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Araştırma Makalesi / Research Article

Prediction of the Numbers of Visitors at the Sinop Museums by Artificial Neural Networks

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Abstract

In this study, the numbers of museums 'visitors (Archaeology, Ethnography and Historical Prison) at the city center of Sinop province have been predicted by Artificial Neural Network structures. Artificial Neural Network models have been created in MATLAB environment. These Artificial Neural Network models are feed forward and trained by Backpropagation Algorithm. For each museum, a Artificial Neural Network with 19-inputs and 1-output have been used separately. As inputs of networks, 10 different meteorological factors, time factor (month, year), tourism income (TL), exchange rate (\$/TL) and monthly-yearly PPI and CPI data have been used. Output of ANNs is the daily average of number of visitors for each month. In order to train and test the Artificial Neural Networks, the number of visitors of museum at city center for total 60 months of years between 2012 and 2017, and other input data have been used. The selection of proper Artificial Neural Networks structure have been achieved by trying backpropagation training functions 50-times on 3-different activation functions structure with 8 different neuron counts at one hidden layer. Totally, 32400-network have been created by training and the best network structure for each museum have been selected. Estimation result obtained by the Artificial Neural Network models have been evaluated and discussed. As a result of this work, it has been proved that estimation of number of visitors visiting museums at Sinop province can be done by using ANN structures.

Keywords: Sinop, Museums, Artifical Neural Networks, Number of Museum Visitors.

Sinop İlindeki Müzelere Gelen Ziyaretçi Sayısının Yapay Sinir Ağları İle Tahmini

Öz

Yapılan çalışmada, Sinop ili merkezinde bulunan müzelere (Arkeoloji, Etnografya ve Tarihi Ceza Evi) gelen ziyaretçi sayılarının Yapay Sinir Ağları modelleri kurularak tahmini yapılmıştır. Yapay Sinir Ağları modelleri oluşturulmasında bilgisayar ortamında MATLAB yazılımı kullanılmıştır. Kullanılan Yapay Sinir Ağları modelleri; ileri beslemeli ve geri yayılımlıdır. Kullanılan Ağ yapıları, 19 girişli, bir çıkışlı, (Arkeoloji, Etnografya ve Tarihi Ceza Evi müzeleri için ayrı olarak oluşturulmuştur. Giriş girdisi olarak; 10 farklı meteorolojik faktör, zaman faktörü (ay, yıl), turizm geliri (TL), döviz (\$/TL), aylık-yıllık ÜFE ve TÜFE verileri kullanılmıştır. Çıkış olarak ise aylara göre aylık günlük ziyaretçi ortalama sayısı kullanılmıştır. Oluşturulan Yapay Sinir Ağları modeller eğitiminde ve testinde 2012 yılından 2017 yılına kadar toplam 60 aylık, ilde bulunan müzelere gelen ziyaretçi sayıları ve bu tarihlere ait giriş verileri kullanılmıştır. Yapay Sinir Ağları modellerinin seçilmesinde 3 farklı geri dağılımlı Eğitim Fonksiyonu, 3 farklı Transfer Fonksiyonu ve 8 farklı gizli katman hücre sayısı ile oluşturulan ağ yapılarının 50 şer kez tekrarlanarak olasılıkları denenmiştir. Toplamda 32400 ağ oluşturulup eğitilerek her bir müze için en iyi sonucu veren ağ yapısı seçilmiştir. Yapay Sinir Ağları modelleri ile elde edilen tahmin sonuçları değerlendirilmiş ve tartışılmıştır. Yapay Sinir Ağları ile Sinop ilinde bulunan müze için gelen ziyaretçi sayılarının tahmininin gerçekleştirilebileceği görülmüştür.

Anahtar Kelimeler: Sinop, Müzeler, Yapay Sinir Ağları, Müze Ziyaretçi Sayısı.

