHI | SHI | SLI | SLI | M | M | HI | SHI |
| V7 | SLI | SLI | SLI | LI | SHI | LI | M | SLI |
| V8 | M | M | SLI | SLI | M | SLI | SHI | M |

low important, LI = low important and VLI = very low important. Linguistic values and corresponding TFNs are presented in Table VI.

The weight vector is obtained as $W' = (0.292, 0.456, 0.833, 1, 0.113, 0.653, 0.128, 0.4)$. Then, the normalized weight vector is computed as $W = (0.075, 0.118, 0.215, 0.258, 0.03, 0.168, 0.033, 0.103)$. The results indicate that the most important variable is AASR while the least important variable is frequency. The reason why the frequency is the least important variable is related with the industry in which the company operates. The company produces TV that is a kind of durable consumer goods, and both production and distribution processes are long and costly. In addition, most of the customers located in geographically dispersed countries over the world and they are far from the production facility. Therefore, the company prefers less frequent, high volume orders instead of frequent and low-volume orders to avoid high setup, production and distribution costs.

Importance levels of the clusters are determined by taking weighted average of the cluster centroids obtained in Section 3.3. Table VII indicates the weighted average of cluster centroids, ranks and sizes of clusters.

### 3.5 *Evaluation of the results*

We segment 317 business customers of the OEM as "best," "valuable," "average," "potential valuable" and "potential invaluable" according to the cluster ranks obtained in Section 3.4. Characteristics of these segments are summarized in Table VIII.

The results reveal that "Cluster five" (best customers) is the most important segment. With respect to "AAD," "AASR" and "LTRP" variables, this cluster has the greatest values among the clusters. The customers in this segment are totally loyal customers and they order products with high volumes. In addition, these customers are the most important source of income for the company. Therefore, they should be retained. Also, some portion of capacity should be reserved for these customers in anticipation of their urgent demands. Further, these customers should have higher priority in order fulfilling.

| Linguistic variable | TFN |
|---|---|
| Very low important (VLI) | (0, 0, 0.10) |
| Low important (LI) | (0.05, 0.15, 0.25) |
| Somewhat low important (SLI) | (0.20, 0.325, 0.45) |
| Medium (M) | (0.40, 0.50, 0.60) |
| Somewhat high important (SHI) | (0.55, 0.675, 0.80) |
| High important (HI) | (0.75, 0.85, 0.95) |
| Very high important (VHI) | (0.90, 1, 1) |

**Source:** Belmokaddem *et al.* (2009)

**Table VI.** Linguistic variables and corresponding TFNs

| Cluster | Weighted average of cluster centroid | Rank | Number of customers |
|---|---|---|---|
| 1 | 0.166 | 3 | 61 |
| 2 | 0.100 | 4 | 109 |
| 3 | 0.243 | 2 | 67 |
| 4 | 0.044 | 5 | 68 |
| 5 | 0.546 | 1 | 12 |

