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Original scientific paper

Arranging Bus Behaviour by Finding the Best Prediction Model with Artificial Neural Networks

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Abstract: Artificial Neural Networks (ANNs) were used in this study to estimate the hourly passenger populations at certain stations in İstanbul. To do this, the details were collected from various sources regarding the passengers in a station. This study aims to show what can be implemented for the passenger numbers in the decision support system and makes some recommendations for the regulation of the bus lines. Trials were conducted using an ANN with a backpropagation model and various inner layers for the estimations. The MAE score was 10.301 for the stations studied. Qualitative interviews were conducted with 32 passengers and 12 drivers, and solutions were searched for the density of the lines. A proposal system was developed with the c# software resulting from the combination of the prediction model with these proposals.

Keywords: Artificial Neural Networks; estimation; İstanbul; public transportation

1 INTRODUCTION

Local authorities effectively benefit from their own internal dynamics, and the regions affiliated with them are gaining more importance for economic development and progress. The policies and strategies implemented by the local authorities are the key factors in the development of regions in a globalized competitive environment. Thus, improving the transportation sector and raising the living standards within a region could enable cultural improvement and equality of opportunity.

The demand for urban roads is inclined to increase in accordance with the development of the automobile industry and the increase in the number of vehicles, which has caused urban transportation systems to grow and become more complicated. In particular, policies were brought forward to develop public transportation systems in order to solve the transportation issues in metropolitan cities where the population and the number of vehicles are intense.

Urban transportation services are the indicators of developed modern societies, economic growth and level of civilization. İstanbul, which is one of the major metropolitan cities of the world, has been suffering from various issues due to immigration for years, which has resulted in more complicated transportation services. Although local authorities are responsible for planning the transportation in İstanbul, it has become a national issue [1].

The studies on forecasting the airport domestic passenger volume were performed by employing artificial neural networks with regression using inputs such as the number of airports, population density, price, seat capacity, distance, transit passes, travel time, travel matching, timing consistency, purchasing power parity and jet fuel prices [2, 3]. Although various methods have been used to forecast the traffic volume, artificial neural networks and variance analysis have yielded the best results [4]. In the estimation of urban transportation demand, successful results were achieved with the inputs such as socio-economic data, ticket count, gross domestic product (GDP), population and car ownership [5, 6].

2 OBJECTIVE

One of the objectives of modern production and management philosophy is to meet the needs and expectations of the users of a product or service. To achieve this objective, consumers' demands and expectations should be estimated and identified correctly.

It is possible to employ mathematical models based on economic or statistical fields for the estimation of transportation requirements. Today, people and products require a more effective, economic and faster transportation system. Pre-estimation is necessary to provide the sufficient and required supply; and mathematical models, statistical data and optimization techniques should be considered to achieve this.

This study aimed to estimate the demands of the passengers at the bus stations in İstanbul. The number of passengers was estimated through the Artificial Neural Networks model and the analysis of past data regarding travel-related variables. In addition, services were evaluated based on the passengers' opinions. Their recommendations were also asked. With these recommendations, it was aimed to obtain the best possible estimates by various programs written in .net 4.0. The estimates were used to develop a system.

3 ARTIFICIAL NEURAL NETWORKS

The term artificial intelligence has gained prominence in the studies that examine thinking and learning skills, which are among the most significant characteristics of humans. Artificial intelligence is described as the development of computational processes that generate results similar to those produced by humans. In other words, it is the attempt to equip computers with thinking skills. Artificial intelligence aims to develop computers operating at a level of human intelligence and to create machines displaying human-like behaviours. Artificial Neural Networks (ANNs) support the study of artificial intelligence. They are considered to serve as a subset of artificial intelligence and constitute a basis for learnable systems. The ANNs aim to imitate the neurons – the main processing elements in a human brain – simply in terms of their shapes and functions. This suggests that ANNs are the programs simply imitating the biological system [7, 8].

ANNs are the parallel and distributed data processing forms developed considering the human brain, which are linked to one another via connections with separate weights and have their own memories [9]. In other words, they are computer programs that imitate biological neural networks [10]. These programs draw more interest every day and they generate the best solutions for the use in modelling, controlling and analysing many problems [11].