1. Introduction

Estimation of tourism demand is very important for tourism and service sectors. This can provide effective information for tourism planning and policies. In order to estimate tourism demand correctly, it is essential to use a valid method. It is important to develop correct estimation methods for the continuation of research and planning of the future. Thus, with the investments to be made in the tourism sector, it will be made an important contribution to increase the employment and trade. There are many national and international studies in the literature made on tourism demand and its estimation. In these studies, Artificial Neural Network (ANN) models have been formed by using the relation between input and output data and it has been found that ANNs provides solutions with acceptable errors. Andrawis et al., (2011) applied ANNs to the problem of tourism demand prediction for the short and long-term periods of Egypt and saw the advantage of the proposed approach. Song et al. (2003), used Feed Forward Backpropagation Neural Networks in order to estimate the revenue from tourism by using the number of tourists visiting Hong Kong city, They have stated that the results of the studies were consistent with the analytical results. Burger et al. in 2001, were used different statistical (moving averages, exponential correction) and heuristic methods (Auto-Regressive Integrated Moving-Average (ARIMA), multiple regression, genetic regression, ANN) to predict the number of visitors to a city of Durban in South Africa from United States of America. By comparing the results of their study with the actual number of visitors, they found that the best result is with ANN. Cuhadar et al. in 2005, estimated the occupancy rates of accommodation companies by using the artificial neural network. Five input variables were used to estimate the occupancy rate. This is the first study for estimation of the occupancy rate in accommodation establishments in Turkey using artificial neural networks. In Çuhadar 2005, the forecasting performances of artificial neural networks and different regression models that used to estimate the demand for German tourists for Antalya province were compared. The result of this work demonstrated that ANN model show better performance than regression models. In Çuhadar et al. 2009, it is aimed to estimate the foreign tourism demand for province Antalya in monthly basis. To do this, they compared the estimation accuracy of two different time series methods and some artificial neural network models in different architectures. As a consequence of this work, Artificial Neural Network is the best method in terms of estimation accuracy. Aladağ, (2010), carried a study about the number of foreign visitors using ANN and in the training of ANNs, 5 different training algorithms have been used. As a result of this work, elastic backpropagation training algorithm has been found the best method amongst other for estimation of number of visitors. In the work of Teixeria and Fernandes have done in 2014, the number of overnight stays and tourism revenue of domestic and foreign tourists for the hotels in the northern part of Portugal have been estimated by

various feedforward ANN models. They have pointed out that the results of feedforward ANNs and analytic method is similar. In a work of Çuhadar et al. 2014, they have used different training algorithm for the estimation of the number of tourists came to Izmir by cruiser tourism per month. For this problem, ANN with radial based functions was considered to be the best (Cuhadar et al.2014). In the work of Karahan carried in 2015, monthly tourism demand of future periods has been estimated by input variables such as weather conditions, revenue from tourism, exchange data, and Consumer Price Index (CPI). According to the correlation between the tourism demand estimation produced by the suggested ANN model and the real tourism demand of the same period, it was seen that the suggested model was highly accurate. In (Ali and Shabri, 2017), the number of tourists going to Malaysia from Singapore in the years 2010-2014 are estimated by the techniques of ANN and support vector machines. Hence, they stated that ANN give better estimation than the support vector machines method.

In this work, the numbers of visitors of the museums (Archaeology, Ethnography and Historical Prison) in the city center of Sinop province have been estimated using artificial neural network (ANN) structures. In order to train and test the ANNs, the number of visitors of museum at city center for total 60 months of years between 2012 and 2017, and other input data have been used. Output of ANNs is the daily average of number of visitors for each month. Estimation results obtained by the ANN models have been evaluated and discussed. As a result of this work, it has been proved that estimation of number of visitors visiting museums at Sinop province can be done by using ANN structures successfully.

2. Materials and Methods

2.1. Artificial Neural Networks (ANN)

ANN is a simulated system using the human brain's ability to perform a function. ANN is composed of interconnected artificial nerve cells and is mostly in the form of layers. It is done with software on computers. It is similar to the information-processing feature of the brain. Analytical methods can solve problems that are difficult to solve effectively. ANN, can effectively solve problems that are difficult to solve by analytical methods. Many functional processes such as the rapid identification, perception, interrelation, evaluation of data of a very different structure can make an active and quickly. In this respect has been widely used in many different disciplines in recent years.