**Table VII.** Results of *k*-means algorithm corresponding to five clusters

**Table VIII.**
Characteristics of the final segments

| | | Segmentation variables | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | V1 | V2 | V3 | V4 | V5 | V6 | V7 | V8 |
| Cluster 1 average | Avg. | 0.667 | 0.094 | 0.000 | 0.000 | 0.291 | 0.106 | 0.021 | 0.006 |
| | Max. | 0.995 | 0.174 | 0.036 | 0.037 | 0.627 | 0.184 | 0.083 | 0.017 |
| | Min. | 1.000 | 0.321 | 0.858 | 0.700 | 1.000 | 0.330 | 0.448 | 0.084 |
| Cluster 2 potential valuable | Avg. | 0.667 | 0.018 | 0.000 | 0.000 | 0.011 | 0.021 | 0.000 | 0.000 |
| | Max. | 0.830 | 0.114 | 0.001 | 0.001 | 0.097 | 0.110 | 0.035 | 0.008 |
| | Min. | 1.000 | 0.343 | 0.006 | 0.012 | 0.295 | 0.352 | 0.712 | 0.094 |
| Cluster 3 valuable | Avg. | 0.667 | 0.321 | 0.000 | 0.001 | 0.128 | 0.301 | 0.009 | 0.003 |
| | Max. | 0.980 | 0.490 | 0.014 | 0.018 | 0.492 | 0.488 | 0.101 | 0.037 |
| | Min. | 1.000 | 0.786 | 0.188 | 0.261 | 1.000 | 0.679 | 0.563 | 1.000 |
| Cluster 4 potential invaluable | Avg. | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.019 | 0.005 |
| | Max. | 0.424 | 0.040 | 0.001 | 0.001 | 0.045 | 0.024 | 0.033 | 0.008 |
| | Min. | 0.500 | 0.182 | 0.004 | 0.007 | 0.312 | 0.090 | 0.162 | 0.033 |
| Cluster 5 best | Avg. | 0.833 | 0.547 | 0.020 | 0.022 | 0.595 | 0.553 | 0.049 | 0.009 |
| | Max. | 0.986 | 0.935 | 0.342 | 0.372 | 0.811 | 0.925 | 0.210 | 0.056 |
| | Min. | 1.000 | 1.000 | 1.000 | 1.000 | 0.981 | 1.000 | 1.000 | 0.366 |

Cluster three (valuable customers) is the second important customer segment. This segment is also an important source of income for the company. The customers in this segment have a long relationship with the company, they have great volume of orders and their orders are generally recent. In addition, they show an increasing trend in AAD and AASR. Therefore, they have high potential for long-term relationships with the company. Cluster one (average customers) is the third important segment. Customers in this segment have an average LoR with the company. They are partially loyal to the company, they have average amount of orders and their LTRP is moderate. Accordingly, the company should make an effort to increase the sales volume of the customers in this segment. Cluster two (potential valuable) is the fourth important segment. Most of the customers in this segment are new customers. Although they have shorter relationship with the company, it can be stated that they have great amount of annual demand. Therefore, the company should focus on developing the relationship with the customers in this segment. Cluster four (potential invaluable) is the fifth important segment. Most customers in this segment do not have recent orders and their relationships with the company are inactive. They have low-volume orders, and accordingly the revenue obtained from them is low. Therefore, they can be qualified as disloyal. In addition, some of them are relatively new customers but they have lower annual demand than the new customers in cluster two. Consequently, relationship with these customers should be reconsidered attentively.

## 4. Conclusions

This study proposes an integrated approach for business customer segmentation. The proposed approach differentiates itself from its counterparts by combining MCDM and clustering in business customer segmentation. In addition, it extends the traditional RFM model by including five novel segmentation variables for business markets namely "loyalty," "average annual demand," "long term relationship potential," "average percentage change in annual demand" and "average percentage change in annual sales revenue."

The proposed approach groups customers in a multi-dimensional way by using hierarchical and partitional clustering algorithms. As clustering does not give any information about the relative importance of clusters when multiple variables are of concern, multi-criteria analysis is combined with clustering by the proposed approach to develop more effective CRM strategies.

To prove the practicality of the proposed approach, a real-world application is presented in this study. Business customers of an international OEM are segmented in the application. Three AHC algorithms namely "Ward's method," "single linkage" and "complete linkage," and a partitional clustering algorithm, "k-means," are employed in the segmentation. To determine the relative importance of the customer segments fuzzy AHP is utilized as the MCDM approach. Thus, imprecise assessments of experts are effectively reflected to the decision process. Finally, segment profiles of the case company are constructed and some CRM strategies are suggested. The results of the application reveal that the proposed approach can effectively be used in practice for business customer segmentation. By making customer segmentation decisions, the proposed approach can provides firms a basis for the development of effective loyalty programs and design of customized strategies for their customers. Thus, it can contribute to gaining sustainable competitive advantage in the market.

In practice, customer base, customer segmentation variables and their importance levels are subject to change over time. Therefore, customer segments should be updated dynamically.

