Mass Appraisal Models of Real Estate Tax Value

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Artificial neural network (ANN)-based analysis can reveal differences in tax leakage loss rates in different geographical regions of countries. Experts can adjust a region's valuation data based on property tax leakage loss rates. Appraisers can contribute to solving the problem by highlighting areas with high tax leakage loss rates and communicating their findings to valuation stakeholders, local administrators, and policymakers. This can lead to more fair and efficient tax policies that benefit the real estate sector and the economy.

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1. Introduction

The collection of the real estate tax in Türkiye has been the responsibility of municipalities since 1986, and it is among the indispensable income sources of the municipalities. Today, municipalities face various problems in determining and collecting real estate tax. The most significant of these problems is the inability to correctly determine real estate tax values. While determining the tax value according to the laws, the square meter of the land and the square meter construction cost of buildings are considered. Land square meter unit values are determined every four years by the valuation commissions established by the municipality. Building construction costs are jointly announced annually by the Ministry of Environment, Urbanization, and Climate Change (MoEU) and the Ministry of Treasury and Finance (HMB).

The construction costs announced by the MoEU and HMB are used as a fixed value annually throughout Türkiye. Construction costs are not the same in every province. In line with the relevant laws, the tax value is calculated according to the cost method using the land and square meter values of the land and the building construction costs. Determining the market value according to the cost method is exceedingly difficult. In addition, the land and square meter values of the land are renewed annually according to the revaluation rate announced by HMB. Revaluation rates also do not reflect real market conditions.

Complaints about real estate tax mainly stem from inadequate valuation and unfair practices. In addition, disproportionate increases during each valuation period, such as 500% in some regions, damage the public trust of taxpayers. The Real Estate Tax Law General Communiqué serial no. 72, which went into force in 2017, limited this disproportionate increase. According to this communiqué, valuation commissions can increase the square land meter unit values by at most 50% in each valuation period compared with the previous year. However, this practice will increase the difference between the market and real estate values in Türkiye, where inflation has rapidly increased.

The real estate tax value is determined according to the provisions of Tax Procedure Law No. 213 and Real Estate Tax Law No. 1319 (EVK). In addition, there is a Bylaw on the Appraisal of Tax Values to be Subject to Real Estate Tax (EVKT). The tax value calculation methods are far from scientific and do not include details about how to perform the valuation.

Due to these valuation problems, municipalities cannot collect much real estate tax. Additionally, in countries like Türkiye, where interest and inflation change frequently, it is impossible to find real estate's market value using only the cost method. Real estate valuation experts also do not prefer this method, except in exceptional cases. Mass appraisal methods should be used instead. For mass appraisal, the parameters that affect the value of real estate should first be determined. Information about real estate parameters should be recorded in an immovable database that minimizes human intervention. Real estate tax values can be calculated for each real estate using mass appraisal methods using the information in the database. Thus, personnel, appraisal costs, and time savings can be achieved. It should be remembered that no method will entirely give the market value of the real estate.

2. Mass Appraisal Models of Real Estate Tax Value

In the literature, the following methods are used for mass appraisal models: multiple regression, hedonic regression, artificial neural networks, fuzzy logic (FL), geographic information system (GIS), analytical hierarchy process (AHP), random forest (RF), classification and regression trees (CART), machine learning, deep web, geographically weighted regression (GWR), ordinary least squares (OLS), and support vector machines (SVMs). Apart from these methods, advanced methods such as XGBoost [1], LightGBM [2][3], and deep learning [4][5] have emerged as a research topic for aggregate valuation in recent years.

The regression model is the most widely used method among practitioners and academics for modeling real estate prices [6][7]. Although it is a widely used method, it fails to effectively capture the non-linear relationship between real estate values and real estate characteristics [8][9][10]. To overcome the deficiencies of the regression approach, the ANN method, which gives more accurate and reliable estimations in real estate appraisal, has been used [11][12]. The method is highly accurate when there are sufficient data: it can effectively represent the non-linear relationship between real estate values and real estate characteristics [13], it can better predict outliers in the dataset [12], and it is impartial [14]. An ANN model is preferred to eliminate the deficiencies of the regression model; however, it has also been criticized in the literature for reasons such as lacking transparency [15][16][17] and requiring more extended training [18].

It should be noted that no appraisal model fully covers all real estate appraisal problems, as all appraisal models have pros and cons [19]. It can be used to estimate rough values in mass appraisal methods and to increase confidence in the valuation result in cooperation with property appraisers [20]. It is stated in the literature that the ANN method has immense potential to give accurate appraisal estimates [14]. In addition, some studies have reported that the ANN method is superior to the regression method [21][22][23][24]. Differences in the results of studies regarding ANN real estate appraisals may be due to the differences in data quality and model structures used in different real estate markets [25]. Data quality is essential for developing accurate real estate appraisal models [26]. Data that may affect the value of real estate can be collected from different big data sources such as the Internet, remote sensing, and the Internet of Things (IoT) [27].

