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The Use of Artificial Neural Networks (ANN) in Forecasting Housing Prices in Ankara, Turkey

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ABSTRACT

The purpose of this paper is to forecast housing prices in Ankara, Turkey using the artificial neural networks (ANN) approach. The data set was collected from one of the biggest real estate web pages during April 2013. A three-layer (input layer – one hidden layer – output layer) neural network is designed with 15 different inputs to forecast the future housing prices. The proposed model has a success rate of 78%. The results of this paper would help property investors and real estate agents in developing more effective property pricing management in Ankara. We believe that the artificial neural networks (ANN) proposed here will serve as a reference for countries that develop artificial neural networks (ANN) method-based housing price determination in future. Applying the artificial neural networks (ANN) approach for estimation of housing prices

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is relatively new in the field of housing economics. Moreover, this is the first study that uses the artificial neural networks (ANN) approach for analyzing the housing market in Ankara/Turkey.

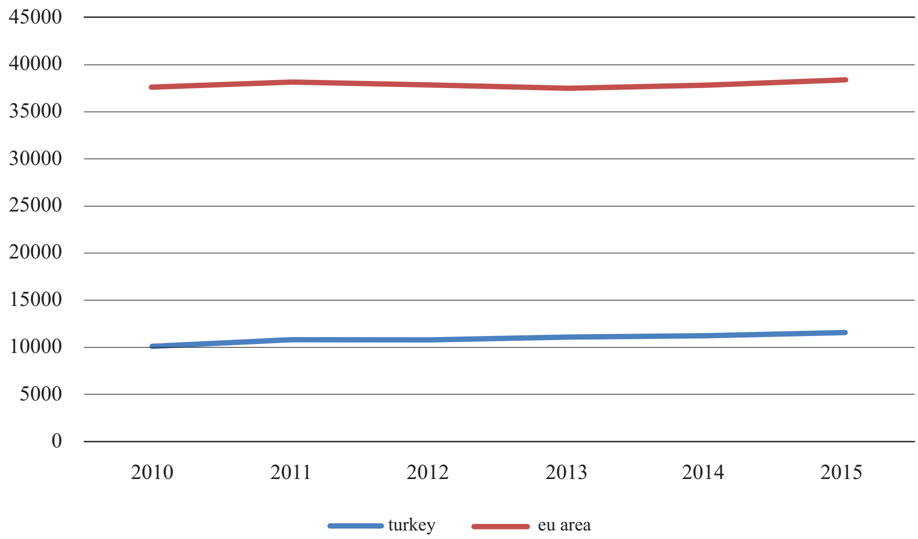
JEL classification: C15, D14, R31

Keywords: Housing, artificial neural networks, forecasting, prices, Turkey

1. INTRODUCTION

Between 2010 and 2015, Turkey had a 13.9% increase in GDP per capita with the average of 2.7% per year. The strong growing potential of the Turkish economy attracted both local and foreign investments which can be seen as different from house buying, opening a new business or entering the Istanbul Stock Exchange. The relation of GDP change between Turkey and the EU region is given in Figure 1.

Figure 1
GDP per capita (in US $) of Turkey and EU region



Over the last decade, Turkey has achieved rapid economic growth, accompanied by fast growth of the real estate sector. For instance, the real estate sector, which includes the housing sector, contributed 19.5 percent of the Turkish total gross domestic product (GDP) in 2013 (Turkish Statistical Institute, 2015). Factors that have been critical to the strong development of this sector include property rights and government policy.

With the opening up of the Turkish market to allow freehold ownership of properties for foreigners in Turkey, international investors have driven a huge demand for property. In April 2015, 1847 houses were sold, which is a 51% increase compared to the same month of 2 previous years (Turkish Real Estate Market Report, 2014).

Our study focuses on forecasting the future house prices in Ankara housing market by using artificial neural networks (ANN) with the data obtained from www.sahibinden.com, which is the biggest real estate web page in Turkey. Examining housing prices using the ANN model is relatively new in the field of housing market. Additionally, this study is the first to use the ANN model to analyze housing market in Ankara and in Turkey. The results of this work would help property investors and real estate agents in developing more effective property pricing management in Ankara. The artificial neural networks (ANN) proposed here will serve as

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a reference for countries that develop artificial neural networks (ANN) method-based housing price determination in future.

