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A Real Estate Appraisal Model with Artificial Neural Networks and Fuzzy Logic: A Local Case Study of Samsun City

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There have been great innovations in the field of real estate appraisal which have replaced the classical methods by recently established modern methods that involve computer technologies known as artificial intelligence. here are several artificial intelligent methods like fuzzy logic and artificial neural networks. In this study, two different real estate appraisal applications that are based on the artificial neural network and fuzzy logic methods are compared. An actual data set is taken from real estate agencies to develop a real estate appraisal model in Samsun city in Turkey. All of the real estate data belong to a certain time interval in May 2020. The selected parameters are scored by a valuation expert and the scores are then subjected to normalization. The obtained values are inputted into a fuzzy logic and artificial neural networks editor in MATLAB software and the valuation model is created. The values we obtain from the artificial neural networks and fuzzy logic are compared with actual sales data. It is observed that using these methods in real estate appraisal provides advantages in terms of time, cost and tangibility, as well as the means to create large database for real estate appraisal in a certain region.

Keywords

Artificial neural networks, Fuzzy logic, Artificial intelligence, Real estate appraisal

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1. Introduction

Valuation can be defined as the process of determining the value of tangible and intangible goods that will ensure circulation in the market. Trading; leasing; establishing easement; real and limited rights in the land registry; partial or complete expropriation; taxation; municipal revenues; insurance; and heritage, mortgage and inheritance transactions depend on knowing the value of the real estate (Erdem, 2017; Utkucu, 2007; Yıldız, 1987). Valuation is also the process of determining the provision of the seller according to the real estate property for investment or long-term use (Brown, 1965). Independent, objective, correct and safe determination of the value of real estate makes up a large part of social wealth; as much as the value concerns the owners and other stakeholders, it also has great importance in terms of the national economy (Açlar and Çağdaş, 2002). The need for real estate valuation was first recognized in the taxation of agricultural lands worldwide. Over a period of time, buying and selling, leasing, expropriation, nationalization, privatization, capital markets, lending, and insurance expanded with purposeful valuations. National real estate valuation systems were established to meet the increasing need for valuation in different countries (Yomralıoğlu et al., 2011).

Nowadays, different methods are used in real estate appraisal. In order to initiate a real estate appraisal with more concrete and reliable values, the appraisal must be integrated with computer technologies. Human thinking and learning can be imitated through artificial intelligence processes. Although the strategies of artificial intelligence are different, the aim is to ultimately bring logic and learning to the computer environment. There are many artificial intelligence techniques, including fuzzy logic and artificial neural networks, which are among the most popular techniques in the literature (Worzala et al., 1995). Fuzzy logic is defined as machine learning technology that is likened to human reasoning (Zadeh, 1997). With this technology, computers analyze data that are not defined numerically in a prudent way and makes them computable. When looking at real estate valuation, fuzzy logic has been used in urban planning decisions and support systems (Bonissone and Cheetham, 1997). In addition, the practicality of fuzzy logic has been examined in real estate appraisal, including for example, the city of Tainan in Taiwan (Lee et al., 2003). Sarpoulaki et al. (2002) recommended fuzzy logic to answer queries to purchase a house in Tehran. Sun et al. (2008) use a fuzzy analytical hierarchy process to assess risks in real estate projects with linguistic variables rather than net values. Furthermore, Cui and Hao (2006) conduct a study that applies fuzzy mathematics to the cost approach for replacing a building and its depreciation over time.

