



FEATURE ANALYSIS FOR MULTI-CRITERIA RATING VALUES OF AIRLINE COMPANIES

Tugba KAYA^{1*}, Zehra Kamisli OZTURK²

¹ Eskisehir Technical University, Faculty of Engineering, Dept. of Computer Engineering, Eskisehir, Turkey

² Eskisehir Technical University, Faculty of Engineering, Dept. of Industrial Engineering, Eskisehir, Turkey

Keywords

Multi Criteria Decision Making, Artificial Neural Network, Multi-layer Perceptron, Promethee II, Airline Companies.

Abstract

The development of information and communication technologies offers the possibility of collecting and sharing customer views, comments and ratings about products and services over the Internet. Customers generally make these evaluations based on multiple criteria. This study uses such data recorded on Skytrax to analyse the performance of leading airlines. It does so using the a multicriteria decision making technique (Promethee II), and the criteria weight values required for the Promethee II method are obtained from a Multi-Layer Perceptron (MLP), an artificial neural network method. According to the results obtained, ANA airline has shown improvements in the years and moved up to the top, while the ranking of United airline within two years has not changed. The paper provides details of the technique and graphically presents results to highlight where airlines possess advantages over their competitors.

HAVAYOLU FİRMALARININ ÇOK KRİTERLİ OY DEĞERLERİ İÇİN NİTELİK ANALİZİ

Anahtar Kelimeler

Çok Kriterli Karar Verme, Yapay Sinir Ağları, Çok Katmanlı Algılayıcı, Promethee II, Havayolu Firmaları.

Öz

Bilgi ve iletişim teknolojilerinin gelişmesi, internette yer alan servisler ve ürünler hakkında müşterinin bakış açısı, yorumları ve oy değerlerinin paylaşılmasına ve toplanmasına imkân sağlamıştır. Müşteriler, bu değerlendirmeleri çoklu kriterlere dayanarak gerçekleştirmektedir. Bu çalışmada, havayolu firmalarının performans analizi için Skytrax' da yer alan veriler kullanılmıştır. Çok kriterli karar verme teknikleri kullanılarak yapılan bu çalışmada, Promethee II için gerekli olan ağırlık değerleri, bir yapay sinir ağları modeli olan Çok Katmanlı Algılayıcı (MLP) ile elde edilmiştir. Elde edilen sonuçlarda ANA havayolu firmasının yıllar içerisinde gelişmeler gösterip üst sıralara taşınırken, United havayolu firmasının iki yıl içerisindeki sıralamasında herhangi bir değişiklik gözlenmemiştir. Bu makalede kullanılan tekniklerin detayları verilirken, elde edilen sonuçlarda havayolu firmaları için rekabette sağladığı avantajlar vurgulanmıştır.

Alıntı / Cite

Kaya, T., Kamisli Ozturk, Z., (2020). Feature Analysis For Multi-Criteria Rating Values of Airline Companies, Journal of Engineering Sciences and Design, 8(2), 333-344.

Yazar Kimliği / Author ID (ORCID Number)

T. Kaya, 0000-0003-2202-7282
Z. Kamisli Ozturk, 0000-0003-3156-6464

Makale Süreci / Article Process

Başvuru Tarihi / Submission Date	12.09.2018
Revizyon Tarihi / Revision Date	20.12.2019
Kabul Tarihi / Accepted Date	20.12.2019
Yayın Tarihi / Published Date	25.06.2020

1. Introduction

Efficiency in the service sectors is getting much more significant issue in global trade. The one of the most important services in global service sector is airline companies. This service grows continuously year by year. A competition between airline companies has begun because of this growth. Therefore, it is aimed to be customer and customer satisfaction with focus to get in this top ranking of the competition. Customers will also make a

* İlgili yazar / Corresponding author: tugbatirkoglu@eskisehir.edu.tr, +90-222-321-3550

decision and select the most appropriate one from among many airline companies. The decision making is the process of finding the best option from all of the feasible alternatives. During the decision making process, the decision maker tries to determine the most appropriate alternative from the limited number of alternatives. But there must be a need to reliable and correct data at the decision-making process.

With the development of technology, there is an increase in the importance of knowledge. Although there exists a lot of data on the Internet, it has significance when these data are useful information. People's decision-making mechanism that use it to accomplish their goals is affected from the data stack. But there must be useful information in data for their decisions. However, this decision may be based on just a single criterion or multi criteria. In addition, whenever the number of criteria increases, the contradictions between them make the decision process more complex. For example, when a customer wants to buy a car, he will look at the fuel consumption and also price, model, color, popularity of this car. Based on this fact, decision makers prefer to use systematic decision making ways like multi criteria decision making (MCDM) techniques. The MCDM has emerged in the 1960s with the need for a number of tools to help decision making process. The MCDM can provide a probing solution with multiple and consistent criteria and ensure that the right choice is made. As Vassilev et al. (Vassilev et al., 2005) indicated, the multicriteria analysis problems can be divided into three types: problems of multicriteria choice, problems of multicriteria ranking and problems of multicriteria sorting. Many real-life problems in management practice may be formulated as problems of choice, ranking or sorting of resources, strategies, projects, offers, policies, credits, products, innovations, designs, costs, profits, portfolios, etc.