4 METHOD

This study estimated the demands of the passengers at bus stations and used the number of departing passengers as dependent variables and output. The following values were considered as independent variables and output:

- Year
- Month
- Day
- Hour
- Temperature
- Weather condition (raining, snowing etc.)
- Day of the week
- Activities (sport games, concerts, fairs, festivals and so on)
- School or working time
- Special days (Ramadan, festivals, New Year celebrations etc.)
- Tourist periods (summer or winter)

An interview method, which enabled us to understand the inner thoughts and the relevant matters from a person's perspective, was used in this study [12]. The data were collected through semi-structured interviews, which provided opportunities to modify and collect data about the bus drivers and passengers on the relevant services that emerged during the interviews; not estimated previously [13]. A pilot interview was carried out with a passenger and a driver, and then the interview form was revised in terms of grammar and comprehensibility. In addition, two experts checked the form and submitted their opinions. These interviews were recorded upon the consent of the people interviewed. The audio records were transferred to written documents on a computer and used during content analysis.

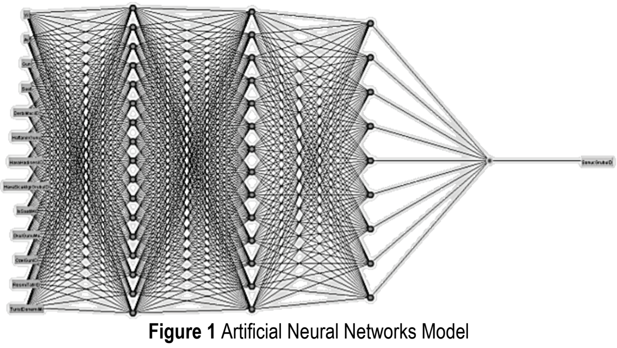

Figure 1 Artificial Neural Networks Model

Artificial Neural Networks are among the best methods used in almost all fields to develop estimation models. However, the number of studies using Artificial Neural Networks is limited compared to the globally available literature. Researchers in Turkey have contributed to the literature by focusing on Artificial Neural Networks to produce solutions for many issues, such as classification, estimation, data conceptualization and control problems [14].

Expert opinions were consulted about estimation, and the method used to design the artificial neural model was discussed. Following the discussions, it was accepted that a hidden 15 × 15 layer would yield the best outcomes. The figures generated by these layers were used in learning tests first. Then, tests were conducted with a different number of layers. At the end of the tests, the error values were examined and the model with the lowest error value was selected. Following the negotiations with the experts, it was decided that it would be more appropriate to perform learning by establishing separate networks for each station instead of including all stations in one model, since conditions were different in each station and therefore estimations should be performed individually. Figure 1 shows a visual form of these networks. The network design had 13 initial variables. It was determined to use two levels in the middle layers and 15 nerves at each level. However, it was recommended that the tests be performed with these nerves and different values to achieve the best results. To sum up, the total number of passengers departing hourly was used as the output data. Then, recommendations for the development of the lines passing the related duties was presented using the software developed based on the obtained data.

4.1 Data Collection Tools

IETT used the smart ticket system from 1995 to December 31, 2014. The smart ticket system, used by 280,000 people, was replaced with the İstanbulkart system using contactless card technology in 2008. The İstanbulkart, used by 15 million people, came into force as of 2009 [15]. In 2015, it was decided that only the İstanbulkart would be used for public transportation in İstanbul.

The data of İstanbulkart, covering the period from 2013 to 2015, was collected for all stations of four bus services: 18Ü and 11ÜS on the Anatolian side and 399C and 559C on the European side. The data of public holidays were collected from the Ministry of National Education (MoNE) under the title of special days [16] and the data regarding the tourist periods (from March 1 to October 31) in İstanbul were obtained from the İstanbul Provincial Directorate of Culture and Tourism [17]. The data regarding the rush hour (08:00 to10:00 and 18:00 to 20:00) traffic in İstanbul were collected from the statistical Yandex reports [18]. Weather information was collected from the Meteorological Data Archive and Management System of Turkey [19].

