Locating using clustering and capabilities of GIS (case study: Bank)

Sara Aryaee
Management Department
University of Tehran
Tehran, Iran
sara.aryaee@ut.ac.ir

Abstract

Organizations follow survival in competitive business environment to be successful. Their aim is to offer better services to their customers. Whether service organizations or production companies are depended on the improvement and development of their services to increase the profitability in the future. To this purpose, selecting an appropriate business location is one of the most important systematic decision especially in the field of services and its outcomes has long-term effects. This research is conducted to scientifically locate Mehr Eghtesad bank branches. First the bank locating criteria are chosen through literature review, interviewing by experts and considering the available information layers in GIS environment. Best-worst method (MWM) is used to obtain the weight of criteria. These weights are the inputs of ArcGIS software. After entering the data into GIS, locating is done. Then the area which gets the highest priority is determined and its points are considered as candidate points in the marked areas which are the outputs of GIS. These points are considered as the entrance of clustering. They are clustered by Fuzzy C-Means method. Then the cluster that obtains the highest priority is determined by TOPSIS method. The points which are in that cluster is prioritized by COPRAS (COmplex PRoportional ASsessment) method. At the end, the proper places are determined to inaugurate the bank branches.

Keywords: locating, Clustering, bank ‹GIS ‹BWM ‹Fuzzy C-Means, TOPSIS‹ COPRAS

1. Introduction

Vast changes in the business environment such as demographics, technology, and globalization changes lead to the competitive atmosphere (Oblinger & Verville, 1998). Many factors like industry, region, and time (Fritsch, Brixy, & Falck, 2006) and having the competitive advantages such as customer value or customer satisfaction (Woodruff, 1997), innovation in services (Nijssen, Hillebrand, Vermeulen, & Kemp, 2006), Information Technology (Powell & Dent-Micallef, 1997) and proper location (Porter, 1994) can help businesses to maintain the more competitive position than other competitors. Among those factors, selecting location is one of the most important systematic decisions (Cabello, 2017) (Turley & Fugate, 1992). Because we can't easily change the location of a facility, locating a company or facility have strategic importance (Cinar, 2010) (Owen & Daskin, 1998). The importance of locating decisions is so much that 80 percent of routine decisions of public and private sectors are directly or indirectly to this field (Kang, Kim, & Jang, 2007). Due to the critical role of locating problem in commercial successes, decisions making on selecting a proper place is convert to one of the important problems especially in developing countries (Fung, 2001). On the other, location decisions are affected by many criteria (Cabello, 2017) that some of them are quantitative and some are qualitative (Chou, Hsu, & Chen, 2008). It converts the locating problems to a multi criteria decision making and guides the researchers to present diverse methods. Due to the increasing share of services in the countries' economics sector, the issue of locating in the service sector has gradually become more important. Among the service areas, one of the areas that has paid particular attention to this issue is the field of banking services. This is because of influence of bank branches location in attracting customers (Okolo, 2016)(Jamal & Naser, 2003), accessing to services and products (Okeahalam, 2009), bank performance (Zimmerman, 1996)(To & Tripe, 2002), maximizing bank profitability (Cabello, 2017) and increasing market share (Cabello, 2017). On the other hand, statistics show that 39% of customers choose their desired bank according to the location of bank (Fung, 2001). These benefits have led to the planning of a branch network as a location problem in the service industry (Hopmans, 1986).

Organizations which conducted scientific location pursue specific goals that can be categorized as below: reducing the farthest distance from existing facilities, reducing overall annual operating costs, increasing servicing, reducing time and average distance traveled, reducing the maximum time and distance traveled, reducing the number of located facilities, and increasing accountability (Farahani, SteadieSeifi, & Asgari, 2010). As mentioned before, scientific locating is applied in service fields, especially in the banks (Cabello, 2017). In the present era, banking services have experienced significant advances. In many developed countries, the rate of access to financial services is about 90%, and the number of people without a bank account is very low (Bilginol, Denli, & Şeker, 2015). The market position of a bank depends directly on the behavior of the choice of branch by potential customers (Hopmans, 1986). Internet-based banking and increasing bank service facilities to get the bank services have pushed banks to work more effectively on customer service than their other competitors. One of the effective factors in presenting the service is the location of the branches. On the basis of conducted research by Foster, 75% of people never change the first bank that they choose unless the change their place of residence (Dupuy, Kehoe, Linneman, Davis, & Reed, 1976). As a result, geographic proximity to customers in the banking industry is an important competitive advantage (Degl'Innocenti, Matousek, Sevic, & Tzeremes, 2017). Also, among all the bank selection criteria that the researchers have reviewed, the most important criterion is the location of branches (Bennett, 1973; Dupuy et al., 1976). But it should be noted that the inaugurating of the bank branch is not easy (Ogwuma, 1993) and requires scientific methods.

Considering the necessity and importance of locating the bank branches, in this paper we will use GIS capabilities, Clustering and MCDM to conduct a scientific locating which is asked by Mehr Eghtesad bank. The area in which the research is conducted is Tehran city (located in Iran). In this research, a list of criteria and sub-criteria for bank location was prepared by reviewing the literature. Then, through interviewing with the experts and considering the available information layers, 6 categories of criteria and 24 sub-criteria were categorized. BW method was used due to the diversity of criteria and with the aim of increasing the convergence of experts' weighting. The resulting weight was entered as the input of ArcGIS software, then locating was performed and the areas were respectively prioritized from the most important to the least important on the map. This is considered as the output. Then, 34 points in the area with the highest priority, considering the minimum distance of 500 meters between these points were determined as the candidate points. Due to the restrictions imposed by the Central Bank on the number of branches and the budgets considered by the target bank, the focus should be on the highest priority of these points. As a result, some of them must be selected among the candidate points. Therefore, 34 points were considered as the candidate sites as the input of the cluster model. These points were clustered using Fuzzy C-Means method and then the most important cluster was determined by TOPSIS method. In order to select the appropriate sites among the candidate points, the points of the most important cluster were prioritized with the COPRAS method and finally, suitable locations to inaugurate the branches were identified.

In the following, the organization of the paper is as follows; first, the locating literature is reviewed. Then, in the problem solving section, the research steps are expressed and then the BW method is introduced to determine the weight of the location criteria. In order to use the GIS capabilities in the field of locating, in the next section, GIS and the research carried out in this area will be explained. In the clustering section, we introduce its techniques, and among these methods the FCM method is described. Then we will explain the TOPSIS and COPRAS method. In the next section, the case study and the target region are introduced. Afterwards, the selected criteria and sub-criteria and the weights obtained by the BW method are presented. Then the GIS output is shown as candidate areas on the map, and the clustering of the candidate points is expressed by the FCM method, and in the next section, prioritization of these clusters is mentioned by the TOPSIS method. Finally, the prioritization of the points within the clusters is indicated by the COPRAS method. In the final section, while analyzing, the research findings are identified and suggestions for future research are presented.

2. Locating

Locating science is a valuable support for process planning and a key to ensure the operational efficiency and competitive advantage in providing goods and services with a relatively long history (Church & Murray, 2009) (Murray, 2010). The location can be defined by determining the appropriate location for a particular activity. This is done through a specific implementation procedure and according to the criteria and factors that affect it (Chu-Fen, LChu-Fen, 2007). Some experts have argued that locating a facility as a classical science came from researches done by people such as Pierre de Fermat, Evagelistica Torricelli (a student of Galileo), and Battista Cavallieri (Farahani et al., 2010). One of the first problems of location science was presented by Pierre de Fermet in the early 1600's (Church & Murray, 2009) and the theory of locating was introduced by Weber in 1909 (Farahani et al., 2010). Location science has gradually found widespread applications in various fields, including public, private (ReVelle & Eiselt, 2005), military, and especially the various business areas (Farahani et al., 2010). Some of these areas include Emergency shelter sites (Liu, Ruan, & Shi, 2011), Casino (Ishizaka, Nemery, & Lidouh, 2013), Railway station (Mohajeri & Amin, 2010), Shopping mall (Cheng, Li, & Yu, 2007), Thermal power plant (Choudhary & Shankar, 2012). As discussed in the introduction section, locating of each facility depends on several criteria, which has led to use various methods in MCDM, which are generally a combination of quantitative methods and mathematical techniques (Cabello, 2017). In this regard, we can mention the following researches:

Kuo (2011) presented a new hybrid approach to select optimal location for international distribution centers. In this paper, the Fuzzy DEMATEL technique was used to determine the proper structure among the criteria, then they used the AHP fuzzy to determine the parameters' weight and choose the best location (Kuo, 2011).

Demirel et al. (2010) have mentioned the following criteria to select multi-criteria warehouse location selection using Choquet integral:

infrastructures (communication, transportation), government rules and regulations, specific policies and management approaches, access and adjacency to main streets and roads, division and regionalization of the region or city, closeness or being far away from other centers (such as welfare, educational, manufacturing, sports, business centers), access to stakeholders (Demirel, Demirel, & Kahraman, 2010).

Wang & Wang (2010) presented a location model with the aim of minimizing costs and maximizing demand coverage. Using mixed integer programming, they determined the number of refueling centers for vehicles of and their locations to serve short and long distances (Y. W. Wang & Wang, 2010).

Toth & et al (2009) developed an exact interval branch-and-bound algorithm to solve simultaneously the problems of locating and designing facilities. They have used factors such as population distribution (fixed, variable, immigrant, etc.), the amount of demand for specific services, available and potential spaces and places (land, etc.) (Tóth, Fernández, Pelegrín, & Plastria, 2009).

Azadeh et al. (2008) presented an integrated hierarchy approach to locate solar power plants with Data Envelopment Analysis (DEA), Principal Component Analysis (PCA), and Numerical Taxonomy (NT). This approach has been tested for 25 different cities in Iran with 6 different regions (Azadeh, Ghaderi, & Maghsoudi, 2008).

Tabari et al. (2008) used the fuzzy AHP method to determine the optimal location. This paper described the procedure with a numerical example. The results showed that any changes in the decisions' priority, the amount and rate of each factors and costs considered in the research model could affect the desirability and value of a particular location. The results of the mathematical model showed the effectiveness and flexibility of the proposed holistic model with real-world issues. In this paper, effective factors in choosing the optimal location were classified into three groups of objective, subjective, and critical factors. The subjective and critical categories were introduced based on decision-makers' judgment. Ultimately, through sensitivity analysis and numerical examples analysis, the effectiveness and applicability of the model has been proven to real world problems (Tabari, Kaboli, Aryanezhad, Shahanaghi, & Siadat, 2008).

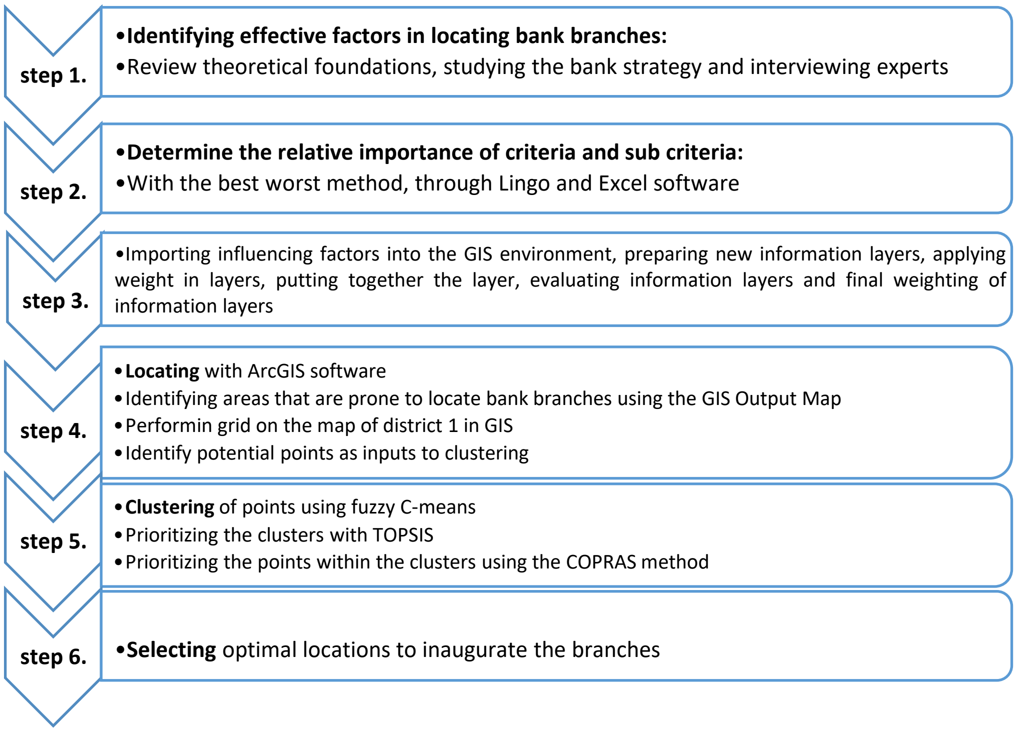
Zanjirani Farahani and Asgari (2007) combined MCDM and covering techniques in a hierarchical model to locate warehouses as distribution centers in the army logistics system. They conducted the research with two goals: First, determine the minimum number of centers needed and second select the appropriate place for them. The former sought to reduce the cost of centers' setting up and the latter sought to improve the quality of decision making in the field of locating. This quality depends on the 23 well known and effective factors in the location selection process. In this paper, TOPSIS technique was chosen as the most appropriate technique among MADM models. Finally, the model was solved by the combination of MODM-TOPSIS, binary planning, and quadratic equations (Farahani & Asgari, 2007).

Sherali et al. (2006) presented a discrete optimization approach to locate automatic license plate recognition devices to monitor the time of road travel. They developed the algorithmic inspection and monitoring technologies to locate optimal places and used INTEGRATION software (Sherali, Desai, & Rakha, 2006).

Jayaraman et al. (2003) have developed a binary integer linear programming method to locate service facilities to solve the problem of closeness of service centers to customers whenever they need service and support. The model used in this paper is as a part of a decision support system that supports an efficient initiative procedure to locate the service centers and assign a kind of service to them (Jayaraman, Gupta, & Pirkul, 2003).

3. Methodology

The necessary steps to go through the scientific method of locating for this research are visible in the flowchart 1.



Flowchart 1. The steps of conducting the research

3.1. Determine the weight of the criteria

3.1.1. weighting

In locating through GIS, weighing is used to obtain the importance of criteria and sub-criteria. Weighting methods include objective methods such as entropy (Xu, 2004), standard deviation (Diakoulaki, Mavrotas, & Papayannakis, 1995)(Deng, Yeh, & Willis, 2000) and CRITIC (Diakoulaki et al., 1995), subjective methods such as SMART (Edwards & Barron, 1994)(Mustajoki, Hämäläinen, & Salo, 2005) and SWING (Mustajoki et al., 2005)(Von Winterfeldt & Edwards, 1993), indirect methods such as SWARA (Mardani et al., 2017), cause and effect methods, such as DEMATEL (Gabus & Fontela, 1972)(Chen, Tzeng, & Huang, 2017) and ISM (Attri, Dev, & Sharma, 2013), paired comparison methods such as AHP (Saaty, 1990), ANP (Saaty, 2004) and BWM (Rezaei, 2015)(Rezaei, 2016), hybrid methods such as the combined method provided by Ma et al. (Ma, Fan, & Huang, 1999), the combined method of Fan et al. (Fan, Ma, & Zhang, 2002) and the combined method of Wang and Parkan (Y.-M. Wang & Parkan, 2006) and the other methods Like the method of cards (Simos, 1990b)(Simos, 1990a), the method of centralized weights (Solymosi & Dombi, 1986), the TACTIC method (Vansnick, 1986), DIVAPIME (Mousseau, 1995), and MACBETH (Bana e Costa, C., de Corte, J. M., Vansnick, 2012), and mixed integer linear programming models (Bisdorff, Meyer, & Veneziano, 2014). In MCDM methods, there are many methods based on pairwise logic, but what is used in GIS literature is AHP logic (Greene, Devillers, Luther, & Eddy, 2011).