Mass appraisal primarily aims to create real estate tax, expropriation, and court appraisals. Methods that give results that cannot be explained or controlled by the courts are likely to be rejected by managers regardless of their statistical estimation ability. Values estimated using ANNs are not transparent enough to provide a clear appraisal model that is defensible against objections [16][28]. The practitioner cannot see the mathematical equation of the ANN model [12][25][29]. This is related to the non-linear nature of the ANN method [29]. However, an ANN is a valuable and powerful method under the right circumstances, especially in the context of mass appraisals for real estate tax purposes. The ANN method has been successfully used in various international real estate markets, giving faster and more accurate estimations [29][30]. An ANN can make house price appraisals after learning the fundamental relationships between input variables and the corresponding outputs. Borst first used the ANN method in real estate in 1991 [31]; the study examined the estimation accuracy of the ANN method in real estate appraisal and revealed that the method could give reliable and accurate valuation estimates [31]. After that study, the ANN method has been widely accepted in real estate appraisal.

ANNs have different parameters such as the optimum input variable, training, and test data rate, neural network model, number of hidden layers, number of neurons in the hidden layer, selection of activation and transfer function, selection of training algorithm, learning rate, and momentum term. For ANNs to run smoothly, these parameters must be determined correctly. Real estate valuation studies with ANNs were examined to determine the trend in the research area. In the literature, researchers have tried different approaches by changing ANN parameters according to their field of study. A summary of these studies, developed by Abidoye and Chan, is given in **Table 1** [29].

Table 1. Summary of Mass Appraisal Studies Conducted with ANN in the Last 10 Years.

Study	Country	Sample/Number of Variables	Training: Test Ratio	Model Structure	Training Algorithm	Software Used
Lai (2011) [24]	Taiwan	2471/9	70:30	9-TE-1	BP	Alyuda
Hamzaoui and Perez (2011) [18]	Morocco	148/13	75:25	13-5-1	LM	MATLAB
Lin and Mohan (2011) [9]	USA	33,342/6	80:20	82-6-1	BP	-
Zurada et al. (2011) [7]	USA	16,366/18	-	-	-	-

Study	Country	Sample/Number of Variables	Training: Test Ratio	Model Structure	Training Algorithm	Software Used
Kontrimas and Verikas (2011) [32]	Lithuania	100/13	-	13-7-1	LM	MATLAB
Amri and Tularam (2012) [11]	Australia	7849/10	-	10-6-4-1	LM	-
McCluskey et al. (2012) [16]	Northern Ireland	2694/6	80:20	6-20-1	BP	-
Tabales et al. (2013) [33]	Spain	10,124/6	80:20	6-6-1	-	Trajan
McCluskey et al. (2013) [28]	Northern Ireland	2694/6	80:20	6/TE/1	BP	DTREG
Morano and Tajani (2013) [23]	Italy	85/6	80:20	6-13-1	-	BKP—Neural Network Simulator
Mimis et al. (2013) [34]	Greece	3150/9	-	9-5-1	-	-
Ahmed et al. (2014) [35]	Bangladesh	100/40	70:30	40-10-1	-	MATLAB
Vo (2014) [36]	Australia	7319/15	80:20	15-8-1	iRPROP +	Encog 3
Morano et al. (2015) [37]	Italy	90/7	80:20	7-13-1	-	BKP—Neural Network Simulator
Sampathkumar et al. (2015) [22]	India	204/13	80:20	13-3-1	LM	-
Feng and Jones (2015) [38]	England	65,302	-	-	-	SPSS 21
Güneş and Yıldız (2015) [39]	Türkiye	2447/10	80:20	10-10-1	-	-
Vo et al. (2015) [40]	Australia	-	-	14-7-1	iRPROP +	Encog 3
Yacim et al. (2016) [41]	South Africa	3494	-	-	BP, CSLM, CSBP	MATLAB