In addition, the data regarding the weather conditions in İstanbul for the previous 10 years were obtained from the Turkish State Meteorological Service, along with the temperature and event details. Weather events from 500,853 records were classified based on their groups, and an ID was assigned to each of them. Air temperature details were classified at the intervals of 8 °C. Data were also collected regarding the games of the three major football teams in İstanbul against other teams. The data of public holidays were grouped by assigning an ID to each holiday. The special days were categorized under three main titles: New Year, elections and other celebrations.

4.2 Data Analysis

The data were analysed on Weka using the Artificial Neural Networks with feedback. The data were kept in the database in the form of relational tables after they were collected from the IETT as separate files for each year. Data conversions were checked with advanced investigations.

Initial and end values were different for each number group of data. Therefore, the data were normalized to prevent the ANN programs from recognizing these data at different significance levels since some of the numbers were greater or smaller than each other. The following mathematical function was used to normalize the data.

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

The data obtained from the IETT were organized as the number of passengers using buses at one-hour intervals. Of the weekly data regarding the departing passengers, two-thirds were categorized as educational data, and one-third was categorized as test data. The data were input to the Artificial Neural Networks as educational and test groups.

Table 1 Details for the Estimated Station

Station Name	Estimated Service	Amount of Educational Data	Amount of Test Data	Total Amount of Data
Altunizade (Üsküdar)	11 ÜS	13,332	6,666	19,999

The interviews carried out with bus drivers and passengers were audio-recorded upon their consent. These records were transferred to a computer. Then, the data content was analysed and themes were identified. The themes were represented through the number of participants in various forms. Samples from the interviews were also included in the study without the names of the participants.

5 FINDINGS

Data obtained from the IETT were organized as the number of passengers using buses in a one-hour interval. The data were kept in an SQL database and examined with the questions first. Then, the data were converted into a format compatible with the analysis software.

5.1 General Overview of the Data

The records with the identified data covered 3 years, 6 months and 21 days. The mean number of departing passengers (daily) was found by dividing the total number of departing passengers at each station into the 1298 days between the start and end dates. The hourly numbers were found by dividing the total daily number of departing passengers into the multiplication of 1298 days with 24 hours.

The total amount of data for each day was calculated, and the daily number of departing passengers was found by dividing this amount into the 185 weeks between the start and end dates. Fig. 2 shows the mean numbers for departing passengers (daily).

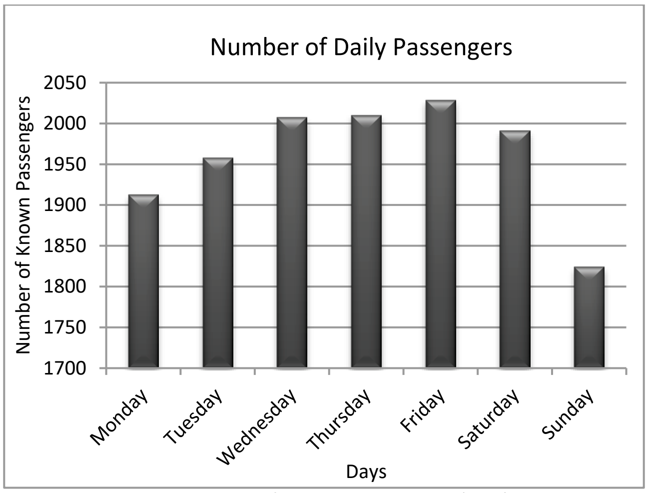

Figure 2 Number of Departing Passengers (Daily)

There are 1298 days between the start and end dates. The mean hourly numbers of departing passengers were found by dividing the total number of departing passengers into 1298. Fig. 3 shows a station-based graph generated by these numbers.