Generally, in the ANN model, the nerve cell receives input signals x1, x2, x3,...xn (X vector). This signal is usually the output cell of another nerve cell. Each X vector is multiplied by the

$$S = \sum_{i=1}^{n} Xi. Wi$$
 (1)

A nerve cell output signal is calculated by f (activation function). The system output of is obtained with Equation 2.

$$\mathbf{y} = \mathbf{f}(\mathbf{S}) \tag{2}$$

The General model of Artificial Neural Network is shown figure 1.

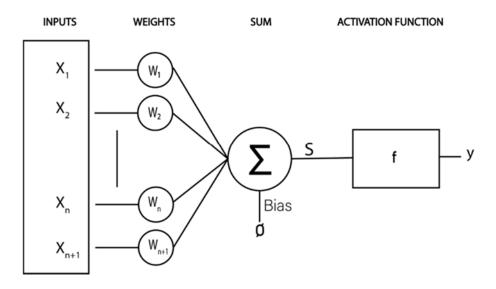


Figure 1. Basic structure of an Artificial Neural Network Neuron (Duman et all.2017).

2.2. Training and Testing of Artificial Neural Network

The literature review shows that meteorological, seasonal and economic factors have effects over the number of visitors while estimating of monthly tourism demand. The number of visitors in this study have been taken from Sinop Provincial Directorate of Culture and Tourism. The variables used as input data have been given in Table 1.As the output of the network, the average numbers of daily visitors that are obtained by dividing the number of visitors per month to number of days of the same month for subjected museum have been used. In the training and testing of the created ANN models, the data of 60 months from 2012 to 2017 have been used.

Year	2016	2016	2016	2016	2016	2016	2016
Months	6	7	7 8		10	11	12
Maximum Temperature(°C)	27	29	30	26	20	17	9
Average Temperature(°C)	26	27	28	24	19	15	8
Minimum Temperature(°C)	24	25	26	22	16	13	6
Rain (mm)	42, 21	1,4	5,41	44,19	22,01	46	106,9
Rainy day rate	0,333333	0,064516	0,096774	0,433333	0,451613	0,4	0,774194
Snow thickness (cm)	0	0	0	0	0	0	3,7
Number of snowy days	0	0	0	0	0	0	0,096774
Average Wind Speeds (mph)	8,1	9,8	8,1	9,2	10,1	10,5	11,4
Cloud percentage (%)	13	7	14	24	45	35	66
Sunshine duration (hours)	146,5	154,8	142,3	106,3	74,8	69,3	35,8
Turkey Consumer Price Index (month) (%)	0,47	1,16	-0,29	0,18	1,44	0,52	1,64
Turkey Consumer Price Index (year) (%)	7,64	8,79	8,05	7,28	7,16	7	8,53
Turkey Producer Price Index (month) (%)	0,41	0,21	0,08	0,29	0,84	2	2,98
Turkey Producer Price Index (year) (%)	3,41	3,96	3,03	1,78	2,84	6,41	9,94
USD/TL Parity (TL)	2,8777	2,9883	2,958	2,9992	3,0939	3,437	3,5277
Euro/TL Parity (TL)	3,1959	3,3391	3,3008	3,3714	3,3974	3,6391	3,7097
Holiday day rate (Number of holiday days/ Month days)	0,266667	0,419355	0,290323	0,4	0,322581	0,266667	0,290323
Ethnography museumdaily average of number	9,1	30,16129	34,19355	29,2	20,19355	7,666667	6,225806

Table 1. Example of the variables used as input data (Alcan and et. 2017, www.worldweatheronline.com,2017; Obtain Information: Sinop Provincial Directorate of Culture and Tourism, 2017).

of visitors for each months.							
Archaeological museum daily average of number of visitors for each months.	31,46667	58,51613	51,35484	40,6	31,09677	10,96667	7,645161
Historic Prison daily average of number of visitors for each months.	316,4333	1469,258	1278,032	951,3333	319,3548	125,8333	61,77419