One of the artificial intelligence methods are artificial neural networks. They can also perform operations such as deriving and discovering new information through learning by imitating the human brain (Zhang et al., 1998). There are billions of nerve cells that are called neurons in the human brain, and infinite number of bonds between them. Thanks to these neuron bonds, complex problems can be solved quickly. Artificial neural networks also learn the selected input and output data by performing iterations (training process) and analyze the input values that are not entered during the test as a result of learning (Arce-Medina and Paz-Paredes, 2009). Higher accuracy can be realized by repeating iterations. Therefore, the ability of artificial neural networks to tolerate errors is quite high. Real estate valuation studies have been carried out with artificial neural networks. Mora-Esperanza (2004) conduct an analysis using 12 parameters in Madrid. As a result of the analysis, the accuracy rate of the ANN is 92%, while the accuracy rate of the multiple regression analysis (MRA) is 86%. Therefore, it is concluded that the ANN is more successful. Worzala et al. (1995) use ANN and MRA in the analysis of house prices in the state of Colorado, USA, and use 7 parameters for model estimation. In their application using all data, they achieve an accuracy rate of 84.5% with ANN and 81.9% with the MRA. Moreover, a study is carried out in Christchurch to determine real estate value by using artificial neural networks (Limsombunchai, 2004). The accuracy rate for that study is 84%. Subsequently, Nguyen and Cripps (2001) use multiple regression and back propagation feed forward neural networks to examine the sales of single family housing. They find that the latter perform better. In this study, we focus on the use of fuzzy logic along with artificial neural networks for the appraisal of real estate, which is the core of the economy of many countries. Moreover, we determine the accuracy of the obtained values and compare the results.

2. Real Estate Appraisal

Real estate appraisal is defined as the process of objectively and impartially evaluating factors that affect the value of property such as its quality, benefits, environment, and conditions of use (American Institute of Real Estate Appraisers, 1952; Boyce, 1975; Büyükkaracığan et al., 2017; Jost et al., 1994; Peterson and Flanagan, 2009). Many methods are used for real estate appraisal. These methods can be categorized into three main groups as given in Table 1 (Yalpir, 2007).

Many of these methods have been developed together with computer technologies, which provide objective and realistic results. Fuzzy logic and artificial neural networks are two of the leading methods, and so they are used in this study.

Table 1 Real Estate Appraisal Methods (Yalpir, 2007)

Traditional Method	Statistical Method	Modern Method
Comparison Method	Nominal Method	Speech Recognition
Income Method	Multiple Regression Method	Fuzzy Logic
Cost Method	Hedonic Pricing Method	Artificial Neural Networks
		Robotics
		Genetic Algorithms
		Computer Vision
		Simulated Annealing
		Expert Systems
		Support Vector Machine
		Machine Learning

3. Fuzzy Logic

Prof. Dr. Lotfi A. Zadeh made the first statement about fuzzy sets in 1965 in his article "Fuzzy Sets" (Zadeh, 1965). In classical logic, an object is either an element of a cluster or it is not. In other words, there is either full existence or complete nonexistence. The concept of fuzzy logic is used to emulate complex human related cognitive abilities by computers such as thinking, learning, and reasoning. Fuzzy logic is a kind of machine intelligence (Yalpir and Ozkan, 2018), where uncountable data are used instead of numerical expressions, which are received by machines on a numerical basis. Fuzzy logic is the approximate finding of a reality (Zadeh, 1997). When a more detailed analysis is necessary, classical logic fails to deliver the desired outcome. In such cases, it is favorable to use fuzzy logic in which a membership function is established and a degree of membership is assigned to uncountable data. The uncountable data assigned to the degrees of membership allows for a more detailed mathematical analysis. In fuzzy logic, the value moves away from the real value as it approaches “0”, and is the closest to the real value as it approaches “1”. In this type of logic, an infinite number of values can be found between 0 and 1 (Şen, 2004). In classical logic, there are certain logical expressions used, such as there is or not, while different expressions such as present or absent are used in fuzzy logic. In the latter, everything is shown with a degree of membership that ranges between 0 and 1. Additionally, it is used in systems for which creating a model is either impossible or challenging. All of the concepts expressed in classical logic can be expressed in fuzzy logic as well. The main points that distinguish fuzzy logic from other types of logic are the existence of multiple logics, models being in a proposition combined form, and having uncountable data with no equations for the analyzed events (Sun et al., 2010). There are two types of fuzzy modeling, which are called Mamdani and Sugeno type fuzzy modeling. The former is mostly used to exhibit human behavior