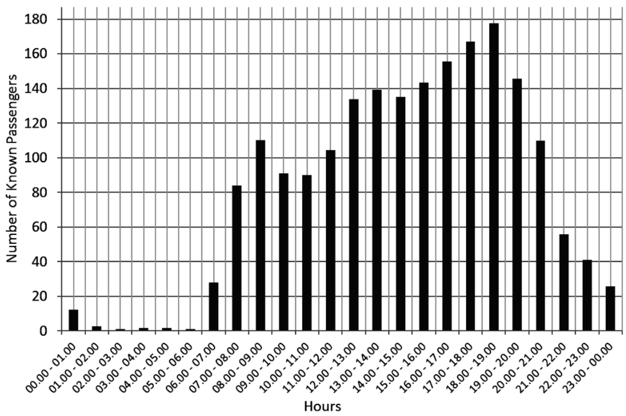

Figure 3 Mean Number of Departing Passengers (Hourly)

Although each station has its own characteristics, morning and evening hours were found to be busier than other hours. These show that time should be present as an initial parameter.

5.2 Estimation with Artificial Neural Networks

An Artificial Neural Network model was generated consisting of the data with 13 inputs and one output. A hidden-layer structure consisting of two layers with 15 nerves at each layer was formed based on the expert opinions. The first trials were performed using this structure. Then, changes were made on the number of nerves at the hidden layers of the model with various shapes. Educational and test data were formed for each station, and the trials were performed independently. The number of hidden layers was changed and the error rates in the test data were compared. The aim here was to achieve the lowest error rate. Tab. 2 shows the error values for four stations.

Error values were different for each model since each station was independently modelled. The mean absolute difference value was 10.301 between the estimated and actual values. Trials were performed with different inner layer configurations, and the results were recorded. The lowest error value was estimated when the number of nerves at the inner layer was 17 × 14 × 9. Tab. 3 shows a list of these records; the services were ordered based on the lowest error rates.

Table 2 Error Estimation Analysis Values

Error Type	Value
Correlation Coefficient	0.8513
Mean Absolute Error	10.301
Mean Square Error	13.494
Percentage Error	9.36%
Percentage Accuracy	90.64%

Table 3 Different Number of Inner Layers and Results of the Trial in ANN Model

Number of Inner Layers	Correlation Coefficient	Mean Number of Absolute Error	Mean Square Error	Percentage Error	Percentage Accuracy
17 × 14 × 9	0.8513	10.301	13.494	9.36	90.64
14 × 13 × 9	0.849	10.373	13.588	9.43	90.57
18 × 15 × 10	0.8484	10.418	13.66	9.47	90.53
20 × 18 × 15 × 10	0.8483	10.454	13.674	9.50	90.50
22 × 14 × 18	0.8415	10.716	14.008	9.74	90.26
16 × 12 × 8 × 5	0.8392	10.747	14.01	9.77	90.23
16 × 15	0.8375	10.830	14.106	9.85	90.15
18 × 15 × 10 × 2	0.8358	10.937	14.213	9.94	90.06
9 × 9 × 8	0.8325	10.962	14.26	9.97	90.03
9 × 9 × 8 × 7	0.8329	10.995	14.242	10.00	90.00
10 × 11 × 1	0.8246	11.29	14.644	10.26	89.74
10 × 10	0.8133	11.51	15.018	10.46	89.54
7 × 8	0.7781	12.558	16.273	11.42	88.58
5 × 5	0.7403	13.59	17.426	12.35	87.65
3 × 3	0.7054	14.643	18.471	13.31	86.69

Tab. 4 shows the actual and estimated values for the test data, and the error values resulting from the difference between them. The values were listed for 10 randomly selected data since all records could not be displayed.

Table 4 10 Estimated Values

Sequence No	Actual Value	Estimation Value	Error
1	80	72.1	−7.9
2	30	21	−9
3	40	38.7	−1.3
4	10	15.1	5.1
5	90	87.1	−2.9
6	80	79.4	−0.6
7	20	16.4	−3.6
8	30	30.3	0.3
9	90	86.9	−3.1
10	70	71.5	1.5

Although the model generates estimations close to the actual value with a 0.1 deviation, it occasionally provides estimations with a high deviation such as 60.6. However, the number of estimations with high deviation is limited, and estimations generally show differences from 8 to 12.

5.3 Interviews Performed with the Passengers and Drivers

Face-to-face interviews were carried out with 48 passengers and 12 drivers in this study. Each participant was asked about their opinions on whether the lines were intense.