ANN has been created separately for each museum. Levenberg - Marquardt backpropagation, scaled conjugate gradient backpropagation and resilient back propagation functions have been tried in the training of network. As activation function: Logarithmic sigmoid, tangent hyperbolic sigmoid and linear activation functions have been used. The combination of the training and activation functions have been run with 50 repetitions as 5, 10, 15, 20, 25, 30, 35, 40 hidden layer cell networks. A total of 32400 trials have been conducted to determine the networks to be selected for 3 museums. The best, the worst and the average R2 (determination coefficient) values in the each 50 tests of the combination for training and activation functions have been computed. Among the results, the best value for the R2 has obtained. From the resulting network set, the R2 value has been chosen to be the best. Equation 3 used in measuring network performance has been given.

$$R^{2} = 1 - \left(\frac{\sum_{t}^{T} \left(y_{g}(t) - y_{d}(t)\right)^{2}}{\sum_{t}^{T} y_{d}(t)^{2}}\right)$$
(3)

3. Findings and Discussion

The combination of the training and activation functions have been run with 50 repetitions as 5, 10, 15, 20, 25, 30, 35, 40 hidden layer cell networks. The best, the worst and the average R2 (determination coefficient) values in the each 50 tests of the combination for training and activation functions have been computed. Some of the results obtained in Table 2 have been given as in the examples. The values given in Table 2; training and activation functions are functions defined in the MATLAB software. These; Levenberg - Marquardt back propagation (trainlm), flexible back propagation (trainrp), gradual gravitational back propagation algorithm (trainscg), hyperbolic tangent activation function (tansig), logarithmic sigmoid activation function (logsig) are the linear activation

function (purelin). These: Levenberg - Marquardt backpropagation, scaled conjugate gradient backpropagation and resilient back propagation and hyperbolic tangent activation function (tansig), logarithmic sigmoid activation function (logsig) are the linear activation function (purelin).