Due to some problems such as large computation and compatibility of comparisons in AHP, in this paper we use the BW method to weigh the criteria and sub criteria.

3.1.2. Best-Worst Method (BWM)

The BWM is a comparison-based MCDM method. The basis of this method is that compares the most important criterion to other criteria and all criteria to the least important criterion (Rezaei, Nispeling, Sarkis, & Tavasszy, 2016). The purpose of this method is to find the optimal weights and the consistency ratio through a simple optimization model that is made by the comparison system (Rezaei et al., 2016). This method was developed by Dr. Rezaei in 2015 to solve discrete MCDM problem (Rezaei, 2015). This method draws the attention of different researchers in various fields and its application is increasing day by day. One can refer to the sample of this method in 2017 (Rezaei, Hemmes, & Tavasszy, 2017), 2016 (Rezaei et al., 2016), and in 2015 (Rezaei, Wang, & Tavasszy, 2015). By reviewing the literature, we found that most of the GIS researches has been used to obtain weight from the hierarchical analysis model or the network analysis process (Malczewski, 2006)(Jankowski, 2006)(Chandio et al., 2013). Therefore, in this study due to fewer computations, fewer paired comparisons, multiplicity of criteria and sub-criteria, and with the aim of increasing the consistency of the weighting of experts, the best-worst method is used to obtain the weight of the criteria. In the following the steps of conducting this research is mentioned:

Step 1. Determine a set of decision criteria

Step 2. Determine the best (the most desirable, the most important) and the worst (the most unfavorable, the least important) criterion

Step 3. Determine the priority of the best criterion to other criteria using a number from 1 to 9
Step 4. Determine the priority of all criteria to the worst criteria using a number from 1 to 9
Step 5. Finding the optimal weights $(w_1^*,\ w_2^*,\ \dots,\ w_n^*)$ by solving the mathematical model given below:

The optimal weight for the criteria is the weight that for each pair $\frac{w_B}{w_j}$,$\frac{w_j}{w_W}$ we have: $\frac{w_B}{w_j} = \boldsymbol{a_{Bj}}$, $\frac{w_j}{w_W} = \boldsymbol{a_{jW}}$. To establish above equations for all j, we need to find a solution that minimizes the maximum absolute difference $\left|\frac{w_B}{w_j} - \boldsymbol{a_{Bj}}\right|$, $\left|\frac{w_j}{w_W} - \boldsymbol{a_{jW}}\right|$ for all js:

$$\min \max_{j} \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right| ,\ \left| \frac{w_j}{w_W} - a_{jW} \right| \right\} \tag{1}$$

s.t. (2)

$$\sum_{j} w_j = 1$$

$$w_j \geq 0 \text{ , for all j} \tag{3}$$

The above problem can be written as a linear programming problem as follows:

$$\min \xi \tag{4}$$

s.t. (5)

$$\left|\frac{w_B}{w_j} - a_{Bj}\right| \leq \xi \text{ , for all j}$$

$$\left|\frac{w_j}{w_W} - a_{jW}\right| \leq \xi \text{ , for all j} \tag{6}$$

$$\sum_{j} w_j = 1 \tag{7}$$

$$w_j \geq 0 \text{ , for all j} \tag{8}$$

By solving the above problem we obtain optimal weights ($\boldsymbol{w_1^*}$, $\boldsymbol{w_2^*}$, …, $\boldsymbol{w_n^*}$) and $\boldsymbol{\xi}^*$(Rezaei, 2015).

3.2. Geographic information system (GIS)

The UK Academy for Information Systems (UKAIS) defines an information system as the way people and organizations use technology to collect, process, store, use, and disseminate information (Peppard & Ward, 2016). GIS is one of the most commonly used information systems to compile and interpret data (Turk, Kitapci, & Dortyol, 2014).

GIS stores, retrieves and combines geographic data in order to create a new representation of geographic space (Rigaux, Scholl, & Voisard, 2001) (Turk et al., 2014). With GIS, geographic reference data can be stored, modified, analyzed and mapped (Burrough, McDonnell, & Lloyd, 2015). The popularity of GIS is due to its widespread benefits. Here are some of them: 1. performing spatial analysis, storing data and linking them to visual representation by spatial databases, very low execution cost (Xia, 2004), quick and easy updating of information, and little need for mathematical knowledge and experience (ELSamen & Hiyasat, 2017).

Today, the use of GIS as an effective tool for data analysis and management has become widespread among business units and service providers, and it is used to better identify and market development and increase profitability (Duggal, 2007). Due to its widespread benefits, the use of GIS has grown substantially today. Some of the GIS capabilities include Bicycle facility planning (Rybarczyk & Wu, 2010), Tourism planning (Bahaire & Elliott-White, 1999), planning urban transport policies (Arampatzis, Kiranoudis, Scaloubacas, & Assimacopoulos, 2004), large-scale facilities asset management (X. Zhang, Arayici, Wu, Abbott, & Aouad, 2009).

On the other hand, GIS plays an important role in the analysis and modeling of location problems (Murray, 2010) and supports various levels of these problems)Hernandez & Bennison, 2000(. In these problems to gather locational information, calculate the intervals and locational analysis, GIS is usually used. The integration of location science, GIS and the development of their applications can provide theoretical and practical advances that will create useful auxiliary tools for decision making (Suárez-Vega, Santos-Peñate, & Dorta-González, 2012). One of the most important locating fields where the application of GIS is prevalent is the banking sector.

Fu (2007) examined GIS application from two aspects in banks' customer service. Firstly, he used GIS to locate banks branches and ATMs. The results of his work proved that GIS has a special role in helping banks and financial and credit institutions to improve their services to customers. Fu believed that the creation of a customer-centric location-based decision making system is a good choice in the current competitive environment (Fu, 2007).

In the context of evaluating and reviewing the location of bank branches and credit and financial institutions, the works of Densham (Densham, 1991), Boufounou (Boufounou, 1995), Morrison & Obrien (Morrison & O'Brien, 2001), MacDonald (MacDonald, 2001), Miliotis et al. (Miliotis, Dimopoulou, & Giannikos, 2002), Zhao (Zhao, 2002), and Panigrahi et al. (Panigrahi P.K., 2003) can be mentioned.

Densham (1991) conducted a research on spatial decision support system (SDSS) and expressed the various dimensions of issues facing bank managers, the need to use GIS, designing at a higher level, and using a SDSS to solve these problems. In his article, he mentioned that in designing a banking network, in developing branches, or in revising a branch network, or in merging banks, three questions should be answered: How many branches are required? 2. Where is the best place to inaugurate branches? 3. What services should be provided to customers in each of the branches? (Densham, 1991).

Boufounou (1995) examined the location and efficiency of the branches of Greek bank in Greece, and provided a complete list of factors and criteria in this field (Boufounou, 1995).

Morrison & O'Brien (2001) designed a GIS-based location gravity model so that the assessment of the branch location enables the logic of the branch network. They used the location gravity model to help managers decide to close some branches in New Zealand and use their model to evaluate the effect of shutting down some branches on the rest of the network (Morrison & O'Brien, 2001).

MacDonald (2001) examined the integration of banks in Canada using GIS through evaluating the amount of contribution market share of each branch and comparing them with each other. He also used the location gravity model to calculate the contribution share of each branch (MacDonald, 2001).

Miliotis et al. (2002) presented a model to solve the revising bank network problem with an emphasis on the efficiency of the integration of demand covering models and GIS. Basically, these models include the use of GIs to provide a variety of criteria taking into account the demand for banking services (geographic, social, economic, etc.) as well as competition in each particular region (Miliotis et al., 2002).

Zhao (2002) integrated GIS and MCDM to analyze bank branches in Australia. To this end, he used the SMART method, which is the way of solving the multi-criteria decision-making methods, and used the AHP method to test the results (Zhao, 2002).

Alexandris & Giannikos (2010) have presented a new integer-based model based on partial coverage to locate bank branches in an area of population so that the highest possible population is covered. They used the capabilities of the GIS (Alexandris & Giannikos, 2010).

The criteria used in some of these studies are visible in the criteria section (Table 1. Criteria in locating bank or ATM).

3.3. Clustering

Data mining is one of the most important steps in extracting a large amount of information designed to explore lots of information to search for consistent patterns and to validate results by patterns that are identified in the new subset of information (Popat & Emmanuel, 2014). The purpose of the data mining technique is to mine information from a bulky data set and create a logical form for it to complementary purposes (Mann & Kaur, 2013). Data mining consists of four tasks: Anomaly detection, Association, Classification, and Clustering (Mann & Kaur, 2013); In this paper, the fourth item is argued. Because of the widespread applicability of grouping in various areas of engineering to medicine (Saxena et al., 2017); for example, grouping different topics in order to read news (Popat & Emmanuel, 2014), categorizing diverse products of a company to evaluate the value of products selling (Rai & Singh, 2010), or grouping patients to determine their therapeutic type (Saxena et al., 2017), researchers have focused their attention on this issue for decades (Saxena et al., 2017). Many researches and studies are continuing in several fields, including OR (Negnevitsky, 2017)(Herrera-Restrepo, Triantis, Seaver, Paradi, & Zhu, 2016). As an example of OR research, we can point out locating, so that the points extracted from GIS are classified according to their degree of importance in groups, and based on those, the higher priority regions were chosen to establish a facility and the lower priority areas were ignored. Eventually the appropriate areas were ranked with one of the MADM methods.

There are various approaches to clustering (Estivill-Castro & Yang, 2000; Rokach & Maimon, 2005), each of which uses a particular rule.
These methods differ in the following cases: 1. Similarity measurement methods (inside or between clusters), 2. Limit thresholds in clusters construction and 3. Clustering mode (Mann & Kaur, 2013). Clustering algorithms include Hierarchical Clustering, Density based algorithms, and Grid Density based algorithms. In review articles , various types of clustering algorithms are mentioned (Saxena et al., 2017). In the following, the Fuzzy C-Means method is reviewed.

3.3.1. Fuzzy C-Means

In this study, one of the Partitioning techniques, called Fuzzy C-Means, developed by Bezdek in 1981 is used (James C Bezdek, 2013). The areas where FCM has been used can be summarized as follows: geostatistical data analysis (James C Bezdek, Ehrlich, & Full, 1984), medical diagnosis (James C Bezdek, 1976), shape analysis (J C Bezdek, Trivedi, Ehrlich, & Full, 1981) irrigation design (James C Bezdek & Solomon, 1981) , medical image segmentation (D.-Q. Zhang & Chen, 2004) and image segmentation (Chuang, Tzeng, Chen, Wu, & Chen, 2006).

Because of the widespread benefits such as reducing clustering error (Likas, Vlassis, & Verbeek, 2003), fast iterative algorithm (Likas et al., 2003), the efficiency of clustering in large data sets (Huang, 1997), good results if clusters are distinct in databases, or well separated (Cebeci & Yildiz, 2015), high speed, robust, and ease of implementation (Cebeci & Yildiz, 2015), this paper uses Fuzzy C-Means algorithm.

3.1.2. Fuzzy C-Means algorithm

Clustering is an important topic in the context of data mining that can be used to classify several alternatives different clusters (Shahsamandi E, Sadi-nezhad, & Saghaei, 2017). Fuzzy C-Means (FCM) is a well-known clustering method. It is of great interest for allocating members to clusters, due to its high reliability and greater flexibility compared to hard clustering techniques (Keskin, 2015). Fuzzy C-means an indefinite cluster of set of objects which are described in the form of U matrix (Bai, Dhavale, & Sarkis, 2014). This matrix has n rows and c columns, representing the number of objects and categories, respectively. The element u_{ik} represents the value of membership for the object i in cluster k. It should be noted that there is no certainty about the membership of an object in one clustering, however the probability of object membership in different clusters is of importance. The partitions of FCM algorithm include a set of n objects, each with a p-character, a data vector and clustered in c clusters. Cluster centers are displayed for each cluster by v_i and $V = \{v_1, v_2, \dots, v_n\}$ and calculated using Equation (13). Moreover, the membership degree for the i-th alternative in the k-th cluster (v_k) is shown as u_{ik}, calculated by Equation (12). Accordingly, the available relationships can be described as follows.

$$u_{ik} \in [0,1] \quad \forall i = 1,2, \dots, n; \quad \forall k = 1,2, \dots, c \tag{9}$$

$$\sum_{k=1}^{c} u_{ik} = 1, \quad \forall i = 1,2, \dots, n \tag{10}$$

$$0 \leq \sum_{i=1}^{n} u_{ik} \leq n \quad \forall k = 1,2, \dots, c \tag{11}$$

The FCM algorithm seeks to minimize the target function shown in Equation (12).

$$\min J(U,V) = \sum_{i=1}^{n} \sum_{k=1}^{c} u_{ik}^{m} \left(\|x_i - v_k\| \right)_A \tag{12}$$

Where, m (m>1) represents an exponential weigh controlling the fuzzy rate of clustering results. This weight is equal to the Euclidean distance of the object x_i from the center of cluster v_k. The solutions for the constrained optimization problem in Equation (12) are expressed in Equations (13) and (14).

$$v_{i,t} = \frac{\sum_{k=1}^{n}(u_{ik})^m x_k}{\sum_{k=1}^{n}(u_{ik})^m}, i = 1,2,\dots,c \tag{13}$$

$$u_{ik,t} = \left[\sum_{j=1}^{c}\left(\frac{\|x_k - v_{i,t-1}\|_A}{\|x_k - v_{j,t-1}\|_A}\right)^{\frac{2}{(m-1)}}\right]^{-1}, i \neq j \tag{14}$$

The recurring steps required to find an optimum solution are (Türksen, 2005).

Step 1: Select (c, m, T, ε)

Step 2: Find cluster centers

Step 3: Repeat the steps above for $t = 1\ to\ T$

Step 4: Calculate the membership value in Equation (13) and calculate cluster centers in Equation (12)

If $t = T$ and $\|v_{i,t} - v_{i,t-1} \leq \varepsilon\|$, then the procedure stops. Otherwise, it continues until finding other t values.

After clustering using the FCM algorithm, each object can be assigned to one cluster according to its membership degree, ranged in the interval [0,1]. The higher the membership degree of an object in a cluster, the higher the probability that the object belongs to that category. The FCM algorithm requires two categories of important information from the user, including the value of c (the number of clusters) and m (the fuzzy value of the cluster). As these two values are subjectively determined by the user, the quality of optimum solution and the membership degree of objects in clusters will be influenced by the choice of these two parameters. The value of c - the number of clusters - affects the causal region of cluster, while the initial value of cluster centers will impact the amount of compression and the accuracy of clusters.

In recent years, the FCM algorithm method has been integrated with several multiple attribute decision-making methods, among which DEA (Azadeh, Anvari, Ziaei, & Sadeghi, 2010), TOPSIS (Bai et al., 2014), VIKOR (Akman, 2015), DEMETAL (Keskin, 2015) can be cited.

In this research, the clustering of the candidate points to inaugurate the branches derived from the GIS is carried out by the FCM method and the clusters are prioritized by the TOPSIS method. Finally, the points within the clusters are prioritized by the COPRAS method.

3.4. TOPSIS method

TOPSIS is a widely-used MADM methods developed by (Hwang & Yoon, 1981). In this method, alternatives are ranked based on their proximity to an ideal solution and distance from the negative-ideal solution. The distance measurement is based on the Euclidean distance (Tzeng & Huang, 2011). The TOPSIS procedure is composed of six steps, described as follows (Lin, Wang, Chen, & Chang, 2008).