The success of the proposed approach relies on the availability and quality of customers' data. Therefore, design of an extensive customer database management system is the foundation for any successful CRM solution offered by the proposed approach. Such a database management system may entail a noteworthy level of investment.

Any future study might apply the clustering algorithms by using different similarity/dissimilarity metrics. In addition, adaptation of the proposed segmentation variables to the consumer markets can be stated as a future research subject.



## References


Ahn, J.S. and Sohn, S.Y. (2009), "Customer pattern search for after-sales service in manufacturing", *Expert Systems with Applications*, Vol. 36 No. 3, pp. 5371-5375.

Ayağ, Z. and Özdemir, R.G. (2006), "A fuzzy AHP approach to evaluating machine tool alternatives", *Journal of Intelligent Manufacturing*, Vol. 17 No. 2, pp. 179-190.

Belmokaddem, M., Mekidiche, M. and Sahed, A. (2009), "Application of fuzzy goal programming approach with different importance and priorities to aggregate production planning", *Journal of Applied Quantitative Methods*, Vol. 4 No. 3, pp. 317-331.

Buckley, J.J. (1985), "Fuzzy hierarchical analysis", *Fuzzy Sets and Systems*, Vol. 17 No. 3, pp. 233-247.

Chan, C.C.H. (2008), "Intelligent value-based customer segmentation method for campaign management: a case study of automobile retailer", *Expert Systems with Applications*, Vol. 34 No. 4, pp. 2754-2762.

Chan, F.T.S., Kumar, N., Tiwari, M.K., Lau, H.C.W. and Choy, K.L. (2008), "Global supplier selection: a fuzzy-AHP approach", *International Journal of Production Research*, Vol. 46 No. 14, pp. 3825-3857.

Chang, D.Y. (1992), "Extent analysis and synthetic decision", *Optimization Techniques and Applications*, Vol. 1, pp. 352-366.

Cheng, C.H. and Chen, Y.S. (2009), "Classifying the segmentation of customer value via RFM model and RS theory", *Expert Systems with Applications*, Vol. 36 No. 3, pp. 4176-4184.

Chiu, C.Y., Chen, Y.F., Kuo, I.T. and Ku, H.C. (2009), "An intelligent market segmentation system using k-means and particle swarm optimization", *Expert Systems with Applications*, Vol. 36 No. 3, pp. 4558-4565.

Csutora, R. and Buckley, J.J. (2001), "Fuzzy hierarchical analysis: the Lambda-Max method", *Fuzzy Sets and Systems*, Vol. 120 No. 2, pp. 181-195.

Deng, X. (2013), "An enhanced artificial bee colony approach for customer segmentation in mobile e-commerce environment", *International Journal of Advancements in Computing Technology*, Vol. 5 No. 1, pp. 139-148.

Dhandayudam, P. and Krishnamurthi, I. (2012), "An improved clustering algorithm for customer segmentation", *International Journal of Engineering Science and Technology*, Vol. 4 No. 2, pp. 695-702.

Doyle, P. and Saunders, J. (1985), "Market segmentation and positioning in specialized industrial markets", *Journal of Marketing*, Vol. 49 No. 2, pp. 24-32.

Dubes, R.C. (1993), *Cluster Analysis and Related Issues*, World Scientific Publishing Co., New Jersey, NJ.

Duran, O. and Aguilo, J. (2008), "Computer-aided machine-tool selection based on a fuzzy-AHP approach", *Expert Systems with Applications*, Vol. 34 No. 3, pp. 1787-1794.

Enea, M. and Piazza, T. (2004), "Project selection by constrained fuzzy AHP", *Fuzzy Optimization and Decision Making*, Vol. 3 No. 1, pp. 39-62.

Fiarni, C., Gunawan, A. and Lestari A. (2013), "Fuzzy AHP based decision support system for SKTM recipient selection", *Information Systems International Conference (ISICO)*, 2-4 December, pp. 288-293.