Mean. 0.941 0.837 0.833 0.884 0.743	Worst 0.335 0.785 0.817 0.852	Best -0.091 -0.192 0.789	Mean.	Worst	Best	Mean	Worst	Hidden Layer	Backpropagation Algorithm	Activation functions	Activation functions
0.837 0.833 0.884	0.785	-0.192		0.224				Count	(BPA)	AF 1	AF 2
0.833	0.817		0.102	-0.221	0.740	0.651	-0.109	5	'trainlm'	'tansig'	'tansig'
0.884		0.789	-0.192	-0.192	0.048	0.048	0.048	5	'trainlm'	'tansig'	'logsig'
	0.852	005	0.736	0.616	0.594	0.593	0.590	5	'trainlm'	'tansig'	'purelin'
0.743		0.857	0.821	0.755	0.828	0.811	0.743	5	'trainlm'	'logsig'	'tansig'
	0.737	0.652	0.619	0.552	0.192	0.192	0.192	5	'trainlm'	'logsig'	'logsig'
0.850	0.773	0.892	0.888	0.816	0.546	0.460	0.192	5	'trainlm'	'logsig'	'purelin'
0.298	0.298	0.902	0.887	0.677	0.564	0.564	0.564	5	'trainlm'	'purelin'	'tansig'
						~					
0.326	0.197	0.811	0.522	0.399	0.114	0.114	0.114	5	'trainrp'	'purelin'	'logsig'
0.844	0.844	0.650	0.650	0.650	0.139	0.139	0.139	5	'trainrp'	'purelin'	'purelin'
-0.020	-0.064	0.503	0.489	-0.203	0.968	0.926	0.868	10	'trainlm'	'tansig'	'tansig'
0.298	0.298	0.627	0.594	0.389	0.600	-0.072	-0.116	10	'trainlm'	'tansig'	'logsig'
0.758	0.140	0.658	0.645	0.581	0.904	0.826	0.263	10	'trainlm'	'tansig'	'purelin'
-0.194	-0.194	0.608	0.608	0.608	0.677	0.677	0.677	10	'trainrp'	'purelin'	'logsig'
						~					
-0.050	-0.190	0.270	0.034	-0.349	0.317	0.225	-0.109	10	'trainrp'	'purelin'	'purelin'
0.969	0.829	0.236	0.204	-0.065	0.742	0.536	0.426	15	'trainlm'	'tansig'	'tansig'
0.767	0.729	0.128	0.128	0.126	0.192	0.054	0.000	15	'trainlm'	'tansig'	'logsig'
0.980	0.876	0.884	0.807	0.024	0.876	0.864	0.765	15	'trainlm'	'tansig'	'purelin'
			1				1	1			
										•	'tansig'
										-	'logsig'
											'purelin'
0.094	0.094	-0.323	-0.323	-0.323	0.806	0.783	0.622	15	'trainscg'	'tansig'	'tansig'
0.854	0 300	0 768	0 578	-0.004	0 935	0 769	-0 049	40	'trainlm'	'lOgsig'	'purelin'
											'purelin'
											'tansig'
											'logsig'
											'purelin'
	0.844 -0.020 0.298 0.758 -0.194 -0.050 0.969 0.767	0.844 0.844 -0.020 -0.064 0.298 0.298 0.758 0.140 -0.194 -0.194 -0.194 -0.194 -0.050 -0.190 0.969 0.829 0.767 0.729 0.980 0.876 -0.082 -0.082 -0.072 -0.072 0.817 0.789 0.094 0.094 0.854 0.300 0.229 0.074 0.667 0.667	Image: Constraint of the section of the sec	Image: state strain stran strain strain strain strain strain strain strain st	Image: Constraint of the section of the sec	0.326 0.197 0.811 0.522 0.399 0.114 0.844 0.650 0.650 0.650 0.139 -0.020 -0.064 0.503 0.489 -0.203 0.968 0.298 0.298 0.627 0.594 0.389 0.600 0.758 0.140 0.658 0.645 0.581 0.904 -0.194 -0.194 0.608 0.608 0.608 0.677 -0.194 0.100 0.270 0.034 -0.349 0.317 -0.050 -0.190 0.270 0.034 -0.349 0.317 0.969 0.829 0.236 0.204 -0.065 0.742 0.767 0.729 0.128 0.128 0.126 0.192 0.980 0.876 0.884 0.807 0.024 0.876 0.981 0.817 0.000 0.000 0.000 0.290 -0.072 -0.072 0.002 0.000 0.200 0.291	0.844 0.650 0.650 0.650 0.139 0.139 -0.020 -0.064 0.503 0.489 -0.203 0.968 0.926 0.298 0.298 0.627 0.594 0.389 0.600 -0.072 0.758 0.140 0.658 0.645 0.581 0.904 0.826 -0.194 -0.194 0.608 0.608 0.608 0.677 0.677 -0.194 0.608 0.608 0.608 0.677 0.677 -0.050 -0.190 0.270 0.034 -0.349 0.317 0.225 0.969 0.829 0.236 0.204 -0.065 0.742 0.536 0.767 0.729 0.128 0.126 0.192 0.546 0.980 0.876 0.884 0.807 0.024 0.876 0.864 0.980 0.876 0.884 0.807 0.024 0.876 0.885 0.072 -0.072 0.000 0.000 0.000 <td>0.326 0.197 0.811 0.522 0.399 0.114 0.114 0.114 0.844 0.650 0.650 0.650 0.139 0.139 0.139 0.0200 -0.064 0.503 0.489 -0.203 0.968 0.926 0.868 0.298 0.298 0.627 0.594 0.389 0.600 -0.072 -0.116 0.758 0.140 0.658 0.645 0.581 0.904 0.826 0.263 -0.194 -0.194 0.608 0.608 0.608 0.677 0.677 0.677 -0.500 -0.190 0.270 0.034 -0.349 0.317 0.225 -0.109 