5.3.1 Busy Bus Services According to the Drivers

Each driver using the lines was asked whether the line in question was intensive. The drivers who indicated that the line was busy were asked to recommend solutions for the intensity, its reasons, and intense hours. The other drivers were asked why their lines were not busy and whether they were pleased with the current situation. The responses were analysed by being allocated into subgroups. Fig. 4 shows the results of the analysis. The frequency of repetition for different drivers was added next to the corresponding code.

Two drivers who stated that the line was not busy reported that there are many alternative lines on the route and the road is open. Of the drivers, 87% indicated that the lines were busy. Most of the drivers who reported intensity in the morning and evening hours indicated that the reasons were the density of population in the region as well as the traffic intensity.

> *D111: What are the reasons for intensity? To go away from the highway. So, the preferred route is not regarded to have traffic by Umraniye passengers because it does not enter the route to Şile. Everyone would prefer, of course. I would prefer if I were.*
> *D1399: It is because of the lack of vehicles and that the workers generally live on this side.*

The reasons for intensity also include the crowded and long route of the lines and the existence of workplaces or schools on the route. When asked for the solutions, a majority of the drivers offered to add more buses. In addition, some drivers recommended taking measures to prevent traffic during the peak hours due to private vehicles.

> *D1559: Everyone should respect each other. When everyone is respectful, I think it would be better to use public transport. Why is there one person in every car? What will happen to a person? A family owns five cars, which results in traffic. What happens then? Density? However, if a family uses one car, then five people will not have to deal with the intensity of five cars. You can*

also see that everybody randomly comes out of the right side, ignoring the road on the left. A taxi stands in the middle of the road. A person stands in the middle of the road. Nobody allows us to use the bus stop; we cannot approach it. Then, people become victims of the commute. They cannot get on, they cannot get off… We have many problems.
D318: As an institution, they are doing their best. However, it is not enough. It cannot be better than that. You see the cars; they are all waiting in a row. The people in Sultanbeyli flourish. That is the reason.

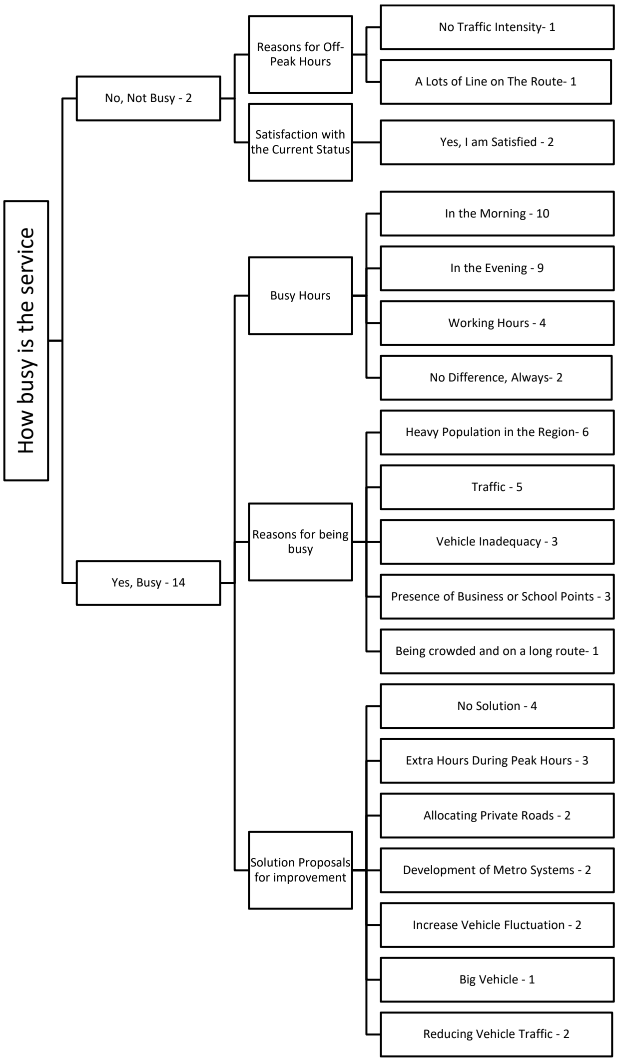

Figure 4 Drivers' opinions on how busy the service is

Some drivers stated that the development of metro systems would be the solution. Some others stated that the use of long vehicles would be a solution. However, most drivers stated that the current situation was the best solution. They also indicated the increased population as a reason for their opinions.