The purpose of this study is to evaluate the decisions of airline companies' passengers. To examine passenger satisfaction, airline companies have always submitted questionnaires on the Internet that are done based on multiple criteria. The passengers are commenting verbally and numerically on these criteria that they are satisfied with or not satisfied with. If the passenger is satisfied with his/her travel, the votes will be a plus for the company. However, if these assessments need to be properly analysed then companies can develop different strategies. These analyses should not be done in terms of a single passenger. Because, the features that make each passenger happy during the traveling can vary. So, if the company tries to develop a strategy by taking into account a single passenger, this tactic will not be applied to other traveling or traveling passengers. For this reason, almost all travelled passengers are considered and their comments are assessed, and different attitudes can be created.

In this study, it is aimed to determine the attitudes of passengers traveling in airline companies and a hybrid MCDM approach is adapted to determine these attitudes. This study consists of four sections. Section 2 contains literature review; information about the methods and algorithms used throughout the study are given in Section 3. Section 4 contains the implementation of the methods, and finally the results are given.

2. Related Work

In the competitive industry such as the airline industry, it is important for firms not only to correctly perceive what their customers want and expect, but also to manage their own resources in meeting their customer expectations appropriately. It has been done much work in the literature regarding the determination of user or customer attitudes and behaviours (Vela and Garcia, 2010; Liou and Tzeng, 2010). In this context, using Miranda and Henriques clustering methodology, airline passenger data were analysed and focused on companies seeking to develop different campaign strategies (Miranda and Henriques, 2013). For this work, the performance of k-means, self-organizing maps (SOM) and hierarchical self-extracting algorithms were evaluated. The analyses were carried out on data of 20,000 passengers. When the results are examined, the k-average is the best, as well as similar results with self-regulating maps. Vela and Garcia also performed clustering on passenger evaluations of different flight qualities and characteristics of the trip (Vela and Garcia, 2010). In their study, they concluded that there were four segments of passengers. These segments are price-sensitive, destination and flight-conscious, non-responsive and business travellers, educators and second-tier tourists. Wang et al. tried to discover a more general structure of the similarity (Wang et al., 2002). The researchers tried to create a new model called pCluster. The study team designed a depth-first algorithm that can effectively expose all pCluster models that are larger than the user-specified threshold value. In another study, Strehl et al. observed clustering quality using similarity measures of euclidean, cosine, Pearson and expanded JacCard (Strehl et al., 2000). They concluded that random, self-extractive maps, hyper-graph partitioning, general k-means, weighted graph partitioning algorithms are better than hypergraph partitioning in performance. Jarvis and Patrick focused on the problem of how data would be clustered in a nonparametric way (Jarvis and Patrick, 1973). The shortest search tree presented a method with apparent similarities with the clustering method. Gourdin categorized airline service quality into three items: price, safety and timelines (Gourdin, 1998). The researchers compared the fuzzy c-means and the possible c-means with the similarity clustering algorithm, which is a combination of the five algorithms. As a result, selected aggregate hierarchical clustering method and similarity-based clustering yield strong clustering results.

Liou and Tzeng reviewed Taiwan airline customers' responses to a simple and multiple-choice questionnaire with rough set-based classification (Liou and Tzeng, 2010). In the end, they found two dominant criteria that affected customers' decision stage; security and wages. Wang et al. compared the operational performance which relationship between four factors: airport, passengers, airline companies and fire services, of ten major airports in Taiwan (Wang et al., 2004). The results indicate that the total performance and the rating of the airports of all classes differ when examined in the context of several efficiency criteria. Feng and Wang tried to construct a performance evaluation process for airlines with financial ratios on five domestic airlines in Taiwan (Feng and Wang, 2000). Their study consists of three parts: production, marketing, execution. Transportation indicators are more suitable to measure the production efficiency than financial ratios and mixed indicators, and the execution efficiency is the best measured by financial ratios.

According to Bongo et al. (Bongo et al., 2017), MCDM approaches are successfully applied for (a) tourism development; (b) selecting aircraft type; (c) assessing productive efficiency in airports; (d) mitigating air traffic flow congestion; and (e) evaluating service quality of airports. In their study, Kurtulmuşoğlu et al. (Kurtulmuşoğlu et al., 2016) gave a brief summary of previous airline service expectation studies between the years 1980-2015. Almost all studies here are about service quality and customer satisfaction for a common airline firm. In addition to these studies, Oz and Koksall (Oz and Koksall, 2016) demonstrated the relative operating efficiencies of the Star Alliance group member airlines using their panel data for the years 2013 and 2014 with Data Envelopment Analysis (DEA) method. They also give a brief review of the studies that used DEA to determine airline industry efficiencies.

Besides these studies Tsaur et al. used the fuzzy set theory to evaluate the service quality of airline with fifteen service criteria (Tsaur et al., 2002). They applied Analytical Hierarchy Process to obtain criteria weights and then ranked the airlines with TOPSIS method. As a result, customers are mainly concerned about physical side of service and courtesy of attendants, safety, comfort and cleanness of seat and responsiveness of attendants are the most important criteria. Barros and Wanke used TOPSIS method. Then, neural networks are combined with TOPSIS results to evaluate Africa airlines. They concluded the results that the first rank is Air Seychelles and the least efficient airline is Egypt Air (Barros and Wanke, 2015). Liou et al. proposed an approach for airline selection. In that study, analytical hierarchy process (AHP) was integrated with a type of preference ordering involving the determination a solution's similarity to an ideal solution (TOPSIS) and multi-segment goal programming (MSGP) (Liou et al., 2011).