The present paper seeks to contribute to this line of research by examining the issue for Turkey. Turkey is the 17th largest economy in the world and 6th largest economy in Europe with a GDP of approximately USD 786 billion. Between 2002 and 2012, the Turkish economy grew remarkably well at an average rate of 5.17 percent per annum (Turkish Statistical Center, 2014). In parallel, it witnessed a run-up in property market, especially in Ankara metropolitan area, the capital city of Turkey.

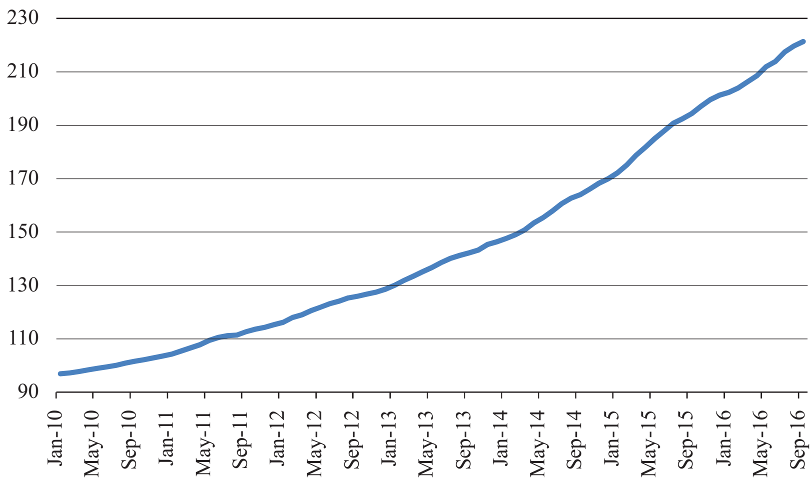
We organize the remainder of this paper as follows. The next section includes some information about Ankara housing market; the following section presents a literature review in housing market forecasting models and artificial neural networks model. In section 5, some interpretations of the results obtained are offered and in the final section, a summary is presented.

2. TURKISH HOUSING MARKET

Turkey has achieved rapid economic growth, accompanied with rapid development of the real estate sector. As a result of rapid economic growth, demand for urban land and new dwelling has increased swiftly, leading to rapid growth of housing prices.

For instance, the Housing Index in Turkey increased to 178.80 Index points in March 2015 from 175.16 Index points in February 2015. The Housing Index in Turkey averaged 147.71 Index points from 2002 until 2015, reaching an all time high of 1358 Index points in January of 2002 and a record low of 96.92 Index points in January of 2010. Figure 2 shows the Turkish House Price Index from January 2010 to September 2016 (Central Bank of the Republic of Turkey, 2016).

Figure 2
Turkish House Price Index from year 2010 to 2016



The housing market has increased substantially and also the construction industry has become one of the key elements in the Turkish economy, because of the government policy during the last decade. Figure 3 shows total house sales in Turkey by year. It depicts a significant jump from the 4th quarter of 2012 to 2013. In total, 2013 house sales have exceeded 2012 levels by 65%. And this increase continues in the following periods (Turkish Statistical Institute, 2016).

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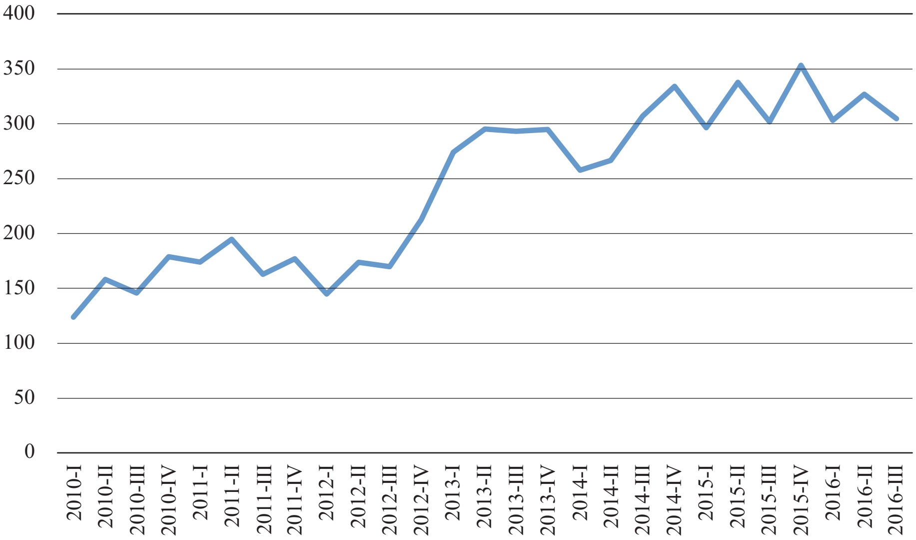
Figure 3
The total house sales in Turkey by month (thousand units)