0.969 0.829 0.236 0.204 -0.065 0.742 0.536 0.426 0.767 0.729 0.128 0.126 0.192 0.544 0.600 0.980 0.876 0.884 0.807 0.024 0.876 0.844 0.082 0.000 0.00</td> <td>0.326 0.197 0.811 0.522 0.399 0.114 0.114 0.114 5 0.844 0.844 0.650 0.650 0.139 0.139 0.139 5 -0.020 -0.064 0.503 0.489 -0.203 0.968 0.926 0.868 10 0.298 0.298 0.627 0.594 0.389 0.600 -0.072 -0.116 10 0.758 0.140 0.658 0.645 0.581 0.904 0.826 0.263 10 -0.194 -0.194 0.608 0.608 0.608 0.677 0.677 0.677 10 -0.050 -0.190 0.270 0.034 -0.349 0.317 0.225 -0.109 10 0.969 0.829 0.236 0.204 -0.055 0.742 0.556 0.426 15 0.767 0.729 0.128 0.128 0.126 0.192 0.554 0.426 15 0.767 0.729<</td> <td>0.326 0.197 0.811 0.522 0.399 0.114 0.114 0.114 5 'trainrp' 0.844 0.650 0.650 0.650 0.139 0.139 0.139 0.139 5 'trainrp' 0.020 -0.064 0.503 0.489 -0.203 0.968 0.926 0.868 10 'trainlm' 0.298 0.298 0.627 0.594 0.389 0.600 -0.072 -0.116 10 'trainlm' 0.758 0.140 0.658 0.645 0.581 0.904 0.826 0.263 100 'trainlm' -0.194 0.608 0.608 0.608 0.677 0.677 1.07 'trainlm' -0.194 0.608 0.608 0.677 0.677 1.07 'trainlm' -0.950 -0.190 0.270 0.034 -0.349 0.317 0.225 -0.109 10 'trainlm' 0.969 0.829 0.236 0.24 0.576 0.426</td> <td>0.326 0.197 0.811 0.522 0.399 0.114 0.114 0.114 5 'trainrp' 'purelin' 0.844 0.844 0.650 0.650 0.650 0.139 0.139 5 'trainrp' 'purelin' -0.020 -0.064 0.503 0.489 -0.203 0.968 0.926 0.868 10 'trainlm' 'tansig' 0.298 0.298 0.627 0.594 0.389 0.600 -0.072 -0.116 10 'trainlm' 'tansig' 0.758 0.140 0.658 0.645 0.581 0.904 0.826 0.623 10 'trainlm' 'tansig' 0.194 -0.194 0.608 0.608 0.677 0.677 0.677 10 'trainrp' 'purelin' -0.050 -0.190 0.270 0.034 -0.349 0.317 0.225 -0.109 10 'trainrp' 'purelin' 0.050 0.290 0.742 0.536 0.426 15</td>	0.326 0.197 0.811 0.522 0.399 0.114 0.114 0.114 0.844 0.650 0.650 0.650 0.139 0.139 0.139 0.0200 -0.064 0.503 0.489 -0.203 0.968 0.926 0.868 0.298 0.298 0.627 0.594 0.389 0.600 -0.072 -0.116 0.758 0.140 0.658 0.645 0.581 0.904 0.826 0.263 -0.194 -0.194 0.608 0.608 0.608 0.677 0.677 0.677 -0.500 -0.190 0.270 0.034 -0.349 0.317 0.225 -0.109 0.969 0.829 0.236 0.204 -0.065 0.742 0.536 0.426 0.767 0.729 0.128 0.126 0.192 0.544 0.600 0.980 0.876 0.884 0.807 0.024 0.876 0.844 0.082 0.000 0.00	0.326 0.197 0.811 0.522 0.399 0.114 0.114 0.114 5 0.844 0.844 0.650 0.650 0.139 0.139 0.139 5 -0.020 -0.064 0.503 0.489 -0.203 0.968 0.926 0.868 10 0.298 0.298 0.627 0.594 0.389 0.600 -0.072 -0.116 10 0.758 0.140 0.658 0.645 0.581 0.904 0.826 0.263 10 -0.194 -0.194 0.608 0.608 0.608 0.677 0.677 0.677 10 -0.050 -0.190 0.270 0.034 -0.349 0.317 0.225 -0.109 10 0.969 0.829 0.236 0.204 -0.055 0.742 0.556 0.426 15 0.767 0.729 0.128 0.128 0.126 0.192 0.554 0.426 15 0.767 0.729<	0.326 0.197 0.811 0.522 0.399 0.114 0.114 0.114 5 'trainrp' 0.844 0.650 0.650 0.650 0.139 0.139 0.139 0.139 5 'trainrp' 0.020 -0.064 0.503 0.489 -0.203 0.968 0.926 0.868 10 'trainlm' 0.298 0.298 0.627 0.594 0.389 0.600 -0.072 -0.116 10 'trainlm' 0.758 0.140 0.658 0.645 0.581 0.904 0.826 0.263 100 'trainlm' -0.194 0.608 0.608 0.608 0.677 0.677 1.07 'trainlm' -0.194 0.608 0.608 0.677 0.677 1.07 'trainlm' -0.950 -0.190 0.270 0.034 -0.349 0.317 0.225 -0.109 10 'trainlm' 0.969 0.829 0.236 0.24 0.576 0.426	0.326 0.197 0.811 0.522 0.399 0.114 0.114 0.114 5 'trainrp' 'purelin' 0.844 0.844 0.650 0.650 0.650 0.139 0.139 5 'trainrp' 'purelin' -0.020 -0.064 0.503 0.489 -0.203 0.968 0.926 0.868 10 'trainlm' 'tansig' 0.298 0.298 0.627 0.594 0.389 0.600 -0.072 -0.116 10 'trainlm' 'tansig' 0.758 0.140 0.658 0.645 0.581 0.904 0.826 0.623 10 'trainlm' 'tansig' 0.194 -0.194 0.608 0.608 0.677 0.677 0.677 10 'trainrp' 'purelin' -0.050 -0.190 0.270 0.034 -0.349 0.317 0.225 -0.109 10 'trainrp' 'purelin' 0.050 0.290 0.742 0.536 0.426 15