Lacic et al. tried to determine which of the ratings and interpretation features are more decisive for passenger satisfaction in their work (Lacic et al., 2016). During the study, researchers examined the data on the Skytrax portal, where airline and airline passenger assessments were shared, and found that waiting time at the airport, comfort in the waiting room, cabin staff for the airline and knee in the seat contributed to overall customer satisfaction.

As seen from the literature review, while determination of user attitudes and behaviours of airline companies have been worked for years, the evaluation of airline companies with hybrid MCDM techniques has not been worked intensively yet. The advantage of this study is the weights of evaluation criteria used in the MCDM method are determined by an artificial neural network model. This hybrid MCDM method is based on Promethee-II and Multi-Layer Perceptron model.

3. Determination of Criteria Weights

This section consists of two main methods. Multi-Layer Perceptron (MLP) and Promethee-II are used for determination of criteria weights and alternative selection, respectively.

3.1. Multi-Layer Perceptron

An artificial neural network consists of artificial neural cells that form parallel connections to each other in various layers. Artificial neural networks have a wide variety of network structures and models. There are many artificial neural network models (Perceptron, MLP, SOM, ART etc.) that can be used for different purposes. The most common one for these models is the Multi-Layer Perceptron (MLP), which is a multi-layer feedforward artificial neural network that is used in this study.

In MLP networks, neurons are organized in layers. The first layer is input layer. Input data exist in this layer. The layer between input and output layer is called as hidden layer. A MLP network can have multiple hidden layers. Figure 1 gives a general MLP network structure.

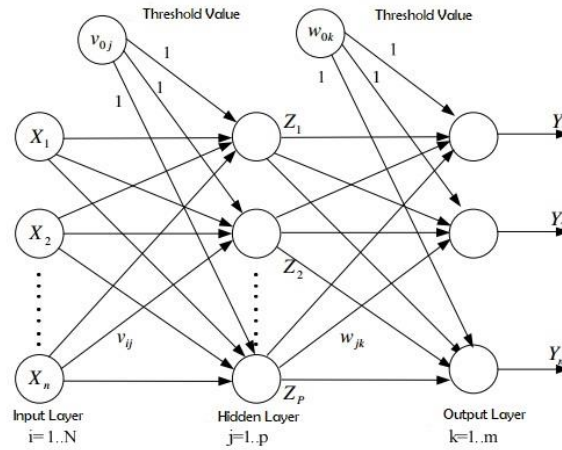


Figure 1. Multi-layer feed forward MLP

The steps of this architecture are given in Figure 2 (Gardner and Dorling, 1998). According to Algorithm 1, firstly initial weights and bias values are chosen randomly. In order to find Z_i values which are input data in hidden layer, these values are processed with input data. The obtained result is given as input to any activation function such as sigmoid, tangent. As a result, Y_k values are obtained by Z_i values which is given in step 2.3.1. With latest error value, feed forward pass process is completed. The next step is backward pass. In this process, V_{ij} , W_{jk} , $b_{j,k}$ values are updated which is given in step 2.6. An epoch is completed with applying all data of feed forward and backward processes. Stopping criteria are determined by decision makers. These criteria may be the number of epoch, not change of weights, etc.

Algorithm 1: MLP Algorithm

Input : Train and Test Data
Output : Output and Weight values

- 1: Initialize bias (b) and random weight (V, W) values
- 2: **while** (until stop criteria)
 - % Feedforward pass
 - 2.1: **for** $i:=1$ to n **do**
 - 2.1.1: $Z_i = activation_function(\sum_{j=1}^p X_j * V_{ji} + b_i)$
 - 2.2: **end for**
 - 2.3: **for** $k:=1$ to m **do**
 - 2.3.1: $Y_k = activation_function(\sum_{j=1}^p Z_j * W_{jk} + b_k)$
 - 2.4: **end for**
 - 2.5: $error = \frac{1}{2} \sum_{k=1}^m (Y_{desired} - Y_k)^2$
 - % Backward pass, update process
 - 2.6: $\Delta W_{jk} = \Delta W_{jk} - \alpha \frac{\partial error}{\partial W_{jk}}$
 - 2.7: $\Delta V_{ij} = \Delta V_{ij} - \alpha (\sum_p W_{pk} \delta_p) * f'_i(Z_i) * X_j$
 $\delta_p = (Y_{desired} - Y_p) * f'_p(Z_p)$
 - 2.8: $\Delta b_{j,k} = \Delta b_{j,k} - \alpha \frac{\partial error}{\partial b_{j,k}}$
- 3: **end while**

Figure 2. MLP Algorithm

3.2. Promethee II

MCDM determines which is the best among all possible efficient alternatives, according to the decision-maker (DM) preferences, taking into account several criteria. There are many techniques that have been developed to help decision-makers rank alternatives according to many criteria. Promethee is one of the outranking models. It has been developed from the difficulties in the implementation phase of current prioritization methods in the literature (Dagdeviren and Eraslan, 2008). The method evaluates alternatives in decision making problems based on determined preference functions and determines partial and complete ranking by means of binary comparison techniques. The Promethee method is one of the most recently developed methods of the MCDM methods and has been licensed by Brans and developed by Brans and Vincke in 1985 (Brans and Vincke, 1985). The basic features

of the Promethee method are simplicity, openness and balanced formation. The method uses preference functions while generating ranking. In order to make his decision easily for the decision maker, all the parameters must be clearly defined. Promethee method allows both partial ordering (Promethee I) and complete ordering (Promethee II) on the final number of alternatives (Brans et al., 1986). The success of the methodology is basically due to its mathematical properties and to its particular friendliness of use (Brans and Mareschal, 2005).