In May 2012, the government passed a bill to attract more foreign homebuyers. Since August 2012, the government has allowed nationals from 183 countries to buy properties in Turkey. In addition, the size of land foreigners can buy without needing a special permission increased from 2.5 hectares, to 33 hectares. Since then, tens of thousands of foreigners have successfully acquired properties in Turkey, most notably in the Marmara and Mediterranean regions, Turkey's major finance and tourist hubs. In 2015, Turkey's Foreign Direct Investment (FDI) inflow was at US$ 16.5 billion, 24.8% of the total FDI (or US$ 4.1 billion) was for real estate and construction, according to the Investment Support and Promotion Agency of Turkey (ISPAT) (www.globalpropertyguide.com).

Housing loan interest rates fell from about 48.43% in 2002 to just 9.7% in 2013. This led to a sharp rise in outstanding housing loans, despite periods when the economy was weak. Over the past decade, housing loans expanded from around 1.91% of GDP in 2005 to around 6.58% of GDP in 2015. Housing loans increased by an average of 27.9% annually from 2006 to 2015. In 2014, the average interest rate for housing loans rose again, and by September 23, 2016, the average interest rate was 12.07% (www.globalpropertyguide.com).

Ankara is the capital city of Turkey and has become Turkey's second largest city after Istanbul. Additionally, according to the report made by Turkish Statistical Institute in 2014, 5,150,072 people lived in Ankara in 2014. According to Port Turkey news, the number of large-scale housing projects continues to increase in Ankara. As a consequence of allowing both internal and external migration, forecasting housing prices in Ankara is becoming an important issue for potential property investors. House price and house sales information about Ankara is given in Table 1.

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Table 1
House Price Index and sales of houses in Ankara

	House Price Index	Sales of Houses		House Price Index	Sales of Houses		House Price Index	Sales of Houses		House Price Index	Sales of Houses
Jan-13	123.62	11215	Jan-14	137.60	10141	Jan-15	152.16	9570	Jan-16	171.59	9012
Feb-13	125.01	11281	Feb-14	139.11	9386	Feb-15	154.19	11063	Feb-16	172.20	10694
Mar-13	126.81	12291	Mar-14	141.10	10693	Mar-15	157.02	14105	Mar-16	172.59	12730
Apr-13	128.61	11889	Apr-14	141.99	9249	Apr-15	158.80	14001	Apr-16	173.48	11843
May-13	129.93	12638	May-14	143.69	11004	May-15	161.02	12816	May-16	176.26	11408
Jun-13	131.29	11692	Jun-14	144.74	10437	Jun-15	162.31	12869	Jun-16	177.55	11695
Jul-13	132.10	12428	Jul-14	146.68	9426	Jul-15	163.83	10722	Jul-16	178.73	7955
Aug-13	132.64	9636	Aug-14	147.64	11836	Aug-15	165.66	13139	Aug-16	178.74	12300
Sep-13	133.28	12206	Sep-14	148.78	12615	Sep-15	166.69	9810	Sep-16	181.35	11564
Oct-13	134.22	8231	Oct-14	150.53	10549	Oct-15	169.02	11028			
Nov-13	135.78	11981	Nov-14	151.39	11695	Nov-15	169.77	11368			
Dec-13	136.35	12285	Dec-14	152.07	14794	Dec-15	170.86	16046			

Data used in the study have been obtained from the data of the online marketplace "www. sahibinden.com" regarding the residences being sold in the pilot study area for the period between December 11, 2011 and April 23, 2012. This online market platform (www.sahibinden.com) founded in 1999 in Turkey is one of the first websites that provide ad search opportunities via the internet. Since its foundation, this website has been the most frequently visited ad and shopping platform of Turkey. On the other hand, five-year neighborhood- and district-level population data obtained from the Turkish Statistical Institute has been used to observe the population development in the study area.

Ankara is divided into nine districts (Yenimahalle, Cankaya, Kecioren, Sincan, Golbasi, Etimesgut, Mamak, Altindag, Akyurt), which are given in Figure 4. In Yenimahalle, Cankaya and Kecioren districts, house is known as a capital good, so house prices in these districts are high. House prices in Golbasi and Sincan districts are average; house prices in Etimesgut, Mamak, Altindag and Akyurt districts are low.