(Takagi and Sugeno, 1993). Besides, it is the most widely used fuzzy model and consists of six parts:

1. Determining the degrees of memberships between 0 and 1 that belong to the input variables
2. Determining the weights of rule
3. Applying logical processors or fuzzy operators (AND or OR)
4. Merging sets that represent the rule outputs
5. Clustering which represents the rule outputs
6. Defuzzifying

Sugeno type modeling was first used in 1985 (Takagi and Sugeno, 1993), and based and emerged from Mamdani type fuzzy modeling. The blurring of the input data and logical operations are identical to those of Mamdani type fuzzy modeling. Output membership functions determine the difference between these two models. The Sugeno type modeling is not used to exhibit human behavior in comparison with the Mamdani's fuzzy inference method. Table 2 shows a comparison between these two types of modeling.

Table 2 Comparison of Mamdani and Sugeno Type Fuzzy Modeling

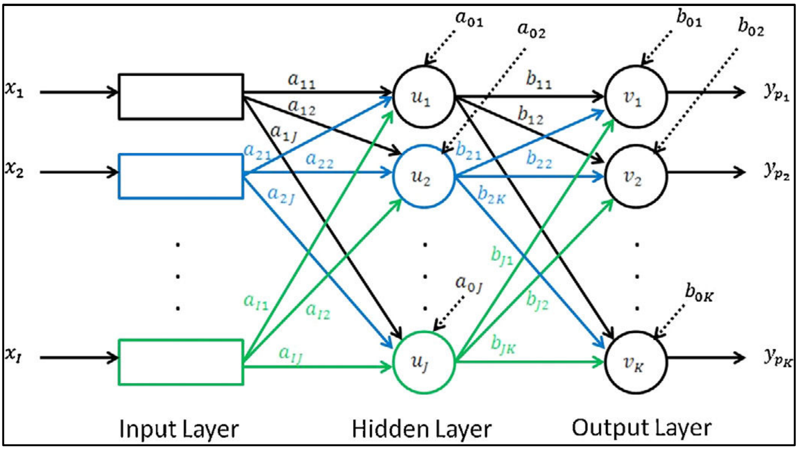
Mamdani	**Sugeno**
Exhibits human behavior	Convenient for calculating
Building a model is easy	Works well with optimization
Forms the basis of other types of modeling	Suitable for mathematical analysis

4. Artificial Neural Networks

Artificial neural networks imitate the cognitive abilities of the human brain, and can be thought as a complex system that results from the connection of many nerve cells that are called neurons in the brain with different levels of effect. In artificial neural networks, the system initially performs a learning process by analyzing the relationship between the data of the input and output layers, and subsequently gives the approximate output data of new input data based on repeated iterations.

Fig. 1 shows a three-layer neural network with a feedforward configuration. The neurons are represented by circles. The other network configurations are described in Himmelblau (2000). Artificial neural networks have input, hidden and output layers. The input layers receives the initial data for processing (Arce-Medina and Paz-Paredes, 2009). These are the independent variables. After the input layer is known, the weights are assigned which point to the importance of a given variable. The output layers are the dependent variables. The hidden layers are the computational steps that lead from the input to the output layer by performing different functions, such as data transformation. The output from the nodes in the output layer is the predicted decision. Artificial neural networks have been widely used, especially in engineering applications because it is difficult to use classical methods to solve engineering problems. Although the human brain has limited mathematical abilities, and can perform only addition, subtraction, multiplication, and division, the brain is still more advanced than machines in many other cognitive processes such as learning, remembering, and predicting. To better understand artificial neural networks, neuron structures should be examined.