In this study, it is focus to find the complete order of the determined airline companies. So, Promethee-II method is used for ranking. Seven general steps for performing the Promethee II method can be listed as (Senkayas and Hekimoglu, 2013):

Step 1: As a first step, the decision maker is asked to define decision points and evaluation factors. Then, the data sets are created by determining the importance weights of the evaluation factors (criteria).

Step 2: This step determines the preference functions. The selected preference functions indicate the structure and internal relations of the criteria.

Step 3: Binary comparisons of decision points are made for each criterion, taking into account the preference functions, and common preference functions are determined.

Step 4: In this step preference indexes are determined using common preference functions.

Step 5: Positive and negative superiority values are determined for decision points.

Step 6: The partial sequence is determined with Promethee I. There are three situations in this comparison. The situations in which the superiority of one decision point to another, difference of decision points and decision points cannot be compared with each other.

Step 7: Promethee II determines the exact order of the decision points.

4. Feature Analysis for Multi-Criteria Rating Values of Airline Companies

In this section, we explain the data set used and the experiments performed.

4.1. Dataset

The main goal of the companies is to consistently provide customer satisfaction. To reach this goal, the companies try to measure their customer satisfaction in different ways to see their good and missing aspects. Skytrax, a consultancy firm located in London, United Kingdom, conducts research and consultancy mostly within the aviation sector (Perezgonzalez, 2011). This company conducts research for airlines to find the best cabin staff, airport, airline, airline lounge, in-flight entertainment, on board-catering and several other elements of air travel. In this study, Skytrax's airline rankings, which are publicly available in Skytrax's interactive web site (www.airlinequality.com), are used. There are latest travel reviews and customer trip ratings use for 681 airlines and 728 airports across the world. Because there are too much passenger data and airline companies, in this study Air China, Lufthansa, United, ANA and THY airline companies are selected to be evaluated. So, the passenger data of these companies are used. Example of customer review data is demonstrated in Figure 3. In this study two data sets are used and we focus on such numerical ratings with other data given in Figure 3 (a) rather than comments in Figure 3 (b). Such ratings also represent useful information that customer has been flown in economy, premium economy or business class and whether the customer recommends or not recommends the airline company to potential customer audience.

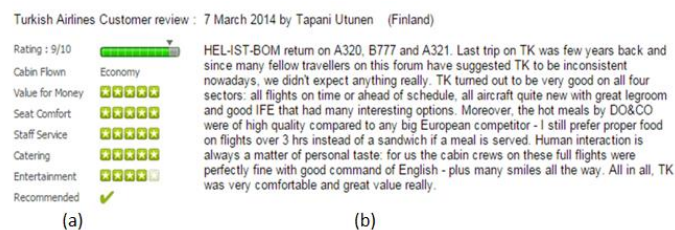


Figure 3. Customer reviews about flight service (www.airlinequality.com)

For the first data set, we select the subset of all of user reviews about airlines which Kaya used in her work (Kaya, 2017). These are costumer review data given from 1 January 2014 to 31 December 2014. There are five airlines and it consists of 1494 users and 13 attributes. For us, numerical ratings are important so, data set consists of five sub ratings and an overall rating. These sub ratings are *value of money* (VM), *seat comfort* (SC), *staff service* (SS), *catering* (Cat) and *entertainment* (Ent). While sub ratings are shown with stars from 1 to 5, overall rating is shown with a bar from 1 to 10.

As the second data set used in this study, same airline companies are chosen like first data set but customer reviews change from 1 January 2015 to 31 December 2015. The difference from the first dataset is there are seven sub ratings in this dataset. These sub ratings are value of money (VM), seat comfort (SC), staff service (SS), catering (Cat), entertainment (Ent), *ground of service* (GS) and *wifi&connectivity* (WC). This dataset consists of 568 (United), 282 (Lufthansa), 97 (Air China), 304 (Turkish) and 61 (ANA) customer reviews.

4.2. Experiment I

In this section, firstly to determine the criteria weights multi-layer perceptron (MLP), which is one of artificial neural network models, is applied to the first dataset. The dataset is classified as train and test. The train is 70 percent of the dataset; the rest is test. Architecture structure of MLP algorithm consists of five input (sub ratings) and an output (overall) neurons. Numbers of hidden neuron are tried to be determined by changing the numbers of hidden neuron according to the obtained error values. As error calculation, mean square error (MSE) is used.

Table 1. Error values according to changing numbers of neuron

Experiment	# of Hidden Neuron	# of Iteration	Train Error	Test Error
1	4	1000	1.7560	1.9045
2	6	1000	1.6590	1.9453
3	8	1000	1.5483	1.8614
4	10	1000	1.4626	2.1095
5	12	1000	1.3972	2.2521

According to Table 1, while the number of hidden neuron is 8, it can be observed that the error value is the smallest one. The MLP architecture consists of 5 input, 8 hidden and an output neuron as given in Figure 4.