Step 1: Normalization of the decision matrix

After the decision matrix, $A = \{a_{i,r} | i = 1,2,\dots,n; r = 1,2,\dots,s\}$, is established in accordance with the logic of other multiple attribute decision-making methods, it must be transformed into a normal decision matrix. The normalized decision matrix is represented by ND, and the elements are obtained by Equations (15) and (16), with respect to benefit or cost criterion, respectively.

$$ND_{i,r} = \frac{a_{ir} - \min(a_{ir})}{\max(a_{ir}) - \min(a_{ir})} \quad (i = 1,2,\dots,n; r = 1,2,\dots,s) \quad \text{Benefit Criteria (Positive)} \tag{15}$$

$$ND_{i,r} = \frac{\max(a_{ir}) - a_{ir}}{\max(a_{ir}) - \min(a_{ir})} \quad (i = 1,2,\dots,n; r = 1,2,\dots,s) \quad \text{Cost Criteria (Negative)} \tag{16}$$

Step 2: Calculate weighted normalized decision matrix

The weighted normalized decision matrix, WD, is calculated by using Equation (17).

$$WD = \{k_{i,r} | i = 1,2,\dots,n; r = 1,2,\dots,s\}$$
$$k_{i,r} = W_i \frac{ND_{i,r}}{\sqrt{\sum_{r=1}^{s} ND_{i,r}^2}} \tag{17}$$

Where, W_i represents the weighting value of *i*-th criterion.

Step 3: Determine ideal and negative-ideal solutions

As the weighted normalized decision matrix developed, the ideal solution and negative-ideal solution are obtained using Equations (18) and (19), represented by PI and NI.

$$PI = \left\{\left(\max_r k_{i,r} | i \in J\right) or \left(\min_r k_{i,r} | i \in J'\right) \middle| r = 1,2,\dots,s\right\} = (k_1^+, k_2^+, \dots, k_n^+) \tag{18}$$
$$NI = \left\{\left(\min_r k_{i,r} | i \in J\right) or \left(\max_r k_{i,r} | i \in J'\right) \middle| r = 1,2,\dots,s\right\} = (k_1^-, k_2^-, \dots, k_n^-) \tag{19}$$

Here, *J* is the set of indexes of positive criteria such as quality; the increase in this set leads to increased desirability. On the other hand, J' is the set of negative indexes for criteria such as cost; an increase in this set results in a decrease in desirability.

Step 4: Calculate distance of alternatives from ideal and negative-ideal solution

The Euclidean method is used to measure this distance. k_r^+ and k_r^- indicate the distance of alternative r from the ideal solution and the anti-ideal solution, respectively. These values can be calculated using Equations (20) and (21).

$$k_r^+ = \sqrt{\sum_{i=1}^{n} (k_{i,r} - k_i^+)^2} \qquad r = 1,2,\dots,s \tag{20}$$

$$k_r^- = \sqrt{\sum_{i=1}^{n} (k_{i,r} - k_i^-)^2} \qquad r = 1,2,\dots,s \tag{21}$$

Step 5: Calculate relative proximity of each alternative to ideal solution

The relative proximity of the alternative r, RS_r, is obtained by Equation (22).

$$RS_r = \frac{k_r^-}{k_r^+ + k_r^+}, \qquad r = 1,2,\dots,s \quad and \quad 0 \le RS_r \le 1 \tag{22}$$

Step 6: Rank criteria based on RS index

Based on the logic of TOPSIS approach, one alternative of the highest RS relative to other alternatives finds the highest priority.

3.5. **The COPRAS (COmplex PRoportional ASsessment) method** (Bitarafan, Zolfani, Arefi, & Zavadskas, 2012)

Decision analysis concerns the situation in which decision makers must choose among a set of criteria, some of which are in conflict with each other. Under such conditions, the complex propprtional evaluation (COPRAS) method developed by Zavadskas and Kaklauskas (E K Zavadskas & Kaklauskas, 1996) can be used.The process of applying the COPRAS method consists of the following steps (Edmundas Kazimieras Zavadskas, Kaklauskas, Turskis, & Tamošaitienė, 2009):

Step 1: Select a set of the most important criteria that describes the alternatives very well.

Step 2: Make Decision Matrix X.

$$X = \begin{bmatrix} [x_{11}] & \cdots & \cdots & [x_{1m}] \\ [x_{21}] & \cdots & \cdots & [x_{2m}] \\ \ddots & \cdots & \ddots & \vdots \\ [x_{n1}] & \cdots & \cdots & [x_{nm}] \end{bmatrix}; j = \overline{1,n} \;\; i = \overline{1,m} \tag{23}$$

Step 3: Determine the importance (weight) of the criterion q_i.

Step 4: Normalize the decision matrix X by the formula (24), which is referred to below.

$$\tilde{x}_{ji} = \frac{\tilde{x}_{ji}}{\sum_{j=1}^{n} \tilde{x}_{ji}} \quad j = \overline{1,n}\,; i = \overline{1,m} \tag{24}$$

$\underline{x}_{ji}$ is the lower limit of criterion i for alternative j. Also, $\overline{x}_{ji}$ is the upper limit of criterion i for alternative j.

m is the number of criteria and n is the number of alternatives. Therefore, the decision matrix is normalized as the above form.

$$\tilde{X} = \begin{bmatrix} [\tilde{x}_{11}] & [\tilde{x}_{12}] & \ldots & [\tilde{x}_{1m}] \\ [\tilde{x}_{21}] & [\tilde{x}_{22}] & \ldots & [\tilde{x}_{2m}] \\ \vdots & \vdots & \ddots & \vdots \\ [\tilde{x}_{n1}] & [\tilde{x}_{n2}] & \ldots & [\tilde{x}_{nm}] \end{bmatrix} \tag{25}$$

Step 5: Calculate the weighted normalized decision matrix $\hat{X}$. The weighted normal $\hat{x}_{ji}$ is calculated as follows.

$$\hat{x}_{ji} = \tilde{x}_{ji} \,.\, q_i \tag{26}$$

where q_i is the weight of criterion i. Therefore, the weighted decision matrix is represented as follows.

$$\hat{X} = \begin{bmatrix} [\hat{x}_{11}] & [\hat{x}_{12}] & \cdots & [\hat{x}_{1m}] \\ [\hat{x}_{21}] & [\hat{x}_{22}] & \ldots & [\hat{x}_{2m}] \\ \vdots & \vdots & \ddots & \vdots \\ [\hat{x}_{n1}] & [\hat{x}_{n1}] & \cdots & [\hat{x}_{nm}] \end{bmatrix} \tag{27}$$

Step 6: Calculate the P_j value as defined below. Its larger values have a higher priority.

$$P_j = \sum_{i=1}^{k} \hat{x}_{ji} \tag{28}$$

Step 6: Calculate the R_j value as defined below. Its larger values have a higher priority.

$$R_j = \sum_{i=k+1}^{m} \hat{x}_{ji} \qquad i = \overline{k, m} \tag{29}$$

m-k is the number of criteria that must be minimized (the number of negative criteria, cost type criteria).

Step 8: Determine the smallest R_j value as follows:

$$R_{min} = \min_j R_j \,, j = \overline{1, n} \tag{30}$$

Step 9: Determine the relative importance of each alternative (Q_j) using the following formula:

$$Q_j = P_j + \frac{\sum_{j=1}^{n} R_j}{R_j \sum_{j=1}^{n} 1/R_j} \tag{31}$$

Step 10: Determine the optimal K value using the following formula:

$$K = \max_j Q_j, j = \overline{1, n} \tag{32}$$

Step 11: Determine the prioritization of alternatives.

Step 12: Determine the utility degree of each of the alternatives using the following formula:

$$N_j = \frac{Q_j}{Q_{max}} \times 100\%. \tag{33}$$

where Q_j and Q_{max} are the importance of the alternatives obtained from formula (31).

4. Case Study

In this research, Mehr Eghtesad Bank located in Iran have been selected. Mehr Eghtesad Bank is a financial and credit institution that has become a bank. It is affiliated with the Foundation of Cooperatives of the Mashhad Basij Organization. In Iranian top companies ranking based on the information of 2013, this bank placed in the 17th highest ranking company in Iran in terms of the amount of sales/revenue, 13th in total, and 6th in 2015 among all banks in Iran. This bank has been very successful in providing a variety of facilities to the general public, and therefore has proven to be well-known among the people. In June 2017, this bank succeeded in attracting doubly public confidence in the list of financial institutions approved by the Central Bank on the Central Bank website and confirmed its legitimacy. This bank is currently working with 800 branches throughout Iran.

According to the decision of the bank's managers, the study area was selected in the district 1 of Tehran. District 1 of Tehran is located in the north of Tehran with an area of 64 km^2 and on the basis of census of 2011, has 439 467 inhabitants. The massive amounts of ready-made and semi-finished buildings in the near future will bring the region's population to 500,000. Considering that this region is located in the best area of Tehran, the price of land is very high, therefore, we may face a shortage of funds for the opening of the branches. On the other hand, as there are many branches in this area, the Central Bank applies restrictions to open new branches. The market needs of the region should also be taken into account, as there are already many rival banks in this area. Given all these issues, we should try to choose the right number of the best candidate locations.

5. Bank locating criteria

As noted earlier, many factors affect the decision to choose a place (Bilginol et al., 2015). Choosing the right place for bank branches is a complex subject that requires detailed analysis of many criteria and sub-criteria. In table 1, some of the bank's location criteria are listed:

Table 1. Criteria in locating bank or ATM

Author(s), Year	**Criteria/ Sub-criteria**	**Title**
Görener et al. (2016) (Görener, A., Dincer, H., & Hacioglu, 2016)	**Demographic:** Total population, Literacy rate (%), Urbanization rate (%), **Economic:** Gross domestic product (millions of US $), Spending on education (% of GDP), Employment rate (%), Inflation rate in consumer prices (%), **Investment and Banking:** Total business spending on investment (% of GDP), Number of domestic companies listed on the stock exchange, Bank capital to assests ratio (%) , Domestic credit by banking sector (% of GDP)	Application of multi-objective optimization on the basis of ratio analysis (MOORA) method for bank branch location selection
Vafadarnikjoo et al. (2015) (Vafadarnikjoo, Mobin, Allahi, & Rastegari, 2015)	**Demographic attributes, Access to public facilities, Transportation, Competition, Cost, Flexibility**	A hybrid approach of intuitionistic fuzzy set theory and DEMATEL method to prioritize selection criteria of bank branches locations
Başar et al. (2014) (Başar, Kabak, & Topçu, 2014)	**Number of potential customers, socioeconomic status, social potential, business potential, competition, financial position, accessibility, growth potential**	Identifying the criteria and their priorities for locating bank branches in turkey
Lotfalipour et al. (2014) (Lotfalipour, Z., Naji- Azimi Z., & Kazemi, 2014)	**Competitive:** The existence of competitors and funds of other banks, **Access:** Locating in the scope of traffic and access to parking, **Security:** Environmental security, **Economic:** Bank's financial resources, Capacity and potential of branches, **Situation:** Proximity to business centers, wealthy residential areas, major economic organizations, and industrial cities and geographical distribution of bank branches	Locating the bank branches using a hybrid method
Tabar et al. (2013) (Tabar, Bushehrian, & Moghadam, 2013)	**Customer needs, local capacities, fair distribution of services**	Locating ATMs in Urban Areas
Cinar & Ahiska (2010) (Cinar & Ahiska, 2010)	**Demographic:** Total population, Urbanization rate, Annual population growth rate, **Socio-economic:** Gross national product per capita(YTL)*, Literacy Rate, Rate of population with higher education, Average household size, Employee rate, Employer rate, **Sectoral employment:** Agricultural employment rate, Manufacturing employment rate, Construction employment rate, Services employment rate, **Banking:** Number of bank, Number of branch, Bank deposit per branch (YTL)*, Credit per branch(YTL)*, Bank deposit per capita(YTL)*, Credit per capita(YTL)*, **Trade potential:** Number of firms, Number of organized industrial zone	A Decision Support Model for Bank Branch Location Selection
Boufounou (1995) (Boufounou, 1995)	**Economic characteristics of the region's people:** employment, income, etc., **socio-cultural characteristics of the region's people:** literacy, etc., **being close or far to other centers:** welfare, educational, manufacturing, sporting, commercial, etc.,	Evaluating bank branch location and performance: A case study

In this study, according to interview with experts, the review of literature and GIS layers given to researchers playing the most important role in the selection of criteria, 6 criteria and 24 sub-criteria to locate new branches were selected as follows: 1. The **economic** and **social** criterion includes the sub-criteria such as number of cooperative companies, chain stores (Shahrvand, Etka, etc.), large shopping malls (passage ...) and gas stations; 2. the **population** criterion includes the sub-criteria such as population of 10 years old and up, the number of households, the employed population, the literate population and the number of residential units; 3. the **accessibility** criterion includes traffic sub-criteria (number of main square and crowded intersections), transportation (number of metro stations, bus rapid transit (BRT) station and taxi stations), number of main streets, subsidiary street and parking; 4. the **existence of bank branches** criterion includes the sub-criteria such as own branches and rival banks; 5. the criterion of **urban services and facilities and public places** includes sub-criteria such as educational and cultural (number of universities, vocational schools, high schools, secondary schools, primary schools, libraries, private institutions, mosques, houses of culture, galleries, kindergartens, churches), administrative (number of municipalities, Embassies, government departments, notaries), recreational (number of recreational complexes, park, green spaces, theater, cinema, sports clubs, hotel, inn), Health & therapy (number of hospitals, pharmacies, clinics, clinics, laboratories, physicians' building, Emergency) and Historical (number of museums, palaces, etc.); 6. The **land use** criteria includes the sub-criteria such as number of industrial places, municipalities (city council, etc.) and police stations.

5.1. Criteria's weight

The weight of each criterion indicates its significance and value relative to other criteria in locating process. Therefore, in order to obtain the weight of the criteria and sub-criteria using the Best-Worst method, first, a questionnaire is given to the experts to determine the most important and the least important criterion and sub criterion (Tehran branches managers). Subsequently, a questionnaire was developed to determine the weight of the criteria and sub-criteria by determining pairwise comparison matrix of criteria and sub-criteria. This questionnaire was completed by the managers of Tehran branches.

Then the weight of criteria and sub-criteria was calculated using Lingo software and the consistency ratio was calculated in Excel. In table 2, the most important and the least important criterion and sub-criterion, the weight of criteria and sub-criteria calculated by BWM, and the final weight as an input to the GIS are shown.

Table 2. Weight of criteria and sub-criteria

Criteria		Weights of criteria	Sub-criteria		Weights of sub-criteria	Final weights (Weights of criteria* Weights of sub-criteria)
Economic and social	W1 (Best)	0.378267391	Shopping center	W51 (Best)	0.48556	0.183669859
			Cooperative companies	W52 (Worst)	0.08771	0.033179415
			Chain store	W53	0.22576	0.08539688
			Gas station	W54	0.20409	0.077200933
Population	W2	0.203535391	Number of residential units	W11 (Best)	0.444061125	0.090382155
			population of 10 years old and up	W12	0.1527582	0.0310917
			Number of households	W13 (Worst)	0.05843188	0.011892956
			Employed population	W14	0.169842358	0.034568931
			Literate population	W15	0.174906433	0.035599649
Access	W3 (Worst)	0.050886284	Transportation	W21 (Best)	0.44059	0.022419945
			Traffic	W22	0.18011	0.009164874

			Main streets	W23	0.17682	0.008997465
			Subsidiary street	W24 (Worst)	0.05976	0.003040982
			Parking	W25	0.14273	0.007263017
Bank	W4	0.142788 47	Rival banks	W31 (Best)	0.82755	0.11816408
			Own branches	W32 (Worst)	0.17245	0.02462439
Urban services and facilities and public places	W5	0.117777 779	Health & therapy	W41 (Best)	0.43928	0.051737209
			Educational and cultural	W42 (Worst)	0.05975	0.007037055
			administrative	W43	0.20211	0.023804163
			Recreational	W44	0.15837	0.01865304
			Historical	W45	0.14049	0.016546312
Land use	W6	0.106744 716	Industrial Places	W61 (Best)	0.61418	0.065560454
			Municipal Places	W62 (Worst)	0.11939	0.012744359
			Police stations	W63	0.26643	0.028439903

Weights are shown in Figure 1. As it is obvious, shopping centers and rival banks have the highest weight.