Figure 1 Schematic Representation of a Three Layer Neural Network (Bhattacharjee and Tollner 2016)



Neurons, which are the main elements of the nervous system and brain functions, consist of three parts: cell body, dendrites and axon. Neurons are the simplest structure of neural network systems. There are approximately 8.6 x 10^{10} neurons in the human brain or 86 billion neurons. There are 104 connections between each neuron. Dendrites collect and receive inputs from the neurons which are transmitted to the soma (cell body of the neuron). Then the cell body determines whether an output pulse should be produced by combining the signals received by the dendrites. The axon then transmits the information from the dendrites to the other neurons. Neurons are separated by synapses which are the points of contact and communication where information is passed from neuron to target cell. Learning and storing information in the brain occur with electrical and chemical signals between the neurons (Grafstein and Forman, 1980; Palay and Palade, 1955; Wolfe, 2010). The nervous system components along with their corresponding artificial neural network components are shown in Table 3. Additionally, Table 4 presents the equivalent statistical terminologies for the terms used in artificial neural networks.

Table 3 Nervous System and Artificial Neural Network Components

Nervous System	Artificial Neural Network
Neuron	Processing Element
Dendrite	Addition Function
Cell Body	Activation Function
Axon	Element Output
Synapse	Weights

Table 4 Terms Used in Artificial Neural Networks and Equivalent Statistical Terminologies (Sarle, 1994)

Artificial Neural Network	Statistical Terminology
Artificial Neural Network	Model
Weight	Parameter
Input	Independent variable
Output	Estimated value
Target	Dependent variable
Error	Residue
Error Line	Confidence Interval

The main characteristics of artificial neural networks are nonlinearity, learning, parallel work, generalization, working with missing data, using a large number of variables and parameters, applicability, fault tolerance and flexibility. Artificial neural networks consist of three main components: the structure, learning algorithm and activation function. The structure consists of the input, hidden and output layers. Learning algorithms deal with the weights in the network and ensures that the weights receive optimal values. In fact, training the network warrants the best value of the weights. The activation function provides matching between the input and output layers in this process (Sarle, 1994).

The artificial neural network processing steps are as follows:

- Determining the network architecture and selection structure properties,
- Deciding the characteristic features of the neuron functions,
- Selecting the learning algorithm and determining the parameters,
- Establishing the training and test data,
- Training and testing the network.

5. Application

In this study, the Büyükoyumca neighborhood in Samsun city of the Atakum district, is the study area, as shown in Figure 2. The Atakum district is one of the most important and most preferred district in Samsun in terms of land valuation. The value of the real estate sales is determined based on a comparison method by real estate agencies. In this study, data are collected from real estate agencies in Atakum in May 2019 (Table 5).

For data quality, valuation reports obtained from real estate valuation companies are taken as the basis. Since these reports are generally prepared for sales and bank requests, they give the average market price. In addition, the large number of real estate sales in the appraisals ensures consistency of the market price. The characteristics and prices of real estate are compared with the prices on real estate sales sites on the internet, thus enhancing the quality of the data.

The parameters of the data were scored by a valuation expert and normalized by using min-max normalization with Equation (1) (Table 6). The floor of the unit and number of floors in the building are normalized together.

$$\chi' = (\chi - min(\chi))/(max(\chi) - min(\chi)) \tag{1}$$

Residential data after normalization are presented in Table 7.

Figure 2 Study Area (Büyükoyumca neighborhood in Samsun city of Atakum district)