Study	Country	Sample/Number of Variables	Training: Test Ratio	Model Structure	Training Algorithm	Software Used
Abidoye and Chan (2017) [42]	Nigeria	321/11	80:20	11-5-1	BP	R programming software
Yalpır (2018) [43]	Türkiye	98/6	80/20	3-model	-	MATLAB
Morillo Balsera et al. (2018) [44]	Spain	9032/15	70:30	15-7-1	-	-
Yacim and Boshoff (2018a) [45]	South Africa	3242/18	70:30	18-20-1	PSOBP	WEKA
Yacim and Boshoff (2018b) [17]	South Africa	3232	70:30	-	LM, PBCG, SCG, BP	MATLAB and WEKA
Abidoye and Chan (2018) [8]	Hong Kong	321/11	80:20	11/5/1	BP	R programming software
Alexandridis et al. (2019) [46]	Greece	36,527/22	85:15	-	LM	-
Rahman et al. (2019) [47]	Malaysia	215/2	90:10	-	BP	-
Kang et al. (2020) [48]	South Korea	9435/33	70:30	-	GA	-
Yacim and Boshoff (2020) [49]	South Africa	3225/11	70:30	11/TE/1	-	-

Note: TE stands for trial and error, "-" indicates unavailable.

It is known that many independent variables affect the values of real estate, and each of them has a different effect on the value [23][43]. In mass appraisal, 5 to 20 input variables are commonly used for the ANN architecture. The studies established ANN models with between 3 and 82 variables. The number of input variables must be sufficient for an ANN model to give an output with high accuracy. Too few input variables may not be sufficient for the ANN method. Too many input variables, on the other hand, may negatively affect model performance as they may be unnecessary. Because the most effective ANN topology is the one with the least number of neurons, the efficiency and accuracy of the model can be increased by optimizing the number of input variables [36][40].

In the literature, variable numbers are sorted using different methods, such as sensitivity and principal component analysis [36][38][40][50][51]. As a result, fewer variables are used than the number of variables determined at the

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beginning. Some studies state that the basic three variables positively affect real estate value [36]. If the appraiser has good knowledge of the real estate market, they can intuitively identify the variables that affect the real estate value more [26].

Several training algorithms are used in ANNs, including derivative-based and me-ta-heuristic algorithms. The backpropagation (BP) algorithm is the most frequently used training algorithm in the mass appraisal of real estate. Most of the studies in the literature used the BP training algorithm [30][42][47]. BP uses the gradient-descent search method to change the link weights to minimize errors between the actual and desired output. The algorithm is simple to implement and suitable for solving different problems. However, the BP algorithm has disadvantages, such as becoming stuck on local minima, more extended convergence, and user-dependent parameter settings. The literature states that the hybrid model, created by combining the convergence rates of derivative-based algorithms and the ability of meta-heuristic algorithms to find the global optimum, can have advanced capabilities [17][40][51]. In addition, in models created with ANNs, the resilient backpropagation algorithm (RPROP) [13], cuckoo search algorithm (CS) [41], genetic algorithm (GA) [17], Powell–Beale conjugate gradient (PBCG) algorithm, and scaled conjugate gradient (SCG) algorithm [45] were also used.

It is ascertained that a single hidden layer is sufficient to achieve appropriate accuracy when using ANNs in any complex non-linear function [9]. The number of neurons in the hidden layers is at the user's discretion using trial and error. In a study conducted to find the optimal number of hidden neurons, it was recommended to start with a smaller number of neurons and increase the number until the desired result is achieved [52]. Studies in the literature show that the number of neurons in the hidden layer ranges from 3 to 20. The number of neurons was determined automatically by the software used in some studies [8][36][53]. Therefore, there is no consensus in the literature on the number of hidden neurons that should be included in an ANN model [13].

Each dataset used in modeling is divided into two parts for training and testing the developed models. In the literature, datasets are commonly split with a ratio of 80:20 to train and test models [33][37][54]. It is also recommended to use the cross-correction method, one of the data-splitting methods, to prevent over-learning while using ANNs [55].

To determine reliability, each model should be tested with IAAO ratio studies and other statistical accuracy tests. It is recommended to use software that offers robust statistical accuracy tests for these tests [17]. Software such as NeuroShell, SPSS, NeuralWare, Spreadsheet, NeuroSolutions–Alyuda, MATLAB, Trajan, DTREG, BKP—Neural Network Simulator, Encog3, SPSS, R programming, and WEKA have been used in the literature. The values estimated using an ANN may vary depending on the software used [56]. For this reason, MATLAB R2015a software was used in the study for the ANN model, which has been widely used in the literature, and SPSS 26 software was used for statistical tests. In the mass appraisal results obtained with the ANN, the mean absolute percentage error (MAPE) was found to range from 5 to 15 percent in general.

Mass appraisal is widely used in many countries to calculate real estate tax [26][32][39][57]. There are two critical obstacles to calculating real estate taxes using mass appraisal. First, there must be a sufficient number of real

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estates with known market value (dependent variable). On the other hand, the properties (independent variables) of the real estate for which the value will be estimated should be recorded [58][59]. Accurate and reliable information about dependent and independent variables is needed [58], so governments should invest in data management and analysis [60].

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