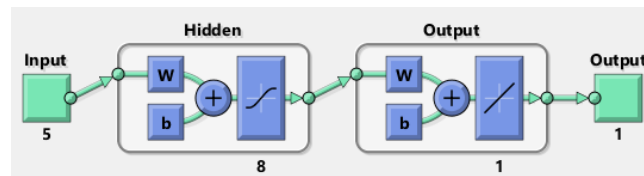


Figure 4. MLP architecture according to the best number of hidden neuron

In the second step, the importance ranking between criteria is determined. Therefore, Promethee II technique is used. Commonly, decision makers give the weights of criteria based on their experiences in Promethee II. But, in this study we use the weights which are obtained from MLP algorithm. These weights are the weights between input and hidden layer. The weight values are selected maximum for each criterion. Table 2 and Table 3 give the weight values, criteria values for each alternative and statistical values of this criteria, respectively.

Table 2. The criteria values for each alternative

	VM	SC	SS	Cat	Ent
Air China	3,45	3,96	3,69	3,47	2,29
ANA	3,27	3,30	3,32	3,27	2,45
Lufthansa	3,08	4,50	4,10	3,10	2,42
THY	2,82	3,70	3,54	3,61	3,05
United	2,71	3,60	3,27	2,01	2,03
Weights	3,32	22,89	2,20	3,51	7,89

Table 3. Statistical values for each criterion (Min: Minimum, Max: Maximum, S.Dev: Standart Deviation)

	VM	SC	SS	Cat	Ent
Min	2,71	3,30	3,27	2,01	2,03
Max	3,45	4,50	4,10	3,61	3,05
Mean	3,07	3,81	3,58	3,09	2,45
S. Dev	0,27	0,40	0,30	0,57	0,34

Figure 5 shows the ranking of the criteria which is obtained by Promethee II.

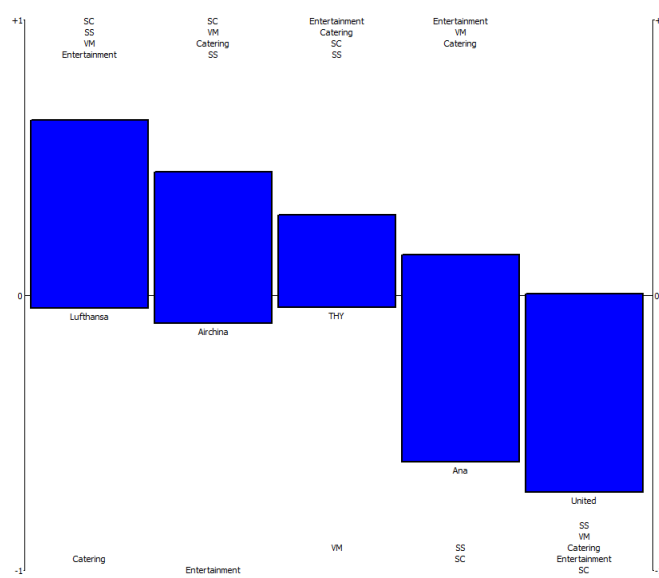


Figure 5. Phi values of criteria for each alternative

The parts shown in blue in Figure 5 represent the passenger numbers in the alternatives. When we examine important ranking of Lufthansa and Air China airlines, seat comfort criteria place the first rank. We can see that this criterion is the least important criterion for ANA and United. But while catering is the last rank for Lufthansa, for Air China entertainment locate to this rank. Generally, seat comfort, entertainment and value of money have high level importance, there is vice versa for staff service and catering.

We see that preference priority of Lufthansa is higher than other airlines. Air China, THY, ANA and United follow to Lufthansa in Figure 6.

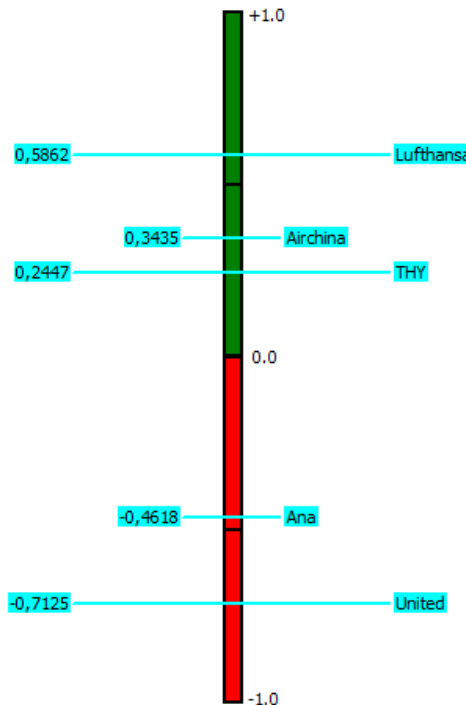


Figure 6. The ranking of each alternatives

Figure 7 shows the selection rank between alternatives in terms of certain criteria.