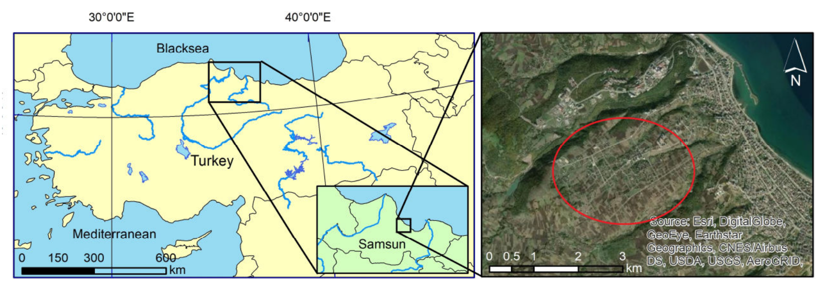


Table 5 Residential Sales Data

No	Area m²	Number of Rooms	Age	Floor	Number of Floors	Heating System	Bathroom	Balcony	Price (TRY)[*]	Price (USD)
1	143	3+1	5-10	7	9	Central	1	1	194,000	23,283.72
2	145	3+1	5-10	1	11	Central	1	1	185,000	22,203.55
3	98	2+1	11-15	5	5	Central	1	1	155,000	18,602.98
4	135	3+1	5-10	9	10	Central	1	1	213,000	25,564.09
5	170	4+1	1	6	10	Central	2	1	410,000	49,207.87
…	…	…	…	…	…	…	…	…	…	…
45	70	2+1	11-15	3	5	Central	1	1	100,000	12,001.92
46	130	3+1	5-10	3	11	Central	1	1	180,000	21,603.46
47	170	4+1	2	2	8	Combi	2	1	380,000	45,607.30
48	145	4+1	5-10	10	10	Central	2	1	400,000	48,007.68
49	85	1+1	11-15	10	14	Combi	1	1	125,500	15,062.41
50	79	1+1	11-15	9	9	Central	1	1	115,000	13,802.21

[*] ***Note:*** 1 USD = 8.332 Turkish ira (***TRY***) (as of May 2020)

Table 6 Score Normalization

Area m²	Number of Rooms	Age	Floor	Heating System	Bathroom	Balcony	Price (TRY)*
52 – 0	1+1– 0	16-20 – 0	Ground – 0	Combi – 0	1 – 0	1 – 1	89,500 – 0
210 – 1	2+1– 0.333	11-15 – 0.2	Attic – 0.5	Central – 1	2 – 1		575,000 – 1
	3+1– 0.667	5-10 – 0.4	Mezza. – 1				
	4+1 – 1	2 – 0.6					
		1 – 0.8					
		0 – 1					

Note*: 1 USD = 8.332 Turkish ira (*TRY***) (as of May 2020)

Table 7 Real Estate Sales Data After Normalization

No	Area m²	Number of Rooms	Age	Floor	Heating System	Bathroom	Balcony	After normalization
1	0.58	0.667	0.4	1	1	0	1	0.215242019
2	0.59	0.667	0.4	0	1	0	1	0.196704428
3	0.29	0.333	0.2	0.5	1	0	1	0.134912461
4	0.53	0.667	0.4	1	1	0	1	0.254376931
5	0.75	1	0.8	1	1	1	1	0.660144181
…	…	…	…	…	…	…	…	…
45	0.11	0.333	0.2	1	1	0	1	0.021627188
46	0.49	0.667	0.4	1	1	0	1	0.186405767
47	0.75	1	0.6	1	0	1	1	0.598352214
48	0.59	1	0.4	0.5	1	1	1	0.639546859
49	0.21	0	0.2	1	0	0	1	0.074150360
50	0.17	0	0.2	0.5	1	0	1	0.052523172

6. Results

Eight parameters (area, number of rooms, age, floor, number of floors, heating, bathroom and balcony) are the modeling inputs for determining the real estate value with use of artificial neural networks and fuzzy logic by using MATLAB software. Then, the values are calculated with artificial neural networks and fuzzy logic tool boxes. The values obtained from the real estate appraisal models are subsequently compared with real sales values. It is observed that using these methods are effective in real estate appraisal as the obtained values are very close to the actual sales values. The normalized data are used in the fuzzy logic application. Subsequently, the rule database is created in the Rule Editor in MATLAB and the values are determined with the Rule Viewer as shown in Fig. 3.

For the artificial neural networks application, the normalized data are defined as the input and output data in the MATLAB artificial neural network editor (nnstart). After training the network several times through iterations, the performance and regression tables are checked. The network was simulated after the optimum values are captured from the performance and regression tables. The regression and performance tables are shown in Figs. 4 and 5, respectively. This study uses feed forward neural networks.