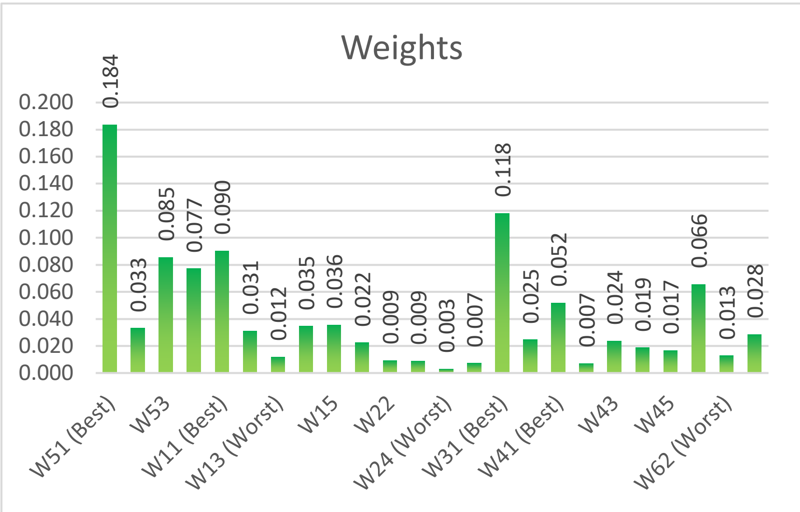
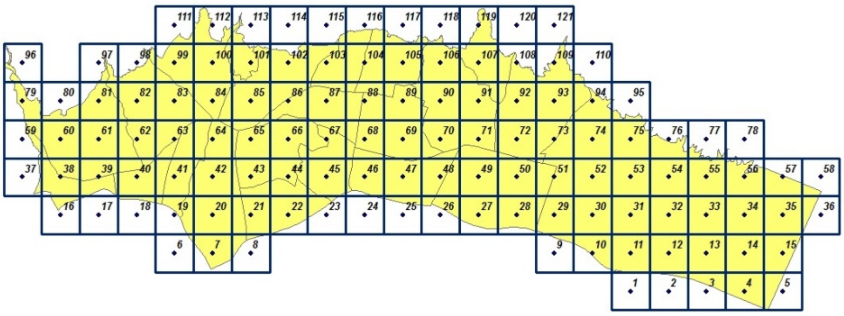


Figure 1. Weight of criteria and sub-criteria

6. Geographic information system (GIS)

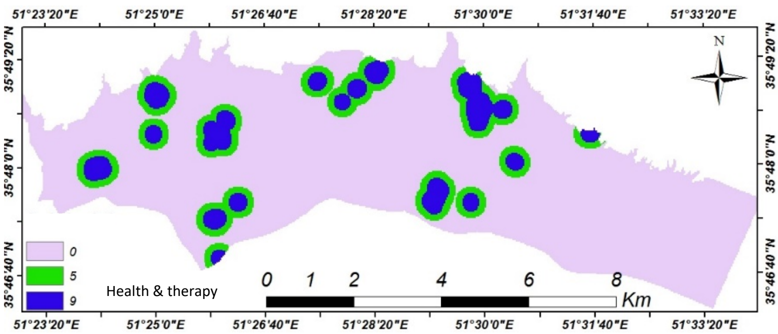
As described in the executive steps, in this research, GIS capabilities are used. The following steps were taken to prepare the information needed to solve the problem. The size of grid considered by the experts as 800 × 800 m^2 was applied to the neighborhoods layer of district 1 and its output was determined as 121 grids and their center of gravity was determined on the map (see Map 1).



Map 1. 800 × 800 m^2 grid size of district 1 of Tehran

The values of all sub-criteria in each grid (121 grid on district 1) were taken from GIS. Some grids are multi-polygonal. In order to solve this problem, each sub-criterion is divided into grid area (640000 square meters), and then the mean of these numbers is taken.

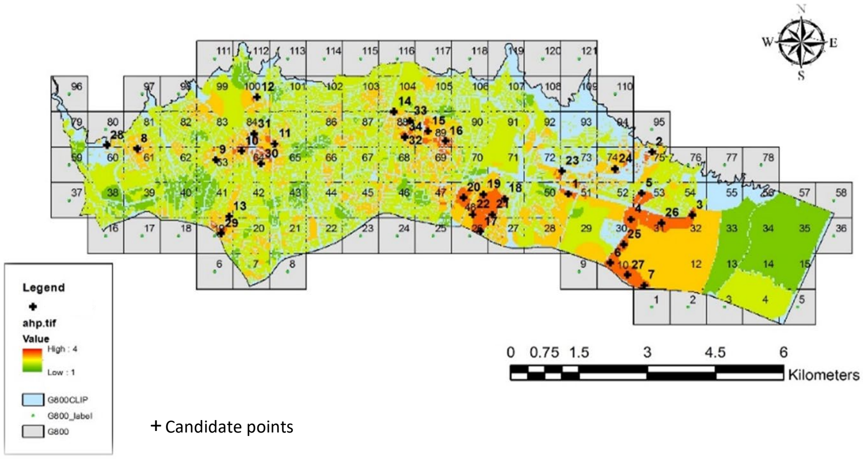
Locating was conducted based on the pairwise logic (based on weighting by BW method) was performed in ArcGIS and potential points were obtained from the GIS. Locating based on this model in ArcGIS was that after collecting the required layers of district 1, according to the sub-criteria in the GIS, the layers were made (the layers were ShapeFile or Polygon). For each layer (sub-criteria) the distance was determined. After converting the layers to raster[1], calculating Euclidean distance, and reclassifying the layers, then the final weights were calculated, multiplied in the corresponding layers, and accumulated. After reclassifying, the final layer was classified into four classes by Equal Interval classification: weak, moderate, good, and very good. For this purpose, the interval [0, 5] was selected and the value of each interval was considered 1.25. On the output maps of GIS, three classes 0, 5, and 9 are marked, respectively indicating bad, average and good areas based on weights shown on the layer. The outputs of solving by GIS are obtained as maps, as an instance see sub-criteria of health & therapy centers' map (Map 2).



Map 2. Sub-criteria of health & therapy centers

In order to obtain potential points, the three existing branches of the bank in district 1 were clipped of their respective layers, and eventually, 34 were identified through solving in ArcMap to inaugurate the branches (see Map 3).

[1] There are two formats to display data in GIS: raster or grid and vector or polygon. In the representation of raster data, each layer contains a large number of square cells which are the same size (rectangles, hexagons, and equilateral triangles) forming a grid. In representing of vector data, the representative points of the coordinates x and y, the lines are the representative of a string of points and polygons are the representative of lines that make up the nearby regions (Lukasheh, Droste, & Warith, 2001).



Map 3. Potential points

The information of these points are shown in Appendix 1.

7. Clustering

As mentioned, due to the budget set by the bank and the limitations of the central bank for the number of branches, there is no possibility to open 34 branches in district 1; therefore, we are going to categorize these points. To this end, the points which are similar to each other and have high priority are clustered by Fuzzy C-Means method. Then, by combining the FCM method with TOPSIS, the highest priority cluster is identified and the branches within each cluster are prioritized trough one of the MCDM methods called COPRAS.

8. Integrating Fuzzy C-Means and TOPSIS

8.1. Fuzzy C-Means (FCM)

The FCM was then utilized to cluster the 34 nominated points using the **initial decision matrix**. Based on the initial review of the applicants' information, the experts decided to classify them into **four** different clusters using the FCM. Therefore, the cluster centers were computed and presented in Table 4. Then the values obtained for the cluster centers, the membership of nominated points in each cluster was calculated, as shown in Table 5. Accordingly, each nominated point is placed in the cluster that has the highest percentage of membership.

Table 4- Calculating Cluster Centers in each cluster

Calculating Cluster Centers

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12
type	cost type	benefit type	cost type	benefit type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	benefit type
cluster 1	0/002511	0/005111	0/040985	0/010428	0/017268	0/009023	0/007846	0/005682	0/013698	0/003755	0/005308	0/003196
cluster 2	0/000385	0/002542	0/0061	0/001937	0/004299	0/001777	0/001808	0/003039	0/009615	0/002857	0/000482	0/000777
cluster 3	0/000677	0/005475	0/012306	0/006723	0/006043	0/005961	0/002077	0/006473	0/012247	0/002952	0/001228	0/002583
cluster 4	0/000592	0/003348	0/010715	0/00251	0/005426	0/002291	0/002439	0/004055	0/017882	0/003189	0/002169	0/000796

	c13	c14	c15	c16	c17	c18	c19	c20	c21	c22	c23	c24
type	cost type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	benefit type
cluster 1	0/003117	0/00097	0/061123	0/002072	0/023945	0/00836	0/010699	0/00222	0/007113	0/005179	0/002843	0/024261
cluster 2	0/000239	0/000125	0/013287	0/00074	0/004169	0/008547	0/001604	0/002177	0/003344	0/002564	0/000955	0/005896
cluster 3	0/000464	0/000264	0/029856	0/000585	0/007138	0/011824	0/005665	0/00225	0/00548	0/001837	0/001149	0/019643
cluster 4	0/000366	0/000252	0/016781	0/00116	0/011154	0/007724	0/00253	0/002042	0/005408	0/001994	0/001062	0/006002

Table 5- nominated points' membership percentage in each cluster

	membership percentage in each cluster			
	cluster 1	cluster 2	cluster 3	cluster 4
node 1	0/017361	0/260488	0/129103	0/593048
node 2	0/084427	0/26215	0/210195	0/443228
node 3	0/659559	0/087624	0/138115	0/114702
node 4	0/586973	0/092143	0/207104	0/11378
node 5	0/299611	0/147441	0/340106	0/212842
node 6	0/315099	0/131529	0/359565	0/193807
node 7	0/665107	0/08907	0/143964	0/101859
node 8	0/039837	0/243501	0/185994	0/530668
node 9	0/006089	0/822342	0/037786	0/133783
node 10	0/003022	0/913727	0/020102	0/063149
node 11	0/027237	0/32204	0/224946	0/425778
node 12	0/018622	0/365163	0/124907	0/491308
node 13	0/020052	0/30961	0/167464	0/502874
node 14	0/031269	0/504866	0/182685	0/281181
node 15	0/047408	0/230369	0/457748	0/264474
node 16	0/035826	0/275213	0/400635	0/288326
node 17	0/025286	0/307986	0/454161	0/212567
node 18	0/020354	0/618228	0/147995	0/213424
node 19	0/041868	0/078154	0/78563	0/094348
node 20	0/024422	0/066457	0/834664	0/074456
node 21	0/018018	0/552462	0/218338	0/211182
node 22	0/041667	0/142613	0/670997	0/144722
node 23	0/012916	0/215779	0/088425	0/68288
node 24	0/016972	0/223373	0/077255	0/682401
node 25	0/036258	0/271104	0/125649	0/566989
node 26	0/790897	0/049503	0/094531	0/065068
node 27	0/752974	0/060381	0/116032	0/070613
node 28	0/021902	0/277855	0/120587	0/579656
node 29	0/021957	0/603469	0/095246	0/279328
node 30	0/014418	0/632253	0/072739	0/280589
node 31	0/003069	0/919017	0/021505	0/056408
node 32	0/00453	0/877575	0/03063	0/087265
node 33	0/010699	0/745419	0/075092	0/168791
node 34	0/016553	0/47616	0/1984	0/308887

8.2. TOPSIS

Following the transformation of the initial decision matrix to a normal matrix, the criteria weight, determined using **Best-Worst method** will be applied to the normalized decision matrix. This is accomplished by multiplying the criteria weight to the corresponding element in the normalized decision matrix to obtain the weighted normal decision matrix. Next, the ideal solution and negative-ideal solution are calculated using Equations (18) and (19); and consequently the distances of the companies in each cluster from the ideal and negative-ideal solutions are obtained using Equations (20) and (21), respectively.

Equation (22) is used to calculate the relative proximity of each cluster and, finally, the clusters are arranged on the basis of relative proximity to the negative-ideal solution. The results are shown in Table 7. To further assess the selected places, they were ranked within each clusters. The TOPSIS ranking procedure was implemented for each clusters.

Table 7- Ranking of clusters using TOPSIS

	distance from ideal	distance from antiideal	score	rank
cluster 1	0/194881	0/128181	0/396769	4
cluster 2	0/16389	0/348034	0/679855	1
cluster 3	0/142493	0/246706	0/633882	2
cluster 4	0/176791	0/301209	0/630144	3

Table 8- Ranking of nominated points in four clusters

C1	P	R	Q	N	rank
node 3	0/02154	0/15416	0/17449	75/48	5
node 4	0/03242	0/13413	0/20821	90/0663	2
node 7	0/07265	0/19003	0/19673	85/099	3
node 26	0/02698	0/14414	0/19056	82/4299	4
node 27	0/07458	0/15057	0/23118	100	1

C2	P	R	Q	N	rank
node 9	0/01301	0/06987	0/08027	60/8903	8
node 10	0/01615	0/06821	0/08505	64/5117	5
node 14	0/01814	0/08466	0/07366	55/8727	11
node 18	0/03625	0/04917	0/13183	100	1
node 21	0/0475	0/07241	0/11241	85/2647	2
node 29	0/00326	0/04417	0/10966	83/1815	3
node 30	0/00798	0/06408	0/08133	61/6903	7
node 31	0/01929	0/06656	0/0899	68/195	4
node 32	0/01955	0/07232	0/08454	64/127	6
node 33	0/01885	0/07849	0/07873	59/7174	9
node 34	0/02819	0/10307	0/0738	55/9759	10

C3	P	R	Q	N	rank
node 5	0/02965	0/1393	0/09187	57/8343	7
node 6	0/03357	0/14964	0/09149	57/591	8
node 15	0/01623	0/09111	0/11135	70/0985	6
node 16	0/01461	0/082	0/1203	75/7305	5
node 17	0/02466	0/06564	0/1567	98/6427	2
node 19	0/03173	0/08988	0/12816	80/675	4
node 20	0/03648	0/08178	0/14246	89/6772	3
node 22	0/04124	0/07368	0/15885	100	1

C4	P	R	Q	N	rank
node 1	0/04877	0/06933	0/13341	100	1
node 2	0/00981	0/10353	0/06648	49/8351	10
node 8	0/02905	0/07867	0/10364	77/6851	4
node 11	0/01945	0/07663	0/09602	71/9765	6
node 12	0/02685	0/08121	0/0991	74/2835	5
node 13	0/02311	0/08473	0/09236	69/2322	8
node 23	0/04019	0/06895	0/12529	93/9147	2
node 24	0/00587	0/06745	0/09287	69/6119	7
node 25	0/00181	0/07959	0/07553	56/6192	9
node 28	0/02324	0/06293	0/11647	87/3073	3

To better illustrate the outcome of the analysis, the results were summarized and shown in Table 9.

Table 9. Ranking of clusters and points in each cluster

		Cluster Ranking			
		1	2	3	4
		C2	C3	C4	C1
Ranking in each cluster	1	n18	n22	n1	n27
	2	n21	n17	n23	n4
	3	n29	n20	n28	n7
	4	n31	n19	n8	n26
	5	n10	n16	n12	n3
	6	n32	n15	n11	
	7	n30	n5	n24	
	8	n9	n6	n13	
	9	n33		n25	
	10	n34		n2	
	11	n14			

Based on the ranking results in Table 9, points of n18, n21 and n29 are the top three nominated places with the best location and top priority to open new bank branches. This will help the bank's decision makers to identify the best locations. The result of this study was submitted to the experts and the bank decision makers. According their feedback, the results showed good agreement with their experience and judgment.