5.3.2 Busy Bus Services According to the Passengers

Passengers were asked whether the bus services they use were busy, and their answers were grouped as busy, not busy and unknown as they rarely used these services. Passengers who stated that the services were busy were asked the time and reasons for this busyness, and their recommendations to solve this issue. The passengers who stated that the services were not busy were asked why they think that and whether they were satisfied with the current status. Fig. 5 shows the busyness rate of the services, the passengers' opinions and the repetition rate for the relevant group are presented.

All passengers reported that the services were busy, except one of them, who stated that the services were not busy since he/she used the service during the non-busy hours.

The passengers were asked the busy hours. They generally stated the evening, morning and working hours rather than indicating a particular time interval. Some of them reported that services were busy only in the evening, while some others reported busyness both in the morning and in the evening.

P811: Working hours; evenings hours are the busiest times, rather than the morning hours.
P1399: Busy hours? Let me explain; services are busy in the morning and during the following hours, particularly 4 or 5 pm. If you go somewhere from this station, the services are busy, but the buses coming to this station are not that busy.

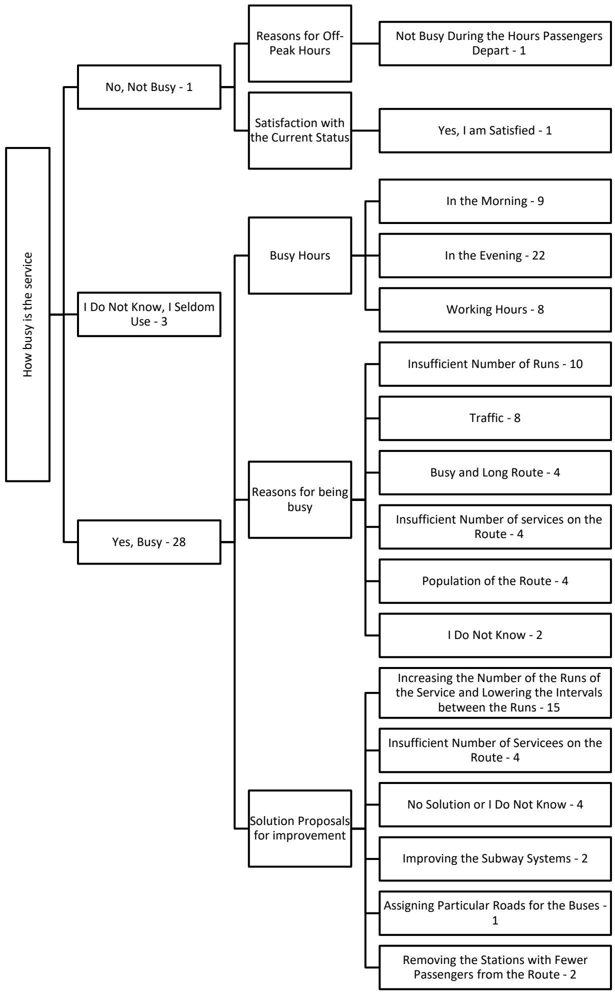

Figure 1 Passengers' opinions on how busy the service is

The participants were asked the reasons for the busyness of the services, and a majority of them indicated the insufficient number of services and the traffic. The passengers also indicated the crowds, long lines and the routes as reasons for busyness.

P3559: The only alternative is the vehicle coming from there that is why.

P511: Of course, we cannot disregard the crowd; I do not know how busy the service is, but I can say the buses are frequent.

The passengers were also asked to make recommendations to improve the service. A majority of them stated that the number of buses should be increased, reducing the intervals between them. In addition, some passengers stated that different services should be added to the relevant route. A remarkable group of passengers showed a pessimistic approach to the issue, stating that no solution can be recommended, or they had no solution proposals.

P7399: Problems with transport services in Istanbul cannot be solved because subways, parks and buildings are constructed everywhere. I do not know how the government will handle the issue.