Gilboa, S. (2009), "A segmentation study of Israeli mall customers", *Journal of Retailing and Consumer Services*, Vol. 16 No. 2, pp. 135-144.

Güngör, Z., Serhadlıoğlu, G. and Kesen, S.E. (2009), "A fuzzy AHP approach to personnel selection problem", *Applied Soft Computing*, Vol. 9 No. 2, pp. 641-646.

Ho, G.T.S., Ip, W.H., Lee, C.K.M. and Mou, W.L. (2012), "Customer grouping for better resource allocation using GA based clustering technique", *Expert Systems with Applications*, Vol. 39 No. 2, pp. 1979-1987.

Hosseini, S.M.S., Maleki, A. and Gholamian, M.R. (2010), "Cluster analysis using data mining approach to develop CRM methodology to assess the customer loyalty", *Expert Systems with Applications*, Vol. 37 No. 7, pp. 5259-5264.

Hosseni, M.B. and Tarokh, M.J. (2011), "Customer segmentation using CLV elements", *Journal of Service Science and Management*, Vol. 4 No. 3, pp. 284-290.

Huang, C.C., Chu, P.Y. and Chiang, Y.H. (2008), "A fuzzy AHP application in government-sponsored R&D project selection", *Omega*, Vol. 36 No. 6, pp. 1038-1052.

Kahraman, C., Cebeci, U. and Ruan, D. (2004), "Multi-attribute comparison of catering service companies using fuzzy AHP: the case of Turkey", *International Journal of Production Economics*, Vol. 87 No. 2, pp. 171-184.

Kahraman, C., Cebeci, U. and Ulukan, Z. (2003), "Multi-criteria supplier selection using fuzzy AHP", *Logistics Information Management*, Vol. 16 No. 6, pp. 382-394.

Kim, S.Y., Jung T.S., Suh, E.H. and Hwang, H.S. (2006), "Customer segmentation and strategy development based on customer lifetime value: a case study", *Expert Systems with Applications*, Vol. 31 No. 1, pp. 101-107.

Kotler, P. (2003), *Marketing Management*, Prentice-Hall, New Jersey, NJ.

Kuo, R.J., Chi, S.C. and Kao, S.S. (2002), "A decision support system for selecting convenience store location through integration of fuzzy AHP and artificial neural network", *Computers in Industry*, Vol. 47 No. 2, pp. 199-214.

Li, D.C., Dai, W.L. and Tseng, W.T. (2011), "A two-stage clustering method to analyze customer characteristics to build discriminative customer management: a case of textile manufacturing business", *Expert Systems with Applications*, Vol. 38 No. 6, pp. 7186-7191.

Liberatore, M.J. and Nydick, R.L. (2008), "The analytic hierarchy process in medical and health", *European Journal of Operational Research*, Vol. 189 No. 1, pp. 194-207.

Liu, D.R. and Shih, Y.Y. (2005), "Integrating AHP and data mining for product recommendation based on customer lifetime value", *Information and Management*, Vol. 42 No. 3, pp. 387-400.

Mark, D. (2001), "Adaptive AHP: a review of marketing applications with extensions", *European Journal of Marketing*, Vol. 35 Nos 7/8, pp. 872-894.

Miglautsch, J.R. (2000), "Thoughts on RFM scoring", *Journal of Database Marketing*, Vol. 8 No. 1, pp. 67-72.

Mikhailov, L. (2003), "Deriving priorities from fuzzy pairwise comparison judgements", *Fuzzy Sets and Systems*, Vol. 134 No. 3, pp. 365-385.

Pham, D.T. and Afify, A.A. (2007), "Clustering techniques and their applications in engineering", *Mechanical Engineering Science*, Vol. 221 No. 11, pp. 1445-1459.

Pohekar, S.D. and Ramachandran, M. (2004), "Application of multi-criteria decision making to sustainable energy planning – a review", *Renewable and Sustainable Energy Reviews*, Vol. 8 No. 4, pp. 365-381.