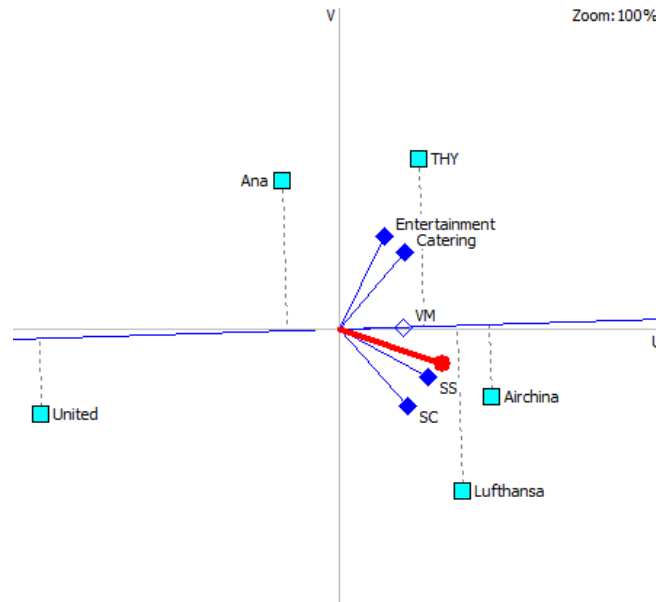


Figure 7. The selection ranks in terms of value of money (VM)

There are selection priorities of airlines according to VM in Figure 7. According to the figure, while value of money is the best selection for Air China, it is the worst selection for Lufthansa and United. If another criterion is wanted to be selected, then a straight line is drawn passed from this criterion and the origin. The alternatives which are close to the drawn line are determined as the best selection in the sense of this criterion. It is assumed that this criterion is entertainment. According to straight line passed from this criterion and origin, we can say that the best choices are THY and ANA. The worst choices are United and Lufthansa for this criterion. By means of these results, according to important criteria of passenger that will travel, this analyses are performed and passenger can travel with the most suitable alternative firm.

4.3. Experiment II

The difference from previous section of this section is that experiments are applied on a different dataset. To the dataset which contains 1312 passenger is firstly applied MLP. The train is 70 percent of the dataset, the rest is test. Architecture structure of MLP algorithm consists of seven input (sub ratings) and an output (overall) neurons. We try to determine numbers of hidden neuron by changing the numbers of hidden neuron according to the obtained error values. Table 4 gives error values according to exchanged number of neuron for hidden layer.

Table 4. Error values according to changing numbers of neuron

Experiment	Number of Hidden Neuron	Number of Iteration	Train Error	Test Error
1	4	1000	1.2244	1.4202
2	6	1000	1.0429	1.7257
3	8	1000	1.0500	1.4280
4	10	1000	0.9361	1.3983
5	12	1000	0.8991	1.7892

When Table 4 is examined, we see that train and overall error are the lowest while numbers of neuron to hidden layer are 10. The error values increase after 10. According to the obtained results, we determine as the optimal number of neuron for hidden layer is 10. The architecture consists of input layer, hidden layer, output layer which has 7, 10 and 1 neuron, respectively. This architecture is displayed in Figure 8.

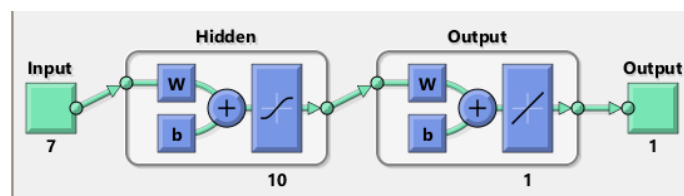


Figure 8. MLP architecture according to the best number of hidden neuron

The last operation is to determine the rank of criterion and alternatives. Weight values which are determined at first step are used by Promethee II. While values of the criteria for each alternative are given in Table 5, Table 6 gives the statistical side of these values. All of these values are used by Promethee then we determine ordering of each criteria for alternatives.

Table 5. The criteria values for each alternative

	VM	SC	SS	GS	WC	Cat	Ent
Air China	2,80	2,73	2,52	1,53	0,14	2,26	1,78
ANA	3,98	3,72	4,65	2,60	0,73	3,91	3,26
Lufthansa	3,75	3,64	4,12	2,23	0,70	3,67	3,20
THY	3,44	3,25	3,38	1,52	0,44	3,73	3,03
United	2,20	2,38	2,48	1,48	0,69	1,92	1,81
Weights	8,89	16,73	2,34	6,31	7,07	2,83	0,18

Table 6. Statistical values for each criteria (Min: Minimum, Max: Maximum, S.Dev: Standart Deviation)

	VM	SC	SS	GS	WC	Cat	Ent
Min	2,20	2,38	2,48	1,48	0,14	1,92	1,78
Max	3,98	3,72	4,65	2,60	0,73	3,91	3,26
Mean	3,23	3,14	3,43	1,87	0,54	3,10	2,62
S. Dev	0,65	0,52	0,86	0,46	0,23	0,83	0,67

Figure 9 gives phi values of 7 criteria values in each alternative. While there is too little passenger in THY, ANA is the most crowded company. For ANA and Lufthansa passengers, their criteria are similar. For the passengers that travel with this airline, staff service and seat comfort are the most important criteria. But these criteria are the last rank for Air China and United. Figure 10 shows phi values of alternatives.