P3399: Buses can operate every five minutes instead of fifteen minutes. The Gazi–Osman–Paşa service, for example. Other lines are not problematic. However, five-minute intervals can be implement between the services in this line, particularly during the evening or midday hours. I do not ask much. More buses should operate between 5 and 7 pm.

Some passengers recommended improving the subway systems as a solution, and some stated that the stations with fewer passengers should be removed. In addition, the passengers thought that the construction of a separate road for the buses, such as metrobuses, could be a solution to this issue.

5.4 Decision Support System

Through the software developed using the Visual Studio 2013 program, the artificial neural network method was applied to the data and the appropriate model was recorded after the training process. This method allows obtaining estimates for future values and presenting the suggestions. Using the developed program, a file prepared based on a specific form must be selected from the raw data. Then, the program will start the training process separately for training and testing. The model is applied to the test data and calculates the mean absolute and mean square errors, as well as the correct and error percentages, using the test data. It also shows the estimates generated for each value in the lower list. The model created at the end of all operations is then recorded. Here, the values of 15 different inner layer numbers were attempted to reach the lowest mean absolute error values. The model that reached the lowest fault was recorded and the results of this model were displayed on the screen. Fig. 6 shows an example of the display.

After the optimum model was created and recorded, the estimations were made through the relevant model. The program automatically selected the relevant model and generated the estimates. The estimated results were displayed on the screen and the same day of the previous week was given along with the number of boarding passes. The difference between them was indicated in percentage as an increase or a decrease. A list of the suggestions, obtained from interviews with passengers and drivers, was presented based on these increases and decreases. The list of suggestions is as follows:

- Reducing or increasing the number of buses
- Increasing the alternative routes on a Route
- Development of Metro Systems
- Additional buses during peak hours
- Special Bus Lanes
- Increasing the Vehicle Flow
- Reducing Vehicle Routes
- Removing the Services to the Neighbourhoods with Fewer Passengers
- Bigger Vehicles.

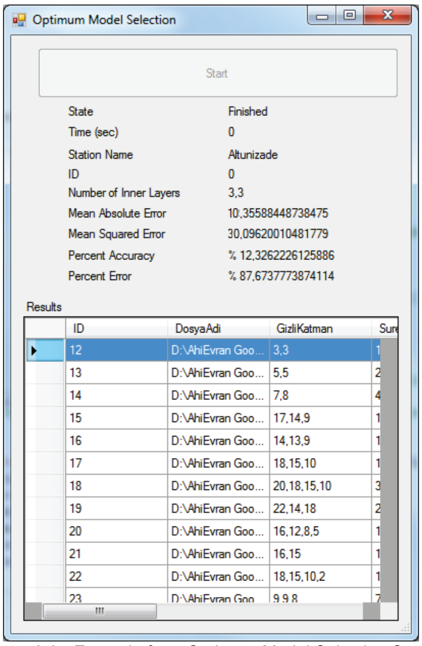

Figure 6 An Example from Optimum Model Selection Screen

This list was suggested by drivers and passengers as solutions to the intensity of bus stops. These suggestions were made if the value of 2/3 was exceeded for the stations with max passenger volumes. Similarly, if the value falls below 1/3 for the stations with max boarding values, the opposite recommendations were made. No suggestions were made if the current situation was considered to be normal.