Figure 3 MATLAB Fuzzy Logic Rule Viewer

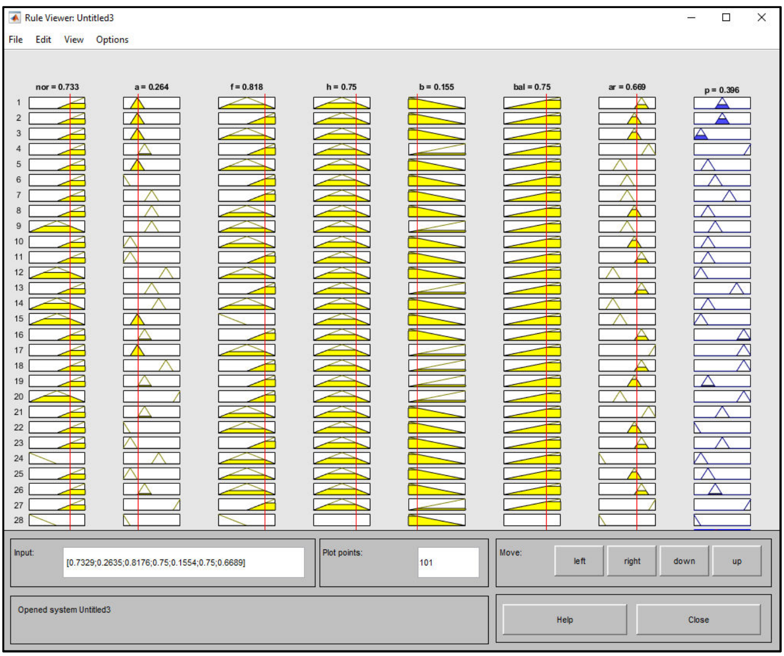


Figure 4 Training Regression

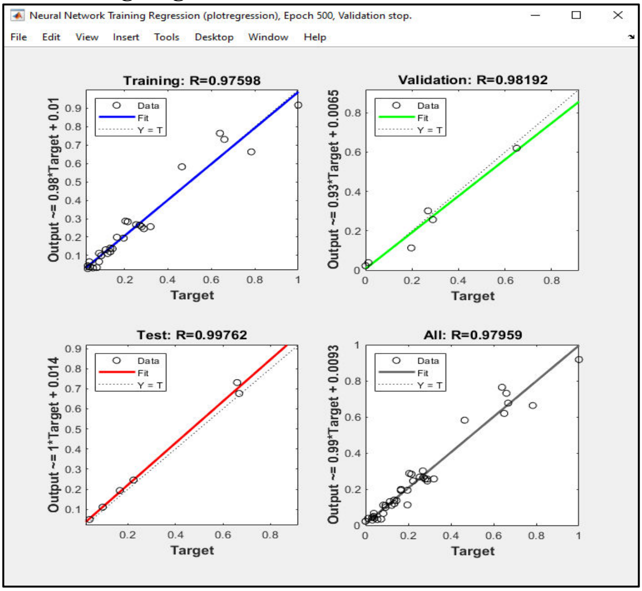
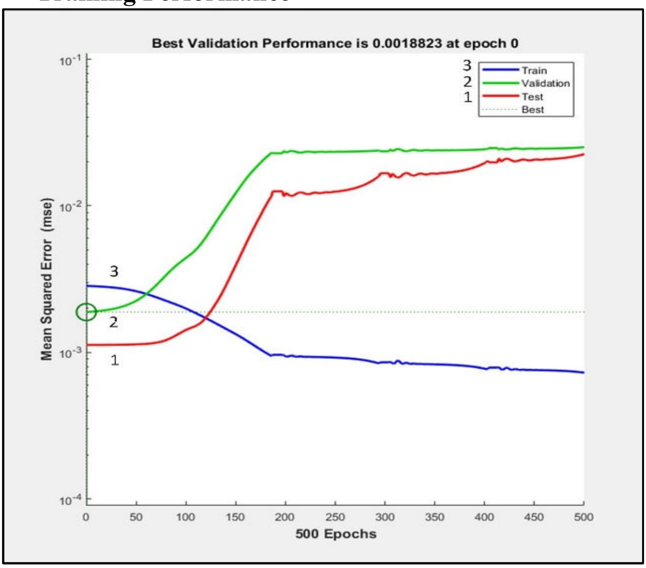