9. The COPRAS (COmplex PRoportional ASsessment) method

In this section, using the COPRAS method, the alternatives are prioritized in each cluster. The initial decision matrix according to the formula 24 is normalized. The initial and normalized decision matrixes are shown in Table 10-13 (first and second part). Then, this matrix is multiplied by the formula 26 in its weights and its output is obtained as a normalized weight matrix (see table 10, the third part and also see Appendix 2). In the following, according to the equations 29-31, 33, the values of P, R, Q, and N were extracted and the final ranking was performed.

Table 10. Cluster 1

initial decision matrix for cluster 1 in COPRAS method

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	c15	c16	c17	c18	c19	c20	c21	c22	c23	c24
type	cost type	benefit type	cost type	benefit type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	benefit type
node 3	530074	1441776	1688125	528567	1023461	501194	325334	653723	1119731	280545	3870462	153279	131183	38283	978717	3297210	3874942	270349	242116	255943	371016	218375	835277	152570
node 4	613591	1081764	806855	1065235	1170122	994927	614111	399871	287294	187290	2821205	219900	558132	389077	987194	2301013	2790269	731695	596569	344982	839744	772011	931600	216323
node 7	1129327	1666964	1480531	2327830	1800233	2138402	1159317	458359	861085	328346	3219684	587627	887339	103088	1575974	2827985	3233262	275317	1105219	383943	1341128	1129091	1411942	584292
node 26	571833	1261770	1247490	796901	1096792	748061	469723	526797	703513	233918	3345834	186590	344658	213680	982956	2799112	3332606	501022	419343	300463	605380	495193	883439	184447
node 27	681491	1267467	1268956	2446490	1392357	2247406	699591	295683	534878	317203	3271207	617581	404944	240603	1112121	2738812	3231998	507262	1161557	278092	885059	665985	942725	614076

normalized decision matrix for cluster 1 in COPRAS method

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	c15	c16	c17	c18	c19	c20	c21	c22	c23	c24
type	cost type	benefit type	cost type	benefit type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	benefit type
node 3	0/15032	0/21456	0/26003	0/07377	0/15787	0/07559	0/09955	0/28004	0/31933	0/20823	0/23417	0/08684	0/05639	0/03888	0/17362	0/23612	0/23537	0/11828	0/06869	0/16371	0/09178	0/06656	0/16689	0/0871
node 4	0/174	0/16098	0/12429	0/14867	0/18049	0/15006	0/18791	0/17129	0/08193	0/13901	0/17069	0/12459	0/23993	0/39511	0/17513	0/16478	0/16949	0/32013	0/16925	0/22066	0/20774	0/23532	0/18613	0/12349
node 7	0/32026	0/24807	0/22806	0/32489	0/27769	0/32253	0/35474	0/19635	0/24557	0/24371	0/1948	0/33294	0/38145	0/10469	0/27958	0/20252	0/19639	0/12045	0/31355	0/24558	0/33177	0/34417	0/28211	0/33356
node 26	0/16216	0/18777	0/19216	0/11122	0/16918	0/11283	0/14373	0/22566	0/20063	0/17362	0/20243	0/10572	0/14816	0/21699	0/17438	0/20045	0/20243	0/2192	0/11897	0/19218	0/14976	0/15094	0/17651	0/1053
node 27	0/19326	0/18862	0/19547	0/34145	0/21477	0/33898	0/21407	0/12666	0/15254	0/23544	0/19791	0/34991	0/17408	0/24433	0/19729	0/19613	0/19632	0/22193	0/32954	0/17787	0/21895	0/203	0/18836	0/35056

normalized weighted decision matrix for cluster 1 in COPRAS method

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	c15	c16	c17	c18	c19	c20	c21	c22	c23	c24
type	cost type	benefit type	cost type	benefit type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	benefit type
node 3	0/00106	0/00528	0/03073	0/00263	0/00817	0/00235	0/00237	0/00796	0/02727	0/00467	0/00387	0/00103	0/00051	0/00012	0/03189	0/00171	0/01817	0/00775	0/00237	0/00209	0/00305	0/00124	0/00153	0/00787
node 4	0/00122	0/00396	0/01469	0/00529	0/00934	0/00467	0/00447	0/00487	0/007	0/00312	0/00282	0/00148	0/00216	0/0012	0/03217	0/0012	0/01308	0/02099	0/00585	0/00281	0/00689	0/00439	0/00171	0/01116
node 7	0/00225	0/00611	0/02695	0/01157	0/01437	0/01003	0/00844	0/00558	0/02097	0/00546	0/00322	0/00396	0/00343	0/00032	0/05135	0/00147	0/01516	0/0079	0/01084	0/00313	0/01101	0/00642	0/00259	0/03015
node 26	0/00114	0/00462	0/02271	0/00396	0/00875	0/00351	0/00342	0/00642	0/01713	0/00389	0/00335	0/00126	0/00133	0/00066	0/03203	0/00146	0/01563	0/01437	0/00411	0/00245	0/00497	0/00282	0/00162	0/00952
node 27	0/00136	0/00464	0/0231	0/01216	0/01111	0/01054	0/0051	0/0036	0/01303	0/00528	0/00327	0/00416	0/00157	0/00074	0/03624	0/00142	0/01516	0/01455	0/01139	0/00227	0/00726	0/00379	0/00173	0/03168

10. Conclusion

As stated, locating decisions are important enough that most of the daily decisions of the private and public sectors are related to this field. Due to the role that location has in business successes, it has become one of the important issues, especially in service businesses, and has attracted the attention of researchers. Choosing the right place for bank branches is a strategic decision that affects the optimal performance of branches, profits and losses, survival in the complex competitive environment of the market, attracting customers and keeping them satisfied. Locating the new branches of the Mehr eghtesad bank in district 1 is the purpose of this research. This problem is solved through the best-worst method, clustering, ranking, and geographic information system approach.

It is worth noting that in this research for the first time weighing the geographic layers is done by best-worst method and the methods of BW, GIS, FCM, TOPSIS, and COPRAS are combined in order to maximize the utilization of these methods' capabilities. Other researchers can use this or similar combination to determine the appropriate location in other fields. There are several criteria involved in locating each of which has different importance and weight, and therefore they influence on output. In this research, due to the lack of information layers, we could not enter all the criteria into the model. In this research, we used the BW method to weight the criteria, if the exact data are available, objective methods can be used. At the time we extracted the weights, we found that the criteria and sub-criteria have inter correlation, therefore it is suggested to use ANP, DOE ... methods. In order to take into account the percentage of uncertainty, researchers can calculate the weights by fuzzy best worst methods. Researchers can use the combined methods such as ARAS, TOPSIS, VIKOR, and TODIM to have a robust ranking.

References

Akman, G. (2015). Evaluating suppliers to include green supplier development programs via fuzzy c-means and VIKOR methods. *Computers & Industrial Engineering*, *86*, 69–82.

Alexandris, G., & Giannikos, I. (2010). A new model for maximal coverage exploiting GIS capabilities. *European Journal of Operational Research*, *202*(2), 328–338.

Arampatzis, G., Kiranoudis, C. T., Scaloubacas, P., & Assimacopoulos, D. (2004). A GIS-based decision support system for planning urban transportation policies. *European Journal of Operational Research*, *152*(2), 465–475.

Attri, R., Dev, N., & Sharma, V. (2013). Interpretive structural modelling (ISM) approach: an overview. *Research Journal of Management Sciences*, *2*(2), 3–8.

Azadeh, A., Anvari, M., Ziaei, B., & Sadeghi, K. (2010). An integrated fuzzy DEA–fuzzy C-means–simulation for optimization of operator allocation in cellular manufacturing systems. *The International Journal of Advanced Manufacturing Technology*, *46*(1), 361–375.

Azadeh, A., Ghaderi, S. F., & Maghsoudi, A. (2008). Location optimization of solar plants by an integrated hierarchical DEA PCA approach. *Energy Policy*, *36*(10), 3993–4004.

Bahaire, T., & Elliott-White, M. (1999). The application of geographical information systems (GIS) in sustainable tourism planning: A review. *Journal of Sustainable Tourism*, *7*(2), 159–174.

Bai, C., Dhavale, D., & Sarkis, J. (2014). Integrating Fuzzy C-Means and TOPSIS for performance evaluation: An application and comparative analysis. *Expert Systems with Applications*, *41*(9), 4186–4196.

Bana e Costa, C., de Corte, J. M., Vansnick, J. C. (2012). MACBETH. *International Journal of Information Technology and Decision Making*, *11*(2), 359–387.

Başar, A., Kabak, Ö., & Topçu, Y. İ. (2014). Identifying the criteria and their priorities for locating bank branches in Turkey.

Bennett, R. O. (1973). Branch banking strategies: an empirical analysis.

Bezdek, J C, Trivedi, M., Ehrlich, R., & Full, W. (1981). Fuzzy clustering: A new approach for geostatistical analysis. *Int. J. Syst., Meas, Decision*, *1*, 13–23.

Bezdek, James C. (1976). Feature selection for binary data: Medical diagnosis with fuzzy sets. In *Proceedings of the June 7-10, 1976, national computer conference and exposition* (pp. 1057–1068). ACM.

Bezdek, James C. (2013). *Pattern recognition with fuzzy objective function algorithms*. Springer Science & Business Media.

Bezdek, James C, Ehrlich, R., & Full, W. (1984). FCM: The fuzzy c-means clustering algorithm. *Computers & Geosciences*, *10*(2–3), 191–203.

Bezdek, James C, & Solomon, K. (1981). Simulation of implicit numerical characteristics using small samples. *Proc. ICASRC*, *6*, 2773–2784.

Bilginol, K., Denli, H. H., & Şeker, D. Z. (2015). Ordinary Least Squares Regression Method Approach for Site Selection of Automated Teller Machines (ATMs). *Procedia Environmental Sciences*, *26*, 66–69.

Bisdorff, R., Meyer, P., & Veneziano, T. (2014). Elicitation of criteria weights maximising the stability of pairwise outranking statements. *Journal of Multi-Criteria Decision Analysis*, *21*(1–2), 113–124.

Bitarafan, M., Zolfani, S. H., Arefi, S. L., & Zavadskas, E. K. (2012). Evaluating the construction methods of cold-formed steel structures in reconstructing the areas damaged in natural crises, using the methods AHP and COPRAS-G. *Archives of Civil and Mechanical Engineering*, *12*(3), 360–367.

Boufounou, P. V. (1995). Evaluating bank branch location and performance: A case study. *European Journal of Operational Research*, *87*(2), 389–402.

Burrough, P. A., McDonnell, R. A., & Lloyd, C. D. (2015). *Principles of geographical information systems*.

Oxford University Press.

Cabello, J. G. (2017). A decision model for bank branch site selection: Define branch success and do not deviate. *Socio-Economic Planning Sciences*.

Cebeci, Z., & Yildiz, F. (2015). Comparison of K-Means and Fuzzy C-Means Algorithms on Different Cluster Structures. *AGRÁRINFORMATIKA/JOURNAL OF AGRICULTURAL INFORMATICS*, *6*(3), 13–23.

Chandio, I. A., Matori, A. N. B., WanYusof, K. B., Talpur, M. A. H., Balogun, A.-L., & Lawal, D. U. (2013). GIS-based analytic hierarchy process as a multicriteria decision analysis instrument: a review. *Arabian Journal of Geosciences*, *6*(8), 3059–3066.

Chen, C.-Y., Tzeng, G.-H., & Huang, J.-J. (2017). Generalized DEMATEL technique with centrality measurements. *Technological and Economic Development of Economy*, 1–15.

Cheng, E. W. L., Li, H., & Yu, L. (2007). A GIS approach to shopping mall location selection. *Building and Environment*, *42*(2), 884–892.

Chou, T.-Y., Hsu, C.-L., & Chen, M.-C. (2008). A fuzzy multi-criteria decision model for international tourist hotels location selection. *International Journal of Hospitality Management*, *27*(2), 293–301.

Choudhary, D., & Shankar, R. (2012). An STEEP-fuzzy AHP-TOPSIS framework for evaluation and selection of thermal power plant location: A case study from India. *Energy*, *42*(1), 510–521.

Chu-Fen, LChu-Fen, L. (2007). P. in B. B. I. M. S. and L. (2007). Problem in Bank Branch Ineficiency: Management. *Scale and Location*.

Chuang, K.-S., Tzeng, H.-L., Chen, S., Wu, J., & Chen, T.-J. (2006). Fuzzy c-means clustering with spatial information for image segmentation. *Computerized Medical Imaging and Graphics*, *30*(1), 9–15.

Church, R. L., & Murray, A. T. (2009). *Business site selection, location analysis, and GIS*. Wiley Online Library.

Cinar, N. (2010). A Decision Support Model for Bank Branch Location Selection. *International Journal of Human and Social Sciences*, *Vol.5*(c), hal.846-851. Dhaka, Bangladesh.

Cinar, N., & Ahiska, S. S. (2010). A decision support model for bank branch location selection. *International Journal of Human and Social Sciences*, *5*(13), 846–851.

Degl'Innocenti, M., Matousek, R., Sevic, Z., & Tzeremes, N. G. (2017). Bank efficiency and financial centres: Does geographical location matter? *Journal of International Financial Markets, Institutions and Money*, *46*, 188–198.

Demirel, T., Demirel, N. Ç., & Kahraman, C. (2010). Multi-criteria warehouse location selection using Choquet integral. *Expert Systems with Applications*, *37*(5), 3943–3952.

Deng, H., Yeh, C.-H., & Willis, R. J. (2000). Inter-company comparison using modified TOPSIS with objective weights. *Computers & Operations Research*, *27*(10), 963–973.

Densham, P. J. (1991). Spatial decision support systems. *Geographical Information Systems. Vol. 1: Principles*, 403–412.

Diakoulaki, D., Mavrotas, G., & Papayannakis, L. (1995). Determining objective weights in multiple criteria problems: The critic method. *Computers & Operations Research*, *22*(7), 763–770.

Duggal, N. (2007). Retail Location Analysis: A Case Study of Burger King & McDonald's in Portage & Summit Counties. *Ohio, the Degree of Masters of Arts*.

Dupuy, G. M., Kehoe, W. J., Linneman, R. F., Davis, R. N., & Reed, J. D. (1976). Comments on" Bank Selection Decision and Market Segmentation". *The Journal of Marketing*, 89–91.

Edwards, W., & Barron, F. H. (1994). SMARTS and SMARTER: Improved simple methods for multiattribute utility measurement. *Organizational Behavior and Human Decision Processes*, *60*(3), 306–325.

ELSamen, A. A. A., & Hiyasat, R. I. (2017). Beyond the random location of shopping malls: A GIS perspective in Amman, Jordan. *Journal of Retailing and Consumer Services*, *34*, 30–37.

Estivill-Castro, V., & Yang, J. (2000). Fast and robust general purpose clustering algorithms. In *Pacific Rim International Conference on Artificial Intelligence* (pp. 208–218). Springer.

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.

Farahani, R. Z., & Asgari, N. (2007). Combination of MCDM and covering techniques in a hierarchical model for facility location: A case study. *European Journal of Operational Research*, *176*(3), 1839–1858.

Farahani, R. Z., SteadieSeifi, M., & Asgari, N. (2010). Multiple criteria facility location problems: A survey. *Applied Mathematical Modelling*, *34*(7), 1689–1709.

Fritsch, M., Brixy, U., & Falck, O. (2006). The effect of industry, region, and time on new business survival–a multi-dimensional analysis. *Review of Industrial Organization*, *28*(3), 285–306.

Fu, Y. (2007). Managing Customer Services Using GIS in Banks: A Case in Chinese Competitive Environment. Institutionen för datavetenskap.

Fung, A. (2001). Half of consumers still prefer branches, poll finds. *American Banker*, 17.

Gabus, A., & Fontela, E. (1972). World problems, an invitation to further thought within the framework of DEMATEL. *Battelle Geneva Research Center, Geneva, Switzerland*.