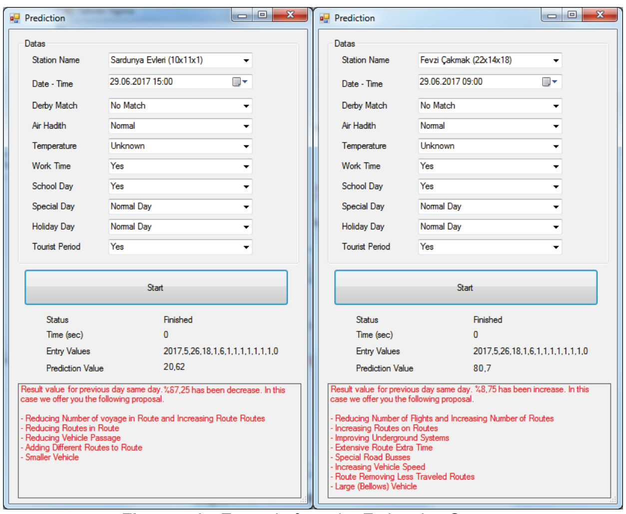

Figure 7 An Example from the Estimating Screen

As shown in Fig. 7, the date and time information to be estimated was specified after the Station Name was selected. In addition to these data, other information for a specific date and time was also selected from the drop-down lists, and then the Start button was clicked. In less than a second, the program produced the estimation results and displayed the final title, Estimation. The same day and hour in the previous week were displayed and compared in the red text below. In addition, a list of suggestions was provided based on the status of the estimated value.

6 DISCUSSION AND OUTCOME

A model with 13 inputs and one output was created for each station using an Artificial Neural Network. The number of the inner layers between the input and output of this model was tested using various numbers of nerves combined with two, three, four and five inner layers. The results of these tests were recorded, and the model with the lowest error rate was selected after the comparisons. Similarly, Keskinkilic [20] and Bilgili [21] conducted tests changing the number of nerves in the inner layer and took the best result into consideration. Each model exhibited different error rates.

In a study by Tsai, Lee and Wei [22] that estimated the short train trips, the data were transferred to the model without grouping the number of passengers. Therefore, the authors recorded deviation rates ranging from 15% to 30% while making estimations with absolute values from 100 to 600. The results were grouped in the present study, and deviation values varied from 9% to 18% for the data. In another study, in which taxi passengers' demands were estimated using the ARIMA model, error rates of up to 25% were obtained [23]. Other studies on the estimation of bus passengers' demands found estimation values of up to 78% [24, 25, 26]. But in some studies there are 89-90% [27, 28]. In the present study, estimations were performed with 90% accuracy rate. Three main challenges exist in the estimation of passengers' demands for bus services: non-homogeneous periods, seasonal periods and normal periods. The differences between the frequencies of these challenges may reflect on the estimation values. In another study, an interaction was established between more than one model (weekly, daily and hourly) to estimate the demands of bus passengers. Estimation was performed with an error rate of 23% in the hourly model, and 9% in the daily and weekly models. However, estimations were performed with an error rate of 5.82% in the interactive hybrid model [29]. The present study showed a lower error rate. Although the ANN method yielded an error rate of 9.81% in above-mentioned study, which was close to the error rate in the present study, the hybrid model generated a lower error rate. The weekday and weekend values are assumed to be similar in both studies.

A study was conducted with 3760 taxis to display the concentration points to taxi drivers through scanners using the place and time data about the passengers' demands¸ and generated estimations with an accuracy rate of 79.6%. Times series and time-dependent clustering methods were used in this study [30]. Estimations were performed with deviation rates from 3.33% to 4.48% with a genetic algorithm in a study conducted on the number of departing passengers and the passenger income per kilometre. The rates in this study were lower than the rates in the present study [31].

In addition to providing analyses using the quantitative data in the present study, interviews were performed with the passengers to obtain their opinions and suggestions about the bus behaviours. These interviews indicated that the busiest hours were in the morning, when people were going to work, and in the evening, when people left the work. The factors such as the limited number of buses, traffic, crowded lines, long routes, the limited number of services on the route, and the population of the route affected the intensity in the services. Recommendations made to solve this issue include increasing the number of buses of the services, decreasing the intervals between the buses, increasing the number of services on a route, developing the subway systems, creating special bus lanes, and removing the routes with fewer passengers. On the other hand, there were pessimistic passengers who thought that no solution could be found or who had no suggestions to solve this issue.

A new program has been written with the c# program to find the model with the lowest mean absolute error value by making experiments on the models with different number of inner layers in order to perform the estimations. This program finds and records the optimum model. On the estimation screen, there is an automatically registered optimum model given as a parameter such as the name of the station, dates, the time of a derby match, weather events, air temperatures, working times, or school days. Estimates are produced based on a tourist period, for instance, in less time than one second and are compared with the same time on the same day of the previous week. The recommendations obtained from the interviews with the passengers and drivers based on the status of the estimated values were presented as a list.

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