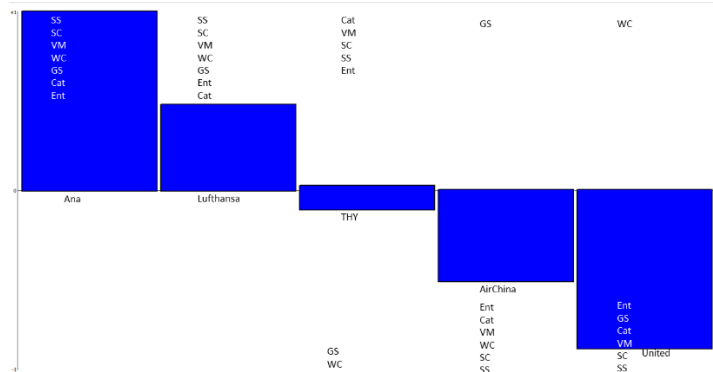


Figure 9. Phi values of criteria for each alternative

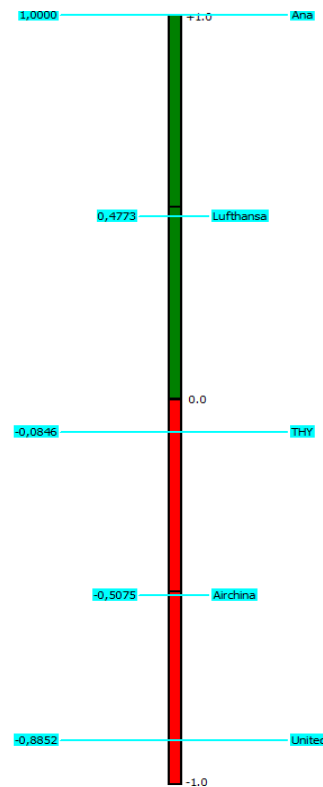


Figure 10. The ranking of each alternatives

ANA which has the highest phi value, takes places on top. ANA is followed by Lufthansa. United, which has the lowest phi value, is in the last rank.

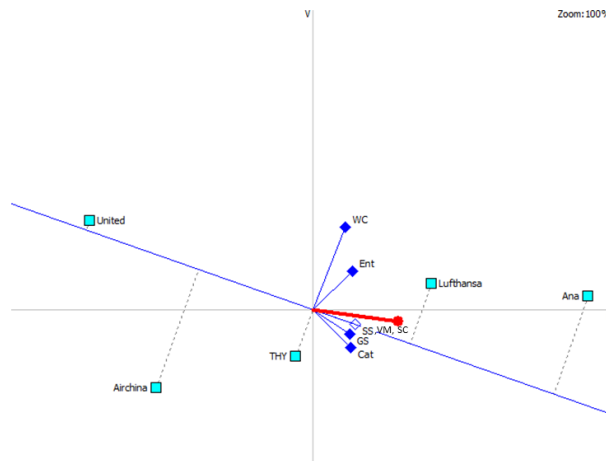


Figure 11. The selection ranks in terms of value of money (VM)

The importance of each criterion in terms of alternatives is shown in Figure 11. There is an important point in Figure 11. Value of money, staff service and seat comfort are located in the same point. This examination is performed in terms of value of money. We conclude the result which United airline firm is the cheapest while ANA and Air China airline firm is the most expensive of all the airlines. This comment is valid for staff service and seat comfort. According to staff service and seat comfort, United is the best firm but the other firms are not. In addition to these comments, Lufthansa and ANA is similar with one another while United varies from the others.

5. Results

Market changes continuously from the past to the present. In the past, while companies are trying to produce products according to their capabilities and deliver them to customers, nowadays products are being tried to be produced in the direction of customers. There is a rule of *what this product is for*, not *what the product is*. The process is developing in a customer-focused manner. Companies want to access to useful information about customer preferences to develop these products. If this useful information about customers is collected and analysed appropriately, companies can use this information to develop different strategies. These analyses allow that companies take a step further in a competitive environment.

In the competitive airline industry, the companies have to manage their resources appropriately to meet their customers' expectations. Consequently, in this study, passengers' reviews of airline companies are analysed based on the annual changes of airline companies using data analysis techniques. Multi-criteria ratings of passengers are analysed by Promethee II. A different approach has been adopted here where the weight values required for the Promethee II are determined by the decision maker. Nevertheless, we try to obtain weight values using MLP which is one of the most common artificial neural network models. These operations are performed on two different sets of data. As a result of these operations, importance orders are similar in terms of criteria in these experiments. While seat comfort, entertainment and value of money qualities are important for passengers in the first experiment, the second experiment is seen to receive staff service instead of entertainment criteria. While the ranking in Experiment I was obtained as Lufthansa, Air China, THY, ANA and United, in Experiment II the order of preference in terms of all airline companies is ANA, Lufthansa, THY, Air China and United. An interpretation can be made that the ANA airline company develops different strategies within a year and increases passenger satisfaction. These developments have not been observed in THY and United companies. It can be said that Air China, which ranks high in Experiment I, has experienced a strategic decrease in the next year. With all these results, it is possible to consider the passenger service priorities in order to improve the quality of the airline customer relationship and to make recommendations that airline companies can develop different tactics like increasing the comfort quality. The airline companies take strategic management decisions for the future through these results.