 Table 2. ANN Training Results.

In the Table 3, the best results from the combinations made for 3 different museums and their characteristics have been given.

	Value Achieved (R)	Hidden Layer Cell Number	Training functions	Activation functions (AF1)	Activation functions (AF2)
Archaeological museum	0,9949	15	'trainlm'	'tansig'	'tansig'
Ethnography museum	0,9970	20	'trainlm'	'logsig'	'purelin'
Historic Prison	0,9989	25	'trainlm'	'tansig'	'tansig'

 Table 3. Selected Neural Networks and Features.

Figures 2, 3, 4, respectively of the structures of ANN models selected for Archaeological, Ethnography and Historic Prison are diagrams. In this study, the best results for the three museums Levenberg - Marquardt with back-propagation training algorithm have been achieved. Archaeological museum 15, Ethnography museum 25 for the Historic Prison 20, hidden layer and cells with the best results have been obtained. The combination of activation functions: tansig - tansig for Archaeological, logsig - purelin for Ethnography, tansig - tansig for the historical prison are shaped.

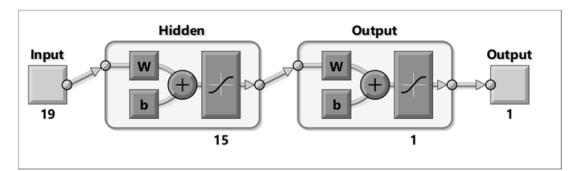


Figure 2: ANN model for number of Archaeological museum visitors.

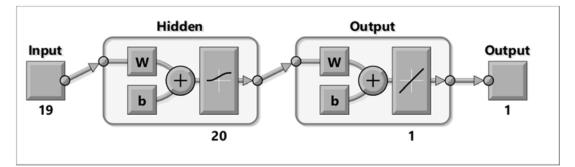


Figure 3: ANN model for number of Ethnography museum visitors.