Punj, G. and Stewart, D.W. (1983), "Cluster analysis in marketing research: review and suggestions for application", *Journal of Marketing Research*, Vol. 20 No. 2, pp. 134-148.

Rajagopal S. (2011), "Customer data clustering using data mining technique", *International Journal of Database Management Systems*, Vol. 3 No. 4, pp. 1-11.

Reinartz, W.J. and Kumar, V. (2000), "On the profitability of long-life customers in a noncontractual setting: an emprical investigation and implications for marketing", *Journal of Marketing*, Vol. 64 No. 4, pp. 17-35.

Rendon, E., Abundez, I., Arizmendi, A. and Quiroz, E.M. (2011), "Internal versus external cluster validation indexes", *International Journal of Computers and Communications*, Vol. 5 No. 1, pp. 27-34.

Sipahi, S. and Timor, M. (2010), "The analytic hierarchy process and analytic network process: an overview of applications", *Management Decision*, Vol. 48 No. 5, pp. 775-808.

Subramanian, N. and Ramanathan, R. (2012), "A review of applications of analytic hierarchy process in operations management", *International Journal of Production Economics*, Vol. 138 No. 2, pp. 215-241.

Teichert, T., Shehu, E. and Wartburg, I. (2008), "Customer segmentation revisited: the case of airline industry", *Transportation Research Part A*, Vol. 42 No. 1, pp. 227-242.

Van Laarhoven, P.J.M. and Pedrycz, W. (1983), "A fuzzy extension of Saaty's priority theory", *Fuzzy Sets and Systems*, Vol. 11 Nos 1-3, pp. 229-241.

Ward, J.H. (1963), "Hierarchical grouping to optimize an objective function", *Journal of the American Statistical Association*, Vol. 58 No. 301, pp. 236-244.

Wei, J.T., Lin, S.Y. and Wu, H.H. (2010), "A review of the application of RFM model", *African Journal of Business Management*, Vol. 4 No. 19, pp. 4199-4206.

Wei, J.T., Lee, M.C., Chen, H.K. and Wu, H.H. (2013), "Customer relationship management in the hairdressing industry: an application of data mining techniques", *Expert Systems With Applications*, Vol. 40 No. 18, pp. 7513-7518.

Wu, R.S. and Chou, P.H. (2011), "Customer segmentation of multiple category data in e-commerce using a soft clustering approach", *Electronic Commerce Research and Applications*, Vol. 10 No. 3, pp. 331-341.

Zadeh, L.A. (1965), "Fuzzy sets", *Information and Control*, Vol. 8 No. 3, pp. 338-353.

## Further reading

Vargas, L.G. (1990), "An overview of the analytic hierarchy process and its applications", *European Journal of Operational Research*, Vol. 48 No. 1, pp. 2-8.

## About the authors

Hülya Güçdemir is a Research Assistant at the Celal Bayar University, Turkey, and a PhD Student in the Dokuz Eylul University Industrial Engineering Department. Her research interests are analytical CRM, data mining, multivariate statistical analysis and simulation optimization.

Hasan Selim is an Associate Professor in the Industrial Engineering Department at the Dokuz Eylul University, Turkey. His research interests include supply chain management, logistics management, risk assessment and management, multi-criteria decision making and fuzzy mathematical modeling. Hasan Selim is the corresponding author and can be contacted at: hasan.selim@deu.edu.tr

**This article has been cited by:**

1. Henry Lau School of Business, The University of Western Sydney, Penrith, Australia Dilupa Nakandala School of Business, The University of Western Sydney, Penrith, Australia Premaratne Samaranayake School of Business, The University of Western Sydney, Penrith, Australia Paul Shum School of Business, The University of Western Sydney, Penrith, Australia . 2016. A hybrid multi-criteria decision model for supporting customer-focused profitability analysis. *Industrial Management & Data Systems* **116**:6, 1105-1130. [Abstract] [Full Text] [PDF]