In this study, the weight values required for Promethee II can be obtained by using different methods. Therefore, in future, the studies can be continued using metrics such as regression and criteria variance or using different methods as Entropy, AHP, ANP, and Fuzzy AHP. A fuzzy set can be used to eliminate the uncertainty that exists in multi-criteria decision-making problems. So, we can perform multi-criteria fuzzy decision making with AHP in future.

Conflict of Interest

No conflict of interest was declared by the authors.

References

- Barros, C., P. and Wanke, P., 2015. An analysis of African airlines efficiency with two-stage TOPSIS and neural networks. *Journal of Air Transport Management*, 44-45, 90-102.
- Bongo, M.F., Alimpangog, K.M.S., Loar, J.F., Montefalcon, J.A., Ocampo, L.A., 2017. An application of DEMATEL-ANP and PROMETHEE II approach for air traffic controllers' workload stress problem: A case of Mactan Civil Aviation Authority of the Philippines. *Journal of Air Transport Management*.
- Brans, J-P., Mareschal, B., 2005. Promethee Methods in: Multipler criteria decision analysis: State of the art surveys. *International Series in Operations Research and Management Science*, New York, Vol. 78.
- Brans, J-P. and Vincke, P., 1985. A preference ranking organization method: The PROMETHEE method for MCDM. *Management Science*, Vol. 31(6), 647-656.
- Brans, J-P., Vinckle, P., and Mareschal, B., 1986. How to select and how to rank projects: The PROMETHEE Method. *European Journal of Operational Research*, Vol. 24, 228-238.
- Dagdeviren, M., and Eraslan, E., 2008. PROMETHEE sıralama yöntemi ile tedarikçi seçimi. *Gazi Üniversitesi Mühendislik Mimarlık Fakültesi Dergisi*, Vol. 23(1), 69-75.
- Feng, C.M. and Wang, R. T., 2000. Performance evaluation for airlines including the consideration of financial ratios. *Journal of Air Transport Management*, 133-142.
- Gardner, M. W. and Dorling, S. R., 1998. Artificial Neural Networks (the Multilayer Perceptron) a review of applications in the atmospheric sciences. *Atmospheric Environment*, Vol. 32, No. 14-15, 2627-2636.
- Gourdin, K., 1998. Bringing quality back to commercial travel. *Transport Journal*, 23-29.
- Jarvis, R.A. and Patrick, E.A., 1973. Clustering using a similarity measure based on shared near neighbors. *IEEE Transaction on Computers*, C22, 1025-1034.
- Kaya, T., 2017. Hybrid approach on airline companies. 8th International Advanced Technologies Symposium, IATS'17, Elazığ.
- Kurtulmusoglu, F.B., Can, G.F. and Tolon M., 2016. A voice in the skies: Listening to airline passenger preferences. *Journal of Air Transport Management*, Vol.57, 130-137.
- Lacic, E., Kowald, D., Lex, E., 2016. High enough? Explaining and predicting traveler satisfaction using airline review. *Proceedings of the 27th ACM Conference on Hypertext and Social Media*, Halifax, Canada.
- Liou, J.J.H., Hsu, C-C., Yeh, W-C., 2011. Lin, R.H., Using a modified grey relation method for improving airline service quality. *Tourism Management*, Vol. 32, 1381-1388.
- Liou, J.J.H. and Tzeng, G.H., 2010. A dominance-based rough set approach to customer behaviour in the airline market. *Information Sciences*, 180, 2230-2238.

- Miranda, H. S. and Henriques, R. (2013). Building clusters for CRM strategies by mining airlines customer data. 8th Iberian Conference on Information Systems and Technologies (CISTI), 1-5.
- Oz, Y. and Koksall, C.D., 2016. Analyzing efficiencies and Total Factor Productivities of Star Alliance Member Airlines. *The Online Journal of Science and Technology*, Vol. 6, Issue 1, 5-12.
- Perezgonzalez, J. D. and Gilbey, A., 2011. Predicting skytrax airport rankings from customer reviews. *Journal of Airport Management*, 5, 336.
- Senkayas H., Hekimoğlu H., 2013. Çok kriterli tedarikçi seçimi problemine PROMETHEE yöntemi uygulaması. *Verimlilik Dergisi*, 63-80.
- Strehl, A., Ghosh, J. and Mooney, R., 2000. Impact of similarity measures on web-page clustering. *Workshop on Artificial Intelligence for Web Search (AAAI 2000)*, 58-64.
- Tsaur, S.H., Chang, T.Y. and Yen, C.H., 2002. The evaluation of airline service quality by fuzzy MCDM. *Tourism Management*, 107-115.
- Vassilev, V., Genova, K, and Vassileva M., 2005. A Brief survey of multicriteria decision making methods and software systems. *Cybernetics and Information Technologies*, Vol. 5, No 1, 3-13.
- Vela, M. R., and Garcia, E. M., 2010. A segmentation analysis and segments profile of budget air travelers. *Cuadernos de Turismo*, 26, 235-25.
- Wang, H., Wang, W., Yang, J. and Yu, P.S., 2002. Clustering by pattern similarity in large data sets. *Special Interest Group on Management of Data (SIGMOD 2002)*, Madison, Wisconsin, USA, 394-405.
- Wang, R., Ho, C-T., Feng, C-M. and Yang, Y-K., 2004. A comparative analysis of the operational performance of Taiwan's major airports. *Journal of Air Transport Management*, 353-360.