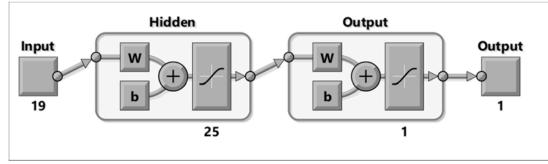


Figure 4: ANN model for number of Historic Prison visitors.

Figure 5, 6, 7 the best results for the museums together with the actual values in the data set have been shown.

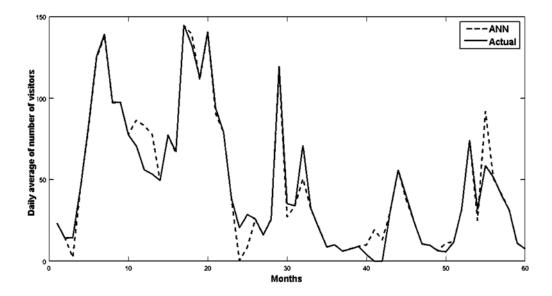
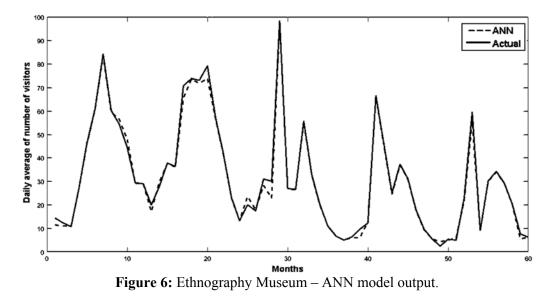
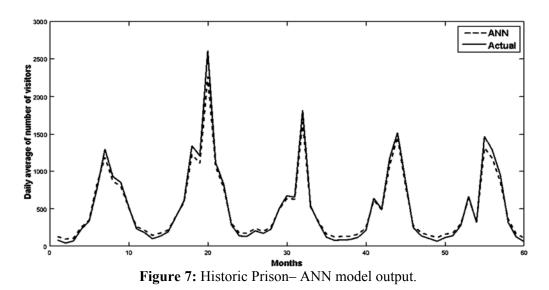


Figure 5: Archaeological Museum-ANN model output.





4. Conclusions and Recommendations

The number of the visitors at the Sinop museums (Archaeology, Ethnography and Historical Prison) is tried to be predicted by using ANN structures in the concept of this study. ANN models have been created in MATLAB environment. These ANN models are feedforward and trained by backpropagation algorithm. For each museum, an ANN with 19-inputs and 1-output have been used separately. As inputs of networks, 10 different meteorological factors, time factor (month, year), tourism income (TL), exchange rate (\$/TL) and monthly-yearly PPI and CPI data have been used. Output of ANNs is the daily average of number of visitors for each month. In order to train and test the ANNs, the number of visitors of museums at city center for total 60 months of years between 2012 and 2017, and other input data have been used.

ANN has been created separately for each museum. Levenberg - Marquardt backpropagation, scaled conjugate gradient backpropagation and resilient back propagation functions have been tried in the training of network. Logarithmic sigmoid, tangent hyperbolic sigmoid and linear activation functions have been used as activation functions. The combination of the training and activation functions have been run with 50 repetitions as 5, 10, 15, 20, 25, 30, 35, 40 hidden layer cell networks. A total of 32400 trials have been conducted to determine the networks to be selected for 3 museums. The best, the worst and the average R^2 (determination coefficient) values in the each 50 tests of the combination for training and activation functions have been computed.

As a result of the study, ANN method has a close estimation rather than other traditional methods and produced solutions in small error rates have been seen. ANN can be evaluated as an alternative method to traditional methods in order to predict the number of the museum visitors. ANN is also considered as a beneficial tool in establishing more fruitful business plan with accurate

estimation results. . Thus, it could be possible the more the number of visitors of historical places and the richer the culture gets

For future studies, it is thought that estimates that are more accurate can be obtained by creating a data set with data from a wider period.

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