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Figure 4
Ankara's districts

3. LITERATURE REVIEW

Much research has been conducted on the factors affecting housing prices and relations between them. An analysis of the housing market and housing price valuation literature indicates two principal research trends: the use of the ***hedonic-based regression approach*** (Lancaster, 1966; Brown and Rosen, 1982; Rabiega et al., 1984; Stevenson, 2004; Shimizu, 2010) which has been adapted to the housing market by Rosen, and this approach is commonly used as an assessment tool for the market analysis. In recent years, the second trend, ***artificial intelligence techniques***, has been used as an alternative tool to model systems of conventional property value (Kuşan et al., 2010). Chen et al. (2007) forecasted housing prices under different submarket assumptions in the city of Knoxville and vicinities. Piazzesi et al. (2007) created a consumption-based asset pricing model where housing is explicitly modeled both as an asset and consumption good. There has been a little amount of literature on the use of artificial intelligence techniques to analyze determinants of house prices. Some of these studies include: Yan et al. (2007), Selim (2007), García et al. (2008), He et al. (2010), Kuşan et al. (2010), Tayyebia et al. (2011), Azadeh et al. (2012), Park and Bae (2015) (Table 2). These studies are conducted following artificial intelligence techniques like neural network and fuzzy linear regression and employ as many variables as possible to capture the main determinants of housing prices in different countries.

There a few studies related to both Turkish real estate market and its pricing that use econometric models to analyze the effects of house pricing.

Yuksel (2016) analyzed the relation between stock and real estate prices in Turkey by using threshold error-correction model. That author compared the effect of pre-crisis and crisis periods using daily Real Estate Investment Trusts Index, stock market index and interest rate data within the framework of a vector error correction model.

Kaya and Atan (2014) used a hedonic price model on the data of house price index obtained from the Central Bank of Turkey. Their study shows that, for the period between December 2010

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and June 2012, under the constant housing features, hedonic price indexes are calculated as 6.21% for Turkey, 5.93% for İstanbul, and 5.05% and 2.83% for Ankara and İzmir respectively.

Coskun and Ertugrul (2016) analyze volatility properties of the house price returns of Turkey and Istanbul, Ankara and Izmir provinces over the period of July 2007–June 2014 using conditional variance models.

In recent years, the ANN approach has been used as an alternative tool to model systems of housing prices determination. This study will employ the ANN approach to evaluate the major determinations of housing prices in Ankara. Related studies including artificial neural networks and house pricing are given in Table 2.

Table 2
The studies related to artificial intelligence techniques in housing market sector

Author(s)	Journal	Artificial Intelligence Analysis Techniques
Yan et al., 2007	Systems Engineering	TEI@I
Garcia et al., 2008	Neurocomputing	Artificial neural network and geographic information system
Selim, 2009	Expert Systems with Applications	Hedonic regression and artificial neural network
He et al., 2010	Procedia Environmental Sciences	Wavelet transformation, hedonic regression
Kusan et al., 2010	Expert Systems with Applications	Fuzzy logic
Tayyebia, et al. 2011	Landscape and Urban Planning	Neural networks, geographic information system and radial parameterization
Azadehet, al. 2012	Expert Systems with Applications	Fuzzy linear regression
Park and Bae, 2015	Expert Systems with Applications	Decision trees, classification

4. ARTIFICIAL NEURAL NETWORKS (ANN)

ANN is a part of machine learning where you can train the user design network to learn a process like forecasting, classification or other rule-based programming. Generally, it is a copy of human brain for information processing and computing. Like our brains, ANN uses artificial nerves and links them together to simulate the capability of a biological neural network. The most significant property of ANN systems is that they can learn from sample data sets like brains, and have the ability to make decisions according to this learning process (Tosun, 2012).

ANNs have been applied to different fields like linear, nonlinear or even nonparametric problems. The basic element of the ANN is called neuron, which is the processing unit that forms a larger network. In regression or forecasting to train a multilayer network, a back-propagation learning algorithm is widely accepted and used. This learning algorithm is preferred to train the network with gradient search to minimize the square of errors between realized and targeted outputs (Pendharkar and Rodgre, 2003).

Generally, a multi-layer perception type of ANN which has three different layers (input, hidden and output layers) is widely used in literature. This type of ANN is fully connected, which means each node (neuron) is connected to every neuron in the next and previous layer. Each layer has a different number of neurons determined by the decision maker. The input layer is the first stage which allows inputs to enter from environment into the network. The output layer transmits the output to the environment. And the hidden layer occurs between the two outer layers. The hidden layer establishes linkages (with a selected transfer function) between input and output layers and provides the generalization of the network (Özdemir and Tekin, 2009; Örkcü and Bal, 2011).