Görener, A., Dincer, H., & Hacioglu, U. (2016). Application of multi-objective optimization on the basis of ratio analysis (MOORA) method for bank branch location selection. *International Journal of Finance & Banking Studies*, *2*(2), 41–52.

Greene, R., Devillers, R., Luther, J. E., & Eddy, B. G. (2011). GIS-Based Multiple-Criteria Decision Analysis. *Geography Compass*, *5*(6), 412–432.

Hernandez, T., & Bennison, D. (2000). The art and science of retail location decisions. *International Journal of Retail & Distribution Management*, *28*(8), 357–367.

Herrera-Restrepo, O., Triantis, K., Seaver, W. L., Paradi, J. C., & Zhu, H. (2016). Bank branch operational performance: A robust multivariate and clustering approach. *Expert Systems with Applications*, *50*, 107–119.

Hopmans, A. C. M. (1986). A spatial interaction model for branch bank accounts. *European Journal of Operational Research*, *27*(2), 242–250.

Huang, Z. (1997). A fast clustering algorithm to cluster very large categorical data sets in data mining. *DMKD*, *3*(8), 34–39.

Hwang, C. L., & Yoon, K. (1981). Attributes decision making methods and applications. Springer, Berlin.

Ishizaka, A., Nemery, P., & Lidouh, K. (2013). Location selection for the construction of a casino in the Greater London region: a triple multi-criteria approach. *Tourism Management*, *34*, 211–220.

Jamal, A., & Naser, K. (2003). Factors influencing customer satisfaction in the retail banking sector in Pakistan. *International Journal of Commerce and Management*, *13*(2), 29–53.

Jankowski, P. (2006). Integrating geographical information systems and multiple criteria decision-making methods. *Classics from IJGIS: Twenty Years of the International Journal of Geographical Information Science and System*, *9*(3), 265–296.

Jayaraman, V., Gupta, R., & Pirkul, H. (2003). Selecting hierarchical facilities in a service-operations environment. *European Journal of Operational Research*, *147*(3), 613–628.

Kang, S., Kim, T., & Jang, S.-G. (2007). Location-based services: enabling technologies and a concierge service model. *Societies and Cities in the Age of Instant Access*, 227–239.

Keskin, G. A. (2015). Using integrated fuzzy DEMATEL and fuzzy C: means algorithm for supplier evaluation and selection. *International Journal of Production Research*, *53*(12), 3586–3602.

Kuo, M.-S. (2011). Optimal location selection for an international distribution center by using a new hybrid method. *Expert Systems with Applications*, *38*(6), 7208–7221.

Likas, A., Vlassis, N., & Verbeek, J. J. (2003). The global k-means clustering algorithm. *Pattern Recognition*, *36*(2), 451–461.

Lin, M.-C., Wang, C.-C., Chen, M.-S., & Chang, C. A. (2008). Using AHP and TOPSIS approaches in customer-driven product design process. *Computers in Industry*, *59*(1), 17–31.

Liu, Q., Ruan, X., & Shi, P. (2011). Selection of emergency shelter sites for seismic disasters in mountainous regions: Lessons from the 2008 Wenchuan Ms 8.0 Earthquake, China. *Journal of Asian Earth Sciences*, *40*(4), 926–934.

Lotfalipour, Z., Naji- Azimi Z., & Kazemi, M. (2014). Locating the bank branches using a hybrid method. *Technical Journal of Engineering and Applied Sciences*, *4*(3), 124–134.

Lukasheh, A. F., Droste, R. L., & Warith, M. A. (2001). Review of expert system (ES), geographic information system (GIS), decision support system (DSS), and their applications in landfill design and management. *Waste Management & Research*, *19*(2), 177–185.

Ma, J., Fan, Z.-P., & Huang, L.-H. (1999). A subjective and objective integrated approach to determine attribute weights. *European Journal of Operational Research*, *112*(2), 397–404.

MacDonald, E. H. (2001). GIS in banking: Evaluation of Canadian bank mergers. *Canadian Journal of Regional Science*, *24*(3), 419.

Malczewski, J. (2006). GIS-based multicriteria decision analysis: a survey of the literature. *International Journal of Geographical Information Science*, *20*(7), 703–726.

Mann, A. K., & Kaur, N. (2013). Review paper on clustering techniques. *Global Journal of Computer Science and Technology*.

Mardani, A., Nilashi, M., Zakuan, N., Loganathan, N., Soheilirad, S., Saman, M. Z. M., & Ibrahim, O. (2017). A systematic review and meta-Analysis of SWARA and WASPAS methods: Theory and applications with recent fuzzy developments. *Applied Soft Computing*.

Miliotis, P., Dimopoulou, M., & Giannikos, I. (2002). A hierarchical location model for locating bank branches in a competitive environment. *International Transactions in Operational Research*, *9*(5), 549–565.

Mohajeri, N., & Amin, G. R. (2010). Railway station site selection using analytical hierarchy process and data envelopment analysis. *Computers & Industrial Engineering*, *59*(1), 107–114.

Morrison, P. S., & O'Brien, R. (2001). Bank branch closures in New Zealand: the application of a spatial interaction model. *Applied Geography*, *21*(4), 301–330.

Mousseau, V. (1995). Eliciting information concerning the relative importance of criteria. In *Advances in multicriteria analysis* (pp. 17–43). Springer.

Murray, A. T. (2010). Advances in location modeling: GIS linkages and contributions. *Journal of Geographical Systems*, *12*(3), 335–354.

Mustajoki, J., Hämäläinen, R. P., & Salo, A. (2005). Decision support by interval SMART/SWING—incorporating imprecision in the SMART and SWING methods. *Decision Sciences*, *36*(2), 317–339.

Negnevitsky, M. (2017). Identification of failing banks using Clustering with self-organising neural networks. *Procedia Computer Science*, *108*, 1327–1333.

Nijssen, E. J., Hillebrand, B., Vermeulen, P. A. M., & Kemp, R. G. M. (2006). Exploring product and service innovation similarities and differences. *International Journal of Research in Marketing*, *23*(3), 241–251.

Oblinger, D. G., & Verville, A.-L. (1998). *What Business Wants from Higher Education. American Council on Education/Oryx Press Series on Higher Education.* ERIC.

Ogwuma, P. (1993). Union Bank and Rural Banking. Ibadan: Annual Conference of Union Banks.

Okeahalam, C. (2009). Bank Branch Location: a Count Analysis. *Spatial Economic Analysis*, *4*(3), 275–300. https://doi.org/10.1080/17421770903114695

Okolo, J. U. (2016). Aspect of Bank Location and the Influence on Customer Banking Behaviour.

Owen, S. H., & Daskin, M. S. (1998). Strategic facility location: A review. *European Journal of Operational Research*, *111*(3), 423–447.

Panigrahi P.K., S. P. V. and R. P. R. (2003). GIS tools for simplifying the collection management system in banks and financial service organization. *Map Asia*.

Peppard, J., & Ward, J. (2016). *The strategic management of information systems: Building a digital strategy*. John Wiley & Sons.

Popat, S. K., & Emmanuel, M. (2014). Review and comparative study of clustering techniques. *International Journal of Computer Science and Information Technologies*, *5*(1), 805–812.

Porter, M. E. (1994). The role of location in competition. *Journal of the Economics of Business*, *1*(1), 35–40.

Powell, T. C., & Dent-Micallef, A. (1997). Information technology as competitive advantage: The role of human, business, and technology resources. *Strategic Management Journal*, 375–405.

Rai, P., & Singh, S. (2010). A survey of clustering techniques. *International Journal of Computer Applications*, *7*(12), 1–5.

ReVelle, C. S., & Eiselt, H. A. (2005). Location analysis: A synthesis and survey. *European Journal of Operational Research*, *165*(1), 1–19.

Rezaei, J. (2015). Best-worst multi-criteria decision-making method. *Omega*, *53*, 49–57.

Rezaei, J. (2016). Best-worst multi-criteria decision-making method: Some properties and a linear model. *Omega*, *64*, 126–130.

Rezaei, J., Hemmes, A., & Tavasszy, L. (2017). Multi-criteria decision-making for complex bundling configurations in surface transportation of air freight. *Journal of Air Transport Management*, *61*, 95–105.

Rezaei, J., Nispeling, T., Sarkis, J., & Tavasszy, L. (2016). A supplier selection life cycle approach integrating traditional and environmental criteria using the best worst method. *Journal of Cleaner Production*, *135*, 577–588.

Rezaei, J., Wang, J., & Tavasszy, L. (2015). Linking supplier development to supplier segmentation using Best Worst Method. *Expert Systems with Applications*, *42*(23), 9152–9164.

Rigaux, P., Scholl, M., & Voisard, A. (2001). *Spatial databases: with application to GIS*. Morgan Kaufmann.

Rokach, L., & Maimon, O. (2005). Clustering methods. In *Data mining and knowledge discovery handbook* (pp. 321–352). Springer.

Rybarczyk, G., & Wu, C. (2010). Bicycle facility planning using GIS and multi-criteria decision analysis. *Applied Geography*, *30*(2), 282–293.

Saaty, T. L. (1990). How to make a decision: the analytic hierarchy process. *European Journal of Operational Research*, *48*(1), 9–26.

Saaty, T. L. (2004). The analytic network process: Dependence and feedback in decision making (Part 1): Theory and validation examples, SESSION 4B: Theory and development of the analytic hierarchy process/analytic network process. In *The 17th International Conference on Multiple Criteria Decision Making* (pp. 6–11).

Saxena, A., Prasad, M., Gupta, A., Bharill, N., Patel, O. P., Tiwari, A., … Lin, C.-T. (2017). A review of clustering techniques and developments. *Neurocomputing*, *267*, 664–681.

Shahsamandi E, P., Sadi-nezhad, S., & Saghaei, A. (2017). Multi-objective complete fuzzy clustering approach. *Intelligent Automation & Soft Computing*, *23*(2), 285–294.

Sherali, H. D., Desai, J., & Rakha, H. (2006). A discrete optimization approach for locating Automatic Vehicle Identification readers for the provision of roadway travel times. *Transportation Research Part B: Methodological*, *40*(10), 857–871. https://doi.org/10.1016/j.trb.2005.11.003

Simos, J. (1990a). Evaluer l'impact sur l'environnement: Une approche originale par l'analyse multicritère et la négociation. In *Evaluer l'impact sur l'environnement: une approche originale par l'analyse multicritère et la négociation*. Presses polytechniques et universitaires romandes.

Simos, J. (1990b). *L'évaluation environnementale: Un processus cognitif négocié*.

Solymosi, T., & Dombi, J. (1986). A method for determining the weights of criteria: the centralized weights. *European Journal of Operational Research*, *26*(1), 35–41.

Suárez-Vega, R., Santos-Peñate, D. R., & Dorta-González, P. (2012). Location models and GIS tools for retail site location. *Applied Geography*, *35*(1), 12–22.

Tabar, M. M., Bushehrian, O., & Moghadam, R. A. (2013). Locating ATMs in Urban Areas. *International Journal on Computer Science and Engineering*, *5*(8), 753.

Tabari, M., Kaboli, A., Aryanezhad, M.-B., Shahanaghi, K., & Siadat, A. (2008). A new method for location selection: a hybrid analysis. *Applied Mathematics and Computation*, *206*(2), 598–606.

To, H. M., & Tripe, D. (2002). Factors influencing the performance of foreign-owned banks in New Zealand. *Journal of International Financial Markets, Institutions and Money*, *12*(4), 341–357.

Tóth, B., Fernández, J., Pelegrín, B., & Plastria, F. (2009). Sequential versus simultaneous approach in the location and design of two new facilities using planar Huff-like models. *Computers & Operations Research*, *36*(5), 1393–1405.

Turk, T., Kitapci, O., & Dortyol, I. T. (2014). The usage of Geographical Information Systems (GIS) in the marketing decision making process: a case study for determining supermarket locations. *Procedia-Social and Behavioral Sciences*, *148*, 227–235.

Türksen, I. B. (2005). *An ontological and epistemological perspective of fuzzy set theory*. Elsevier.

Turley, L. W., & Fugate, D. L. (1992). The multidimensional nature of service facilities. *Journal of Services Marketing*, *6*(3), 37–45.

Tzeng, G.-H., & Huang, J.-J. (2011). *Multiple attribute decision making: methods and applications*. CRC press.

Vafadarnikjoo, A., Mobin, M., Allahi, S., & Rastegari, A. (2015). A hybrid approach of intuitionistic fuzzy set theory and DEMATEL method to prioritize selection criteria of bank branches locations. In *Proceedings of the International Annual Conference of the American Society for Engineering Management.* (p. 1). American Society for Engineering Management (ASEM).

Vansnick, J.-C. (1986). On the problem of weights in multiple criteria decision making (the noncompensatory approach). *European Journal of Operational Research*, *24*(2), 288–294.

Von Winterfeldt, D., & Edwards, W. (1993). Decision analysis and behavioral research.

Wang, Y.-M., & Parkan, C. (2006). A general multiple attribute decision-making approach for integrating subjective preferences and objective information. *Fuzzy Sets and Systems*, *157*(10), 1333–1345.

Wang, Y. W., & Wang, C. R. (2010). Locating passenger vehicle refueling stations. *Transportation Research Part E: Logistics and Transportation Review*, *46*(5), 791–801. https://doi.org/10.1016/j.tre.2009.12.001

Woodruff, R. B. (1997). Customer value: the next source for competitive advantage. *Journal of the Academy of Marketing Science*, *25*(2), 139–153.

Xia, J. (2004). Library space management: a GIS proposal. *Library Hi Tech*, *22*(4), 375–382.

Xu, X. (2004). A note on the subjective and objective integrated approach to determine attribute weights. *European Journal of Operational Research*, *156*(2), 530–532.

Zavadskas, E K, & Kaklauskas, A. (1996). Determination of an efficient contractor by using the new method of multicriteria assessment. In *International Symposium for "The Organization and Management of Construction". Shaping Theory and Practice* (Vol. 2, pp. 94–104).

Zavadskas, Edmundas Kazimieras, Kaklauskas, A., Turskis, Z., & Tamošaitienė, J. (2009). Multi-attribute decision-making model by applying grey numbers. *Informatica*, *20*(2), 305–320.

Zhang, D.-Q., & Chen, S.-C. (2004). A novel kernelized fuzzy c-means algorithm with application in medical image segmentation. *Artificial Intelligence in Medicine*, *32*(1), 37–50.

Zhang, X., Arayici, Y., Wu, S., Abbott, C., & Aouad, G. (2009). Integrating BIM and GIS for large-scale facilities asset management: a critical review.

Zhao, L. (2002). *The integration of Geographical information systems and multicriteria decision making models for the analysis of branch bank closures*. University of New South Wales.

Zimmerman, G. C. (1996). Factors influencing community bank performance in California. *Economic Review-Federal Reserve Bank of San Francisco*, (1), 26.

Biographies

Sara Aryaee holds a Bachelor of Engineering degree in Industrial Engineering from Payam Noor University of Mashhad and a Master of Science degree in Industrial Management –Operation Research (OR)- from University of Tehran. Now, she is a Ph.D. Candidate in Operation Research at University of Tehran.

Appendix 1.