Figure 5 Training Performance



The accuracy value is 97% in the artificial neural networks. In order to verify the models, residential values according to real estate sales prices as well as the prices calculated by using artificial neural networks and fuzzy logic are given in Table 8. The difference between the values obtained from the models and the real estate agencies along with the proportional differences are calculated.

Table 8 **Real Estate Sales Prices and Calculated Values**

No	Sales Price (TRY)	Sales Price (USD)	Value, Calculated by Artificial Neural Networks (TRY)	Value, Calculated by Artificial Neural Networks (USD)	Price Consistency Rate (%)	Value, Calculated by Fuzzy Logic (TRY)	Value, Calculated by Fuzzy Logic (USD)	Price Consistency Rate (%)
1	400,000.00	48,007.68	396,617.60	47,601.73	99.15	390,524.00	46,870.38	97.63
2	100,000.00	12,001.92	111,876.09	13,427.28	88.12	124,582.00	14,952.23	75.42
3	210,000.00	25,204.03	203,142.62	24,381.02	96.73	195,284.00	23,437.83	92.99
4	100,000.00	12,001.92	111,057.58	13,329.04	88.94	108,685.00	13,044.29	91.32
5	400,000.00	48,007.68	385,051.78	46,213.61	96.26	402,258.00	48,278.68	99.44
6	125,000.00	15,002.40	108,916.56	13,072.08	87.13	132,547.00	15,908.19	93.96
7	115,000.00	13,802.21	119,665.26	14,362.13	95.94	128,927.00	15,473.72	87.89

* ***Note:*** 1 USD = 8.332 Turkish ira (***TRY***) (as of May 2020)

It can be said that the artificial neural networks provide more accurate values than the fuzzy logic method. The accuracy values are shown in Table 9.

Table 9 **Price Consistency Average**

Artificial Neural Networks (%)	Fuzzy Logic (%)
93.18	91.23

In addition, when the results obtained from traditional valuation and artificial intelligence methods are compared, it is seen that the latter generally give values close to those of the former. In some of the data, when real estate properties are examined, it is thought that the real value may be closer to the value obtained from the artificial intelligence methods. In this respect, artificial intelligence methods are thought to complement traditional valuation methods.

7. Conclusion and Recommendations

This study shows that artificial neural networks and fuzzy logic can be used for real estate valuation, and done by selecting parameters that are appropriate for local constructs. It is seen that artificial neural networks and fuzzy logic give results within acceptable limits for residential valuation. For more sensitive and better results, large databases should be used in artificial neural networks and iterations should be repeated several times to train the network thoroughly. More input and output values used to train artificial neural networks result in higher the accuracy and sensitivity of the network. In fuzzy logic, larger rule databases mean higher accuracy and precision. Artificial neural networks take less time than fuzzy logic because they do all the operations automatically in the hidden layer. It is not necessary to define rules individually as in fuzzy logic. Expert opinion may be required in fuzzy logic, but artificial neural networks analyze input and output values and create an algorithm within those values. Artificial neural networks perform all operations automatically using the created algorithms. In summary, this study shows that real estate valuation modeling can be done in any region using the same methodology. The parameters that affect the residential values might vary according to regional preferences. Therefore, if the most common parameters are selected, the most realistic results can be obtained. Real estate appraisal is an important topic for the economies of countries and helps to determine the actual market value of properties. Thus, developing models to achieve objective and accurate results will not only ease the appraisal process, but also avoids wasting time and labor and reduces the economic costs.

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