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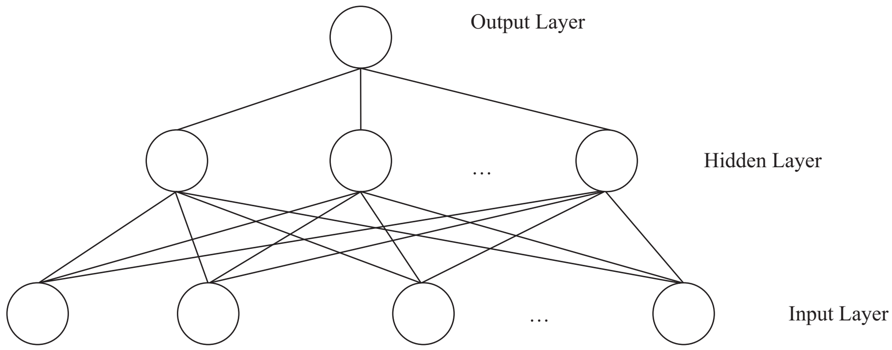
The connections between the neurons of consecutive layers create the processing abilities of any ANN. Each layer has neurons linked together with different weights. These weights are calculated by a trial-error process (known as learning) which aims to minimize the error between the output value and the desired value. By selecting a suitable set of connecting weights and transfer functions, an ANN can learn to achieve a given task.

Figure 5
A neural network model



Generally, for each input variable in the dataset, there is one corresponding node in the input layer. The number of nodes in the hidden layer determines the complexity of the network model and needs to be empirically determined to best suit the data considered. While larger networks easily overfit (in other words, memorize) the data, too few hidden layer nodes can hinder learning of an adequate separating region. Although having more than one hidden layer provides no advantage in terms of nature of forecasting accuracy, it can in certain cases provide for faster learning (Pendharkar and Rodgre, 2003).

A back propagation neural network is widely preferred for prediction or classification of problems (Liang and Wu, 2005). Therefore, this algorithm is used in this study.

In the back propagation algorithm, the related input data are repeatedly presented to the neural network. The output of the neural network is compared to the targeted output and an error is calculated for each iteration. This error is then back propagated to the neural network and used to adjust the weights so that the error may decrease with each iteration and the designed model gets closer and closer to produce the desired output. This learning process is known as training (Wu et al., 2006).

Using the learning rules, the weights are iteratively changed to reach the best weight values which provide the most satisfactory outputs. This can depend on min MSE (min squared error) or other user-defined performance indicators. The network with the best performance measure is accepted as the best network. For obtaining the best network structure, many trials are needed in order to find the best numbers of hidden layers and the best numbers of neurons in those layers (Tosun, 2012).

ANN provides many advantages to decision makers, especially for complex problem solutions. They not only have ability to learn from sample sets, but their results can also be generalized to other data sets. A learned ANN can do the same tasks for other similar data sets. They can be especially powerful when the underlying data relationship is unknown. Noisy or imprecise data or even complex and non-linear data sets do not prevent the learning process. Hence, ANN is used in a wide range of applications in business management practices (Özdemir and Temur, 2009).

One of the most important features of neural networks is their ability to learn and generalize from a set of training data. After the training phase, a network establishes correlated patterns between input data sets and its corresponding targets. Thus, a well-trained network can be used to predict the outcomes of new independent input data (Jha, 2007).

One major disadvantage of ANN is that it is impossible to know the effect or the relationship between the inputs and the outputs with certainty, where the connection weights in the network do not indicate which input has more or less effect on the outcome of the network. In other words,

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one can consider ANN as a black box that supplies good outcomes without indicating how or why. Apart from defining the general architecture of a network and perhaps initially seeding it with a random numbers, the user has no other role than to enter the inputs and watch the network train by itself and await the output. Another limitation of ANN is finding the right topology for the network, most importantly choosing the number of the hidden nodes, the initial weights for the connecting paths, and the proper learning algorithm with its parameters (Rao and Ali, 2002).

5. NETWORK DESIGN AND APPLICATION

Generally, before training a neural network, a decision maker must decide on the network properties by specifying the number of neurons in the input layer, the number of hidden layers (one or more layers), the number of neurons in each hidden layer, and the number of neurons in the output layer (Emrouznejad and Shale, 2009).