Table 1. Decision matrix of potential points

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12
type	cost type	benefit type	cost type	benefit type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	benefit type
node 1	298673	628606	170727	721653	426721	707120	205568	186507	791017	122696	2198016	122964
node 2	152553	713725	1021561	99794	309649	94934	230201	495631	939175	135882	2842317	29906
node 3	530074	1441776	1688125	528567	1023461	501194	325334	653723	1119731	280545	3870462	153279
node 4	613591	1081764	806855	1065235	1170122	994927	614111	399871	287294	187290	2821205	219900
node 5	319546	883808	1080536	1043345	855370	987634	265821	365927	587437	106097	3193211	296270
node 6	394929	777742	937425	1229888	956370	1130280	447951	234874	725597	225954	2888754	310367
node 7	1129327	1666964	1480531	2327830	1800233	2138402	1159317	458359	861085	328346	3219684	587627
node 8	94986	1691892	337648	288724	262267	280885	173458	558931	1657743	282869	1118011	95252
node 9	71606	596153	120022	150146	360320	148256	123781	220390	580621	122230	140115	52274
node 10	74069	458207	138003	198567	314201	197190	132442	193298	469449	153755	127439	70212/5
node 11	102327	705933	256521	205550	260602	203731	299441	224126	727395	340612	219764	69845
node 12	185759	913397	244438	291983	637139	303983	185406	334032	872732	940480	18616	91944
node 13	101137	994296	180861	229264	746791	226553	214480	422684	1008000	180610	223560	82439
node 14	114268	1138738	176693	199096	308217	200060	182384	179544	322420	182465	200294	66566
node 15	173253	1690939	311949	448879	221824	452713	153583	453066	735510	341681	254841	144090
node 16	155928	1521846	280755	403992	199642	407442	138225	407760	661959	307513	229357	129681
node 17	77289	1416465	212411	784432	539429	760045	104932	445885	341249	138546	25096	243196
node 18	82490	597051	94830	456950	104712	420897	104916	397808	181224	41524	181501	158623
node 19	164672	1576310	372424	991070	327702	938529	126390	610614	639497	205463	692332	323625
node 20	155071	1550357	305490	1167603	395339	1100917	110999	627480	618207	183375	491552	376682
node 21	79889/5	1006758	153621	620691	322071	590471	104924	421847	261237	90035	103299	200910
node 22	145471	1524405	238556	1344137	462977	1263305	95609	644347	596917	161287	290771	429738
node 23	256849	588872	198784	588983	391373	577161	198472	211619	859221	120013	2149653	101903
node 24	89551	429938	311014	58305	249982	57323	170088	312068	1132035	109282	1956202	17660
node 25	108367	288016	605894	13285	520382	13153	196311	174065	916316	134704	2506300	3152
node 26	571833	1261770	1247490	796901	1096792	748061	469723	526797	703513	233918	3345834	186590
node 27	681491	1267467	1268956	2446490	1392357	2247406	699591	295683	534878	317203	3271207	617581
node 28	75989	1353514	270119	230980	209814	224708	138767	447145	1326195	226296	894409	76202
node 29	11845	522501	137583	22882	181440	22673	91043	69003	512031	24853	364929	6716
node 30	102118	705296	145865	75673	321780	74858	148796	173768	718940	127393	145292	26901
node 31	76532	320261	155983	246988	268082	246123	141102	166206	358276	185280	114763	88151
node 32	131601	359518	187708	253948	294212	258011	120008	224156	330733	366805	62348	83019
node 33	122935	749128	182201	226522	301215	229036	151196	201850	326577	274635	131321	74792/5
node 34	152427	1025229	249829	351414	258018	355362	136796	338611	533122	354243	158595	113555

	c13	c14	c15	c16	c17	c18	c19	c20	c21	c22	c23	c24
type	cost type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	benefit type
node 1	82632	115788	295841	1566437	2128701	289589	442476	242829	305988	198844	275102	118658
node 2	54958	23472	197710	2437926	2991896	631641	33305	260569	467870	157334	174571	29542
node 3	131183	38283	978717	3297210	3874942	270349	242116	255943	371016	218375	835277	152570
node 4	558132	389077	987194	2301013	2790269	731695	596569	344982	839744	772011	931600	216323
node 5	69330	30805	583171	2620414	3174059	427016	411251	235964	449129	275887	447995	295397
node 6	222570	135747	635912	2403701	2949314	416652	583994	284233	738968	415184	568500	308599
node 7	887339	103088	1575974	2827985	3233262	275317	1105219	383943	1341128	1129091	1411942	584292
node 8	29454	34076	306444	2576768	891012	135187	106730	327561	1309819	236658	320530	95181
node 9	16282	25000	208153	1401992	316970	325657	55800	377111	296686	654529	494140	51767
node 10	30282	19159	215942	1154141	319449	372042	70886	381975	294260	492798	356402	69498
node 11	27154	10474	500173	610540	877125	267168	72616	307167	290332	387009	611515	69669
node 12	56285	67291	248364	1406101	1045732	607777	119451	412400	667039	245441	891964	91581
node 13	20793	19415	378320	1517761	722001	710738	87544	244638	790896	554698	386715	82004
node 14	27595	16559	236083	275128	530866	1404671	76780	321035	346979	222172	377323	65107
node 15	44410	35026	533877	533883	688124	1347525	154132	364711	735510	57068	384514	141378
node 16	39969	31524	480490	480495	619312	1212773	138719	328240	661959	51362	346063	127241
node 17	33620	45825	355900	436266	630531	888228	281376	309532	341249	204286	269494	242172
node 18	20661	27117	262429	242716	214977	93354	198661	79061	181224	21735	178661	158607
node 19	38676	39761/3	677920	450841	751007	427751	391134	317359	639497	225772	402993	322015
node 20	40556	44262/9	553634	426872	637229	526730	461301	315518	618207	207525	353937	375214
node 21	27140/5	36471	309165	339491	422754	490791	240019	194297	261237	113011	224078	200390
node 22	42436	48764/5	429349	402904	523451	625708	531467	313677	596917	189278	304881	428414
node 23	72155/2	97701/4	278652	1555097	2125549	283418	358121	251539	344834	205130	292092	98450/6
node 24	30248	25355	209895	1509737	2112941	258732	20701	286381	500218	230272	360051	17621
node 25	40195	30891	159702	2068589	2666629	326042	6430	290374	592877	164382	194275	3122
node 26	344658	213680	982956	2799112	3332606	501022	419343	300463	605380	495193	883439	184447
node 27	404944	240603	1112121	2738812	3231998	507262	1161557	278092	885059	665985	942725	614076
node 28	23564	27261	245156	2061415	712810	108150	85384	262049	1047856	189327	256424	76145
node 29	4473	5851	38724	748650	343150	62725	8032	135740	432456	179638	88601	6698
node 30	12581	9403	73422	837409	485243	424623	28594	142017	635886	136580	129471	26790
node 31	44282	13318	223730	906289	321928	418426	85972	386838	291834	331066	218664	87229
node 32	33661	20472	216624	1136170	552294	338755	98931	315283	220785	281667	342241	82714
node 33	30628	18515/5	226354	705649	541580	871713	87855/5	318159	283882	251920	359782	73910/5
node 34	39035/5	27749	375251	835027	620209	843140	126532	339997	478148	169368	363378	112046

Appendix 2.

Table 1. Cluster 2

initial decision matrix for cluster 2 in COPRAS method

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	c15	c16	c17	c18	c19	c20	c21	c22	c23	c24
type	cost type	benefit type	cost type	benefit type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	benefit type
node 9	71606	596153	120022	150146	360320	148256	123781	220390	580621	122230	140115	52274	16282	25000	208153	1401992	316970	325657	55800	377111	296686	654529	494140	51767
node 10	74069	458207	138003	198567	314201	197190	132442	193298	469449	153755	127439	70212/5	30282	19159	215942	1154141	319449	372042	70886	381975	294260	492798	356402	69498
node 14	114268	1138738	176693	199096	308217	200060	182384	179544	322420	182465	200294	66566	27595	16559	236083	275128	530866	1404671	76780	321035	346979	222172	377323	65107
node 18	82490	597051	94830	456950	104712	420897	104916	397808	181224	41524	181501	158623	20661	27117	262429	242716	214977	93354	198661	79061	181224	21735	178661	158607
node 21	79889/5	1006758	153621	620691	322071	590471	104924	421847	261237	90035	103299	200910	27140/5	36471	309165	339491	422754	490791	240019	194297	261237	113011	224078	200390
node 29	11845	522501	137583	22882	181440	22673	91043	69003	512031	24853	364929	6716	4473	5851	38724	748650	343150	62725	8032	135740	432456	179638	88601	6698
node 30	102118	705296	145865	75673	321780	74858	148796	173768	718940	127393	145292	26901	12581	9403	73422	837409	485243	424623	28594	142017	635886	136580	129471	26790
node 31	76532	320261	155983	246988	268082	246123	141102	166206	358276	185280	114763	88151	44282	13318	223730	906289	321928	418426	85972	386838	291834	331066	218664	87229
node 32	131601	359518	187708	253948	294212	258011	120008	224156	330733	366805	62348	83019	33661	20472	216624	1136170	552294	338755	98931	315283	220785	281667	342241	82714
node 33	122935	749128	182201	226522	301215	229036	151196	201850	326577	274635	131321	74792/5	30628	18515/5	226354	705649	541580	871713	87855/5	318159	283882	251920	359782	73910/5
node 34	152427	1025229	249829	351414	258018	355362	136796	338611	533122	354243	158595	113555	39035/5	27749	375251	835027	620209	843140	126532	339997	478148	169368	363378	112046

normalized decision matrix for cluster 2 in COPRAS method

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	c15	c16	c17	c18	c19	c20	c21	c22	c23	c24
type	cost type	benefit type	cost type	benefit type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	benefit type
node 9	0/07022	0/07971	0/06889	0/05357	0/11875	0/05405	0/08612	0/08521	0/12637	0/06355	0/081	0/05551	0/05681	0/11384	0/08724	0/16335	0/06788	0/05768	0/05176	0/12606	0/07968	0/2293	0/15773	0/05538
node 10	0/07263	0/06127	0/07921	0/07084	0/10355	0/07189	0/09214	0/07473	0/10217	0/07995	0/07367	0/07456	0/10565	0/08724	0/09051	0/13447	0/06841	0/0659	0/06575	0/12769	0/07903	0/17264	0/11377	0/07435
node 14	0/11205	0/15226	0/10141	0/07103	0/10158	0/07294	0/12689	0/06942	0/07017	0/09487	0/11578	0/07069	0/09628	0/0754	0/09895	0/03206	0/11369	0/2488	0/07122	0/10732	0/09319	0/07783	0/12045	0/06965
node 18	0/08089	0/07983	0/05443	0/16303	0/03451	0/15345	0/07299	0/1538	0/03944	0/02159	0/10492	0/16844	0/07208	0/12348	0/10999	0/02828	0/04604	0/01653	0/18428	0/02643	0/04867	0/00761	0/05703	0/16968
node 21	0/07834	0/13461	0/08817	0/22145	0/10614	0/21527	0/073	0/1631	0/05686	0/04681	0/05971	0/21334	0/09469	0/16607	0/12958	0/03956	0/09054	0/08693	0/22264	0/06495	0/07016	0/03959	0/07153	0/21438
node 29	0/01162	0/06986	0/07896	0/00816	0/0598	0/00827	0/06334	0/02668	0/11144	0/01292	0/21095	0/00713	0/01561	0/02664	0/01623	0/08723	0/07349	0/01111	0/00745	0/04538	0/11615	0/06293	0/02828	0/00717
node 30	0/10014	0/09431	0/08372	0/027	0/10605	0/02729	0/10352	0/06718	0/15647	0/06624	0/08399	0/02857	0/04389	0/04282	0/03077	0/09757	0/10392	0/07521	0/02652	0/04747	0/17078	0/04785	0/04133	0/02866
node 31	0/07505	0/04282	0/08953	0/08812	0/08835	0/08973	0/09817	0/06426	0/07798	0/09634	0/06634	0/09361	0/1545	0/06064	0/09377	0/1056	0/06894	0/07411	0/07975	0/12931	0/07838	0/11598	0/0698	0/09332
node 32	0/12905	0/04807	0/10773	0/0906	0/09696	0/09406	0/08349	0/08666	0/07198	0/19072	0/03604	0/08816	0/11744	0/09322	0/09079	0/13238	0/11828	0/06	0/09177	0/10539	0/0593	0/09868	0/10925	0/08849
node 33	0/12055	0/10017	0/10457	0/08082	0/09927	0/0835	0/10519	0/07804	0/07108	0/1428	0/07591	0/07942	0/10686	0/08431	0/09487	0/08222	0/11598	0/1544	0/08149	0/10635	0/07624	0/08825	0/11485	0/07907
node 34	0/14947	0/13708	0/14339	0/12538	0/08503	0/12956	0/09517	0/13092	0/11603	0/18419	0/09168	0/12058	0/13619	0/12635	0/15728	0/09729	0/13282	0/14934	0/11737	0/11365	0/12842	0/05933	0/11599	0/11987

normalized weighted decision matrix for cluster 2 in COPRAS method

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	c15	c16	c17	c18	c19	c20	c21	c22	c23	c24
type	cost type	benefit type	cost type	benefit type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	benefit type
node 9	0/00049	0/00196	0/00814	0/00191	0/00614	0/00168	0/00205	0/00242	0/01079	0/00142	0/00134	0/00066	0/00051	0/00035	0/01602	0/00119	0/00524	0/00378	0/00179	0/00161	0/00264	0/00428	0/00145	0/00501
node 10	0/00051	0/00151	0/00936	0/00252	0/00536	0/00224	0/00219	0/00213	0/00873	0/00179	0/00122	0/00089	0/00095	0/00027	0/01662	0/00098	0/00528	0/00432	0/00227	0/00163	0/00262	0/00322	0/00104	0/00672
node 14	0/00079	0/00375	0/01198	0/00253	0/00526	0/00227	0/00302	0/00197	0/00599	0/00213	0/00192	0/00084	0/00087	0/00023	0/01817	0/00023	0/00878	0/01631	0/00246	0/00137	0/00309	0/00145	0/0011	0/0063
node 18	0/00057	0/00197	0/00643	0/0058	0/00179	0/00477	0/00174	0/00437	0/00337	0/00048	0/00174	0/002	0/00065	0/00038	0/0202	0/00021	0/00355	0/00108	0/00637	0/00034	0/00161	0/00014	0/00052	0/01534
node 21	0/00055	0/00331	0/01042	0/00788	0/00549	0/00669	0/00174	0/00464	0/00486	0/00105	0/00099	0/00254	0/00085	0/00051	0/0238	0/00029	0/00699	0/0057	0/0077	0/00083	0/00233	0/00074	0/00066	0/01938
node 29	8/17E-05	0/00172	9/33E-03	0/00029	3/09E-03	0/00026	1/51E-03	7/59E-04	9/52E-03	2/90E-04	3/49E-03	8/5E-05	1/40E-04	8/10E-05	2/98E-03	6/34E-04	5/67E-03	7/28E-04	0/00026	5/78E-04	3/85E-03	1/17E-03	2/59E-04	0/00065
node 30	0/0007	0/00232	0/00989	0/00096	0/00549	0/00085	0/00246	0/00191	0/01336	0/00149	0/00139	0/00034	0/00039	0/00013	0/00565	0/00071	0/00802	0/00493	0/00092	0/00061	0/00567	0/00089	0/00038	0/00259
node 31	0/00053	0/00105	0/01058	0/00314	0/00457	0/00279	0/00234	0/00183	0/00666	0/00216	0/0011	0/00111	0/00139	0/00018	0/01722	0/00077	0/00532	0/00486	0/00276	0/00165	0/0026	0/00216	0/00064	0/00843
node 32	0/00091	0/00118	0/01273	0/00323	0/00502	0/00292	0/00199	0/00246	0/00615	0/00428	0/0006	0/00105	0/00106	0/00028	0/01668	0/00096	0/00913	0/00393	0/00317	0/00134	0/00197	0/00184	0/001	0/008
node 33	0/00085	0/00247	0/01236	0/00288	0/00514	0/0026	0/0025	0/00222	0/00607	0/0032	0/00126	0/00094	0/00096	0/00026	0/01743	0/0006	0/00895	0/01012	0/00282	0/00136	0/00253	0/00165	0/00105	0/00715
node 34	0/00105	0/00338	0/01694	0/00446	0/0044	0/00403	0/00227	0/00372	0/00991	0/00413	0/00152	0/00143	0/00123	0/00038	0/02889	0/00071	0/01025	0/00979	0/00406	0/00145	0/00426	0/00111	0/00106	0/01083