There are no certain rules to define the right or proper number of hidden layer units. Network design is a trial and error process. The initial values of the weights may also affect the resulting accuracy. Once a network has been trained and its accuracy is not considered acceptable, the training process should be repeated with a different network topology or a different set of initial weights (Emrouznejad and Shale, 2009).

A three-layer (input layer – one hidden layer – output layer) neural network is used for the study. For ANN, a program is written in Matlab by using Neural Network Toolbox. In this study, the output is the price of the houses and inputs are the variables used to forecast the house price. The variables used in the study with their descriptive statistics are given in Table 3. Thus, there are fifteen neurons in the input layer and one in the output layer. These variables are selected from the database based on the opinions of real estate agencies or marketing specialists. According to these experts, the main criteria reflecting the buying or renting decision of the customers are selected.

The age of home variable is given in groups on the web site. Therefore, we give numbers for each group: 0 for a new building, 1 if the age is 1–4, 2 if the age is 5–10, 3 if the age is 11–15, 4 if the age is 16–20 years and 5 if the building is 20 years or older.

Table 3
Variables, minimum, maximum and mean values

Variables	Definition of the variables	Min	Max	Mean
Price	Value of the home in TL	15,000	1,050,000	129,770.37
Size	Size of the home in square meters	50	571	126.96
Rooms	Number of rooms	1	8	4.09
Bathroom	Number of bathrooms	1	4	127
Floor	Floor at which the home is located	0	18	4.34
Parking	1 if there is a parking place for cars	0	1	0.64
Age	Age of the home	0	5	1.49
Elevator	1 if there is an elevator	0	1	0.32
Heating	1 if there is central heating	0	1	0.92
Location	1 if the home is in or near the city center	0	1	0.40
Site	1 if the house is in an apartment complex	0	1	0.15
Insulation	1 if the house/building has an insulation	0	1	0.56
Kitchen	1 if the kitchen has kitchen cabinets	0	1	0.14
Home-Floor	Floor of the house. 1 if hardwood, 2 if laminate and 0 if vinyl covering	0	2	1.52
Road	1 if near the main city roads	0	1	0.53
Subway	1 if near a subway station	0	1	0.08

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For a better classification, the data is normalized to [0, 1] by using the equation below:

$$X_{normalized} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

There are 1500 observations in the dataset. In the study, the dataset is divided into three parts randomly: 70% is used for training the network and remaining data is divided equally for testing and validation. In order to find the optimum number of neurons in the hidden layer, a simple experimental design is used. First, the training process was started with a network of five neurons in the hidden layer and this network is run 15 times. Then, this process was repeated for an increased number of neurons in the hidden layer of up to 20.

The most effective neuron numbers are chosen according to the performance measure. In this study, the mean square error (MSE) is taken into consideration as a performance measurement. The selection of the best ANN system depends on the value of MSE. The minimum MSE found through the experiment is 0.0023, which occurs in 4 different network structures (number of hidden neurons of 6, 12, 14 and 15). The best network is chosen on the basis of both CPU time and the coefficient of regression. The network with 12 hidden neurons has the coefficient of regression of 0.7878. The results of the best network after the training process are seen in Table 4.

Table 4
Training results

	Training Results	
Best Network	Network architecture	15 – 12 – 1
	Activation function	logsig/linear
	Training algorithm	Levenberg-Marquardt
	Minimum MSE	0.0023

The best network has 15 neurons in the input layer, 12 neurons in the hidden layer and one in the output layer. For hidden layer log sigmoid and for the output layer pure-linear, transfer functions are used. Levenberg-Marquardt algorithm is used for the training.

6. CONCLUSION

In this study, an artificial intelligence based decision support method is proposed for estimating housing prices. This method aims to help decision makers to analyze the market structure and compare the recent prices with their findings. In the model, 15 different inputs, from house price to its location, are used for the inputs. The output of the system is the future price of houses.

The aim of this study is to provide a decision tool for decision makers in the very complicated housing market for both real estate firms and final consumers. Buying a house or using a mortgage is a very difficult opinion for most people. A proper price forecast can be very helpful for future references. Thus, the proposed method can be utilized to ease the decision making process. This utilization is of interest particularly for both property investors and final consumers.

Perhaps the main limitation of this study is the selection of input and output variables. Comprehensive literature research is done for this purpose. But it should be known that selecting different variables can affect the outcome of the forecasts. This effect can be analyzed in further studies.

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