Table 2. Cluster 3

initial decision matrix for cluster 3 in COPRAS method

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	c15	c16	c17	c18	c19	c20	c21	c22	c23	c24
type	cost type	benefit type	cost type	benefit type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	benefit type
node 5	319546	883808	1080536	1043345	855370	987634	265821	365927	587437	106097	3193211	296270	69330	30805	583171	2620414	3174059	427016	411251	235964	449129	275887	447995	295397
node 6	394929	777742	937425	1229888	956370	1130280	447951	234874	725597	225954	2888754	310367	222570	135747	635912	2403701	2949314	416652	583994	284233	738968	415184	568500	308599
node 15	173253	1690939	311949	448879	221824	452713	153583	453066	735510	341681	254841	144090	44410	35026	533877	533883	688124	1347525	154132	364711	735510	57068	384514	141378
node 16	155928	1521846	280755	403992	199642	407442	138225	407760	661959	307513	229357	129681	39969	31524	480490	480495	619312	1212773	138719	328240	661959	51362	346063	127241
node 17	77289	1416465	212411	784432	539429	760045	104932	445885	341249	138546	25096	243196	33620	45825	355900	436266	630531	888228	281376	309532	341249	204286	269494	242172
node 19	164672	1576310	372424	991070	327702	938529	126390	610614	639497	205463	692332	323625	38676	39761/3	677920	450841	751007	427751	391134	317359	639497	225772	402993	322015
node 20	155071	1550357	305490	1167603	395339	1100917	110999	627480	618207	183375	491551/5	376682	40556	44262/9	553634	426872	637229	526730	461301	315518	618207	207525	353937	375214
node 22	145471	1524405	238556	1344137	462977	1263305	95609	644347	596917	161287	290771	429738	42436	48764/5	429349	402904	523451	625708	531467	313677	596917	189278	304881	428414

normalized decision matrix for cluster 3 in COPRAS method

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	c15	c16	c17	c18	c19	c20	c21	c22	c23	c24
type	cost type	benefit type	cost type	benefit type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	benefit type
node 5	0/20146	0/08077	0/28895	0/14074	0/21608	0/14027	0/18415	0/09655	0/11973	0/06353	0/39589	0/13146	0/13043	0/07482	0/13721	0/33788	0/31826	0/07272	0/13925	0/09556	0/09393	0/16963	0/14553	0/13185
node 6	0/24898	0/07108	0/25068	0/1659	0/24159	0/16053	0/31032	0/06197	0/14789	0/13531	0/358143	0/13772	0/4187	0/32971	0/14962	0/30994	0/29573	0/07095	0/19774	0/11511	0/15455	0/25528	0/18468	0/13774
node 15	0/10923	0/15454	0/08342	0/06055	0/05604	0/0643	0/1064	0/11954	0/14991	0/20461	0/031595	0/06394	0/08355	0/08507	0/12561	0/06884	0/069	0/22947	0/05219	0/1477	0/15383	0/03509	0/12491	0/0631
node 16	0/09831	0/13908	0/07508	0/0545	0/05043	0/05787	0/09576	0/10759	0/13492	0/18415	0/028435	0/05754	0/07519	0/07657	0/11305	0/06196	0/0621	0/20652	0/04697	0/13293	0/13844	0/03158	0/11242	0/05679
node 17	0/04873	0/12945	0/0568	0/10581	0/13627	0/10795	0/07269	0/11765	0/06955	0/08297	0/003111	0/10791	0/06325	0/1113	0/08374	0/05625	0/06322	0/15126	0/09527	0/12536	0/07137	0/12561	0/08754	0/10809
node 19	0/10382	0/14406	0/09959	0/13369	0/08278	0/1333	0/08756	0/16111	0/13034	0/12304	0/085834	0/1436	0/07276	0/09657	0/1595	0/05813	0/0753	0/07284	0/13244	0/12853	0/13375	0/13882	0/13091	0/14373
node 20	0/09777	0/14169	0/08169	0/1575	0/09987	0/15636	0/0769	0/16556	0/126	0/10981	0/060942	0/16714	0/0763	0/10751	0/13026	0/05504	0/0639	0/0897	0/15619	0/12778	0/12929	0/1276	0/11498	0/16747
node 22	0/09171	0/13932	0/06379	0/18131	0/11695	0/17942	0/06623	0/17001	0/12166	0/09658	0/036049	0/19069	0/07983	0/11844	0/10102	0/05195	0/05249	0/10655	0/17995	0/12703	0/12484	0/11638	0/09904	0/19122

normalized weighted decision matrix for cluster 3 in COPRAS method

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	c15	c16	c17	c18	c19	c20	c21	c22	c23	c24
type	cost type	benefit type	cost type	benefit type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	benefit type
node 5	0/00142	0/00199	0/03414	0/00501	0/01118	0/00436	0/00438	0/00275	0/01022	0/00142	0/006551	0/00156	0/00117	0/00023	0/0252	0/00245	0/02457	0/00477	0/00481	0/00122	0/00312	0/00316	0/00133	0/01192
node 6	0/00175	0/00175	0/02962	0/00591	0/0125	0/00499	0/00739	0/00176	0/01263	0/00303	0/005926	0/00164	0/00377	0/001	0/02748	0/00225	0/02283	0/00465	0/00684	0/00147	0/00513	0/00476	0/00169	0/01245
node 15	0/00077	0/00381	0/00986	0/00216	0/0029	0/002	0/00253	0/0034	0/0128	0/00459	0/000523	0/00076	0/00075	0/00026	0/02307	0/0005	0/00533	0/01504	0/0018	0/00188	0/0051	0/00065	0/00114	0/0057
node 16	0/00069	0/00342	0/00887	0/00194	0/00261	0/0018	0/00228	0/00306	0/01152	0/00413	0/00047	0/00068	0/00068	0/00023	0/02076	0/00045	0/00479	0/01354	0/00162	0/00169	0/00459	0/00059	0/00103	0/00513
node 17	0/00034	0/00319	0/00671	0/00377	0/00705	0/00336	0/00173	0/00335	0/00594	0/00186	5/15E-05	0/00128	0/00057	0/00034	0/01538	0/00041	0/00488	0/00992	0/00329	0/0016	0/00237	0/00234	0/0008	0/00977
node 19	0/00073	0/00355	0/01177	0/00476	0/00428	0/00414	0/00208	0/00458	0/01113	0/00276	0/00142	0/00171	0/00065	0/00029	0/0293	0/00042	0/00581	0/00478	0/00458	0/00164	0/00444	0/00259	0/0012	0/01299
node 20	0/00069	0/00349	0/00965	0/00561	0/00517	0/00486	0/00183	0/00471	0/01076	0/00246	0/001008	0/00199	0/00069	0/00033	0/02392	0/0004	0/00493	0/00588	0/0054	0/00163	0/00429	0/00238	0/00105	0/01514
node 22	0/00065	0/00343	0/00754	0/00645	0/00605	0/00558	0/00158	0/00484	0/01039	0/00217	0/000596	0/00227	0/00072	0/00036	0/01855	0/00038	0/00405	0/00699	0/00622	0/00162	0/00414	0/00217	0/00091	0/01728

Table 3. Cluster 4

initial decision matrix for cluster 4 in COPRAS method

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	c15	c16	c17	c18	c19	c20	c21	c22	c23	c24
type	cost type	benefit type	cost type	benefit type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	benefit type
node 1	298673	628606	170727	721653	426721	707120	205568	186507	791017	122696	2198016	122964	82632	115788	295841	1566437	2128701	289589	442476	242829	305988	198844	275102	118658
node 2	152553	713725	1021561	99794	309649	94934	230201	495631	939175	135882	2842317	29906	54958	23472	197710	2437926	2991896	631641	33305	260569	467870	157334	174571	29542
node 8	94986	1691892	337648	288724	262267	280885	173458	558931	1657743	282869	1118011	95252	29454	34076	306444	2576768	891012	135187	106730	327561	1309819	236658	320530	95181
node 11	102327	705933	256521	205550	260602	203731	299441	224126	727395	340612	219764	69845	27154	10474	500173	610540	877125	267168	72616	307167	290332	387009	611515	69669
node 12	185759	913397	244438	291983	637139	303983	185406	334032	872732	940480	18616	91944	56285	67291	248364	1406101	1045732	607777	119451	412400	667039	245441	891964	91581
node 13	101137	994296	180861	229264	746791	226553	214480	422684	1008000	180610	223560	82439	20793	19415	378320	1517761	722001	710738	87544	244638	790896	554698	386715	82004
node 23	256849	588872	198784	588983	391373	577161	198472	211619	859221	120013	2149653	101903/2	72155/2	97701/4	278652	1555097	2125549	283418	358121	251539	344834	205130	292092	98450/6
node 24	89551	429938	311014	58305	249982	57323	170088	312068	1132035	109282	1956202	17660	30248	25355	209895	1509737	2112941	258732	20701	286381	500218	230272	360051	17621
node 25	108367	288016	605894	13285	520382	13153	196311	174065	916316	134704	2506300	3152	40195	30891	159702	2068589	2666629	326042	6430	290374	592877	164382	194275	3122
node 28	75989	1353514	270119	230980	209814	224708	138767	447145	1326195	226296	894409	76202	23564	27261	245156	2061415	712810	108150	85384	262049	1047856	189327	256424	76145

normalized decision matrix for cluster 4 in COPRAS method

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	c15	c16	c17	c18	c19	c20	c21	c22	c23	c24
type	cost type	benefit type	cost type	benefit type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	benefit type
node 1	0/20371	0/07566	0/04746	0/26449	0/10629	0/26291	0/10216	0/0554	0/07732	0/04731	0/155591	0/177882	0/1889	0/25632	0/1049	0/09049	0/1308	0/08003	0/332	0/08415	0/04843	0/0774	0/0731	0/17399
node 2	0/10405	0/08591	0/28396	0/03657	0/07713	0/0353	0/1144	0/14721	0/09181	0/05239	0/2012	0/043263	0/12564	0/05196	0/0701	0/14084	0/18384	0/17456	0/02499	0/0903	0/07406	0/06124	0/04639	0/04332
node 8	0/06478	0/20364	0/09385	0/10582	0/06533	0/10444	0/0862	0/16601	0/16205	0/10907	0/079141	0/137793	0/06733	0/07544	0/10866	0/14886	0/05475	0/03736	0/08008	0/11352	0/20732	0/09212	0/08517	0/13957
node 11	0/06979	0/08497	0/0713	0/07533	0/06491	0/07575	0/14881	0/06657	0/07111	0/13134	0/015556	0/101039	0/06208	0/02319	0/17735	0/03527	0/0539	0/07384	0/05449	0/10645	0/04596	0/15064	0/1625	0/10216
node 12	0/12669	0/10994	0/06795	0/10701	0/1587	0/11302	0/09214	0/09921	0/08531	0/36264	0/001318	0/133008	0/12867	0/14896	0/08806	0/08123	0/06426	0/16797	0/08963	0/14292	0/10558	0/09554	0/23702	0/13429
node 13	0/06898	0/11968	0/05027	0/08402	0/18601	0/08423	0/10659	0/12554	0/09854	0/06964	0/015825	0/119258	0/04753	0/04298	0/13414	0/08768	0/04436	0/19642	0/06569	0/08478	0/12519	0/21591	0/10276	0/12025
node 23	0/17518	0/07088	0/05526	0/21586	0/09748	0/21459	0/09863	0/06285	0/08399	0/04628	0/152168	0/147415	0/16495	0/21629	0/0988	0/08984	0/13061	0/07833	0/26871	0/08717	0/05458	0/07985	0/07762	0/14436
node 24	0/06108	0/05175	0/08645	0/02137	0/06227	0/02131	0/08453	0/09269	0/11066	0/04214	0/138474	0/025547	0/06915	0/05613	0/07442	0/08722	0/12983	0/0715	0/01553	0/09925	0/07918	0/08963	0/09568	0/02584
node 25	0/07391	0/03467	0/16842	0/00487	0/12962	0/00489	0/09756	0/0517	0/08957	0/05194	0/177414	0/00456	0/09189	0/06838	0/05663	0/1195	0/16385	0/09011	0/00482	0/10063	0/09384	0/06398	0/05162	0/00458
node 28	0/05183	0/16291	0/07508	0/08465	0/05226	0/08355	0/06896	0/13281	0/12964	0/08726	0/063313	0/110235	0/05387	0/06035	0/08693	0/11909	0/0438	0/02989	0/06407	0/09082	0/16586	0/07369	0/06814	0/11165

normalized weighted decision matrix for cluster 4 in COPRAS method

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	c15	c16	c17	c18	c19	c20	c21	c22	c23	c24
type	cost type	benefit type	cost type	benefit type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	cost type	cost type	benefit type	cost type	cost type	cost type	cost type	benefit type
node 1	0/00143	0/00186	0/00561	0/00942	0/0055	0/00817	0/00243	0/00158	0/0066	0/00106	0/002574	0/002116	0/0017	0/00078	0/01927	0/00066	0/0101	0/00525	0/01148	0/00107	0/00161	0/00144	0/00067	0/01573
node 2	0/00073	0/00212	0/03355	0/0013	0/00399	0/0011	0/00272	0/00419	0/00784	0/00117	0/003329	0/000515	0/00113	0/00016	0/01288	0/00102	0/01419	0/01144	0/00086	0/00115	0/00246	0/00114	0/00043	0/00392
node 8	0/00046	0/00501	0/01109	0/00377	0/00338	0/00325	0/00205	0/00472	0/01384	0/00245	0/001309	0/001639	0/00061	0/00023	0/01996	0/00108	0/00423	0/00245	0/00277	0/00145	0/00688	0/00172	0/00078	0/01261
node 11	0/00049	0/00209	0/00843	0/00268	0/00336	0/00236	0/00354	0/00189	0/00607	0/00294	0/000257	0/001202	0/00056	7/1E-05	0/03257	0/00026	0/00416	0/00484	0/00188	0/00136	0/00152	0/00281	0/00149	0/00923
node 12	0/00089	0/00271	0/00803	0/00381	0/00821	0/00351	0/00219	0/00282	0/00729	0/00813	2/18E-05	0/001582	0/00116	0/00045	0/01617	0/00059	0/00496	0/01101	0/0031	0/00182	0/0035	0/00178	0/00217	0/01214
node 13	0/00049	0/00295	0/00594	0/00299	0/00962	0/00262	0/00254	0/00357	0/00841	0/00156	0/000262	0/001418	0/00043	0/00013	0/02464	0/00064	0/00342	0/01288	0/00227	0/00108	0/00415	0/00403	0/00094	0/01087
node 23	0/00123	0/00175	0/00653	0/00768	0/00504	0/00667	0/00235	0/00179	0/00717	0/00104	0/002518	0/001753	0/00148	0/00066	0/01815	0/00065	0/01008	0/00514	0/00929	0/00111	0/00181	0/00149	0/00071	0/01305
node 24	0/00043	0/00127	0/01022	0/00076	0/00322	0/00066	0/00201	0/00264	0/00945	0/00094	0/002291	0/000304	0/00062	0/00017	0/01367	0/00063	0/01002	0/00469	0/00054	0/00126	0/00263	0/00167	0/00088	0/00234
node 25	0/00052	0/00085	0/0199	0/00017	0/00671	0/00015	0/00232	0/00147	0/00765	0/00116	0/002936	5/42E-05	0/00083	0/00021	0/0104	0/00087	0/01265	0/00591	0/00017	0/00128	0/00311	0/00119	0/00047	0/00041
node 28	0/00036	0/00401	0/00887	0/00301	0/0027	0/0026	0/00164	0/00378	0/01107	0/00196	0/001048	0/001311	0/00048	0/00018	0/01597	0/00086	0/00338	0/00196	0/00221	0/00116	0/0055	0/00137	0/00062	0/01009