Neuronal Network Artificial Model for Real Estate Appraisal: Logic, controversies, and utility for the Romanian context

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Abstract

The requirement for statistical techniques in the appraisal process is far-reaching for every country. Market price accuracy for properties is mean in economics filed, mass appraisal, and for all users of appraisals reports. Studies were developing for econometric models that can be applied in real estate issues. Literature dominates for the USA and UK and stands a need to be tested for emerging (developing) markets. The paper aims to give some hints of the logic, the problems, benefits, and a guide of the ANN (Artificial neuronal network) technique. In the study, much practical information for ANN's representing an encouragement and a tool for other emerging countries to append the technique. We conclude that ANN is critical to be applied in property valuation for emerging countries in the global environment.

Key words: Artificial Neural Network model, market value, appraisal, emerging countries, accuracy
J.E.L. classification: R30, R31, L85

1. Introduction

Classical approaches to property valuation (by market, income, and cost) standardized by valuation bodies and applied by appraisers in professional practice involve a consistent dose of reasoning, inherently related to subjectivism. This has led to some distrust of the market value estimated by the valuators and published in their reports. Numerous studies emphasize the need for confidence in the accuracy of the market value expressed by the valuator given its implications for the economy and the large number of users. Nicolae Cinteză, Director of the NBR's Supervisory Department, points out: "In a period in which the level of value moves mountains of money from one possessor to another, it's correct determination even makes the difference between freedom and its lack!" (Vascu, 2015). Pagourtzi (2003) specified the connection between the market value and each branch of the economy. Ayedun et al. (2011) and Abidoye et al. (2018) empirically verified the accuracy of the market value, noting the need to apply statistical-mathematical methods in the valuation process.

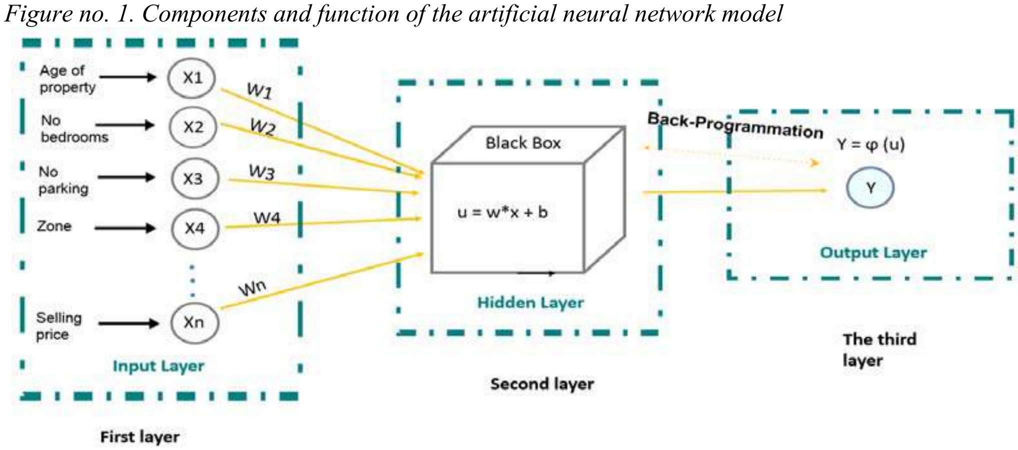
The objective of this paper is to explain the logic of the Artificial Neuronal Network (ANN) model, to highlight its weaknesses that are remediable, in order to build a model specific to the Romanian market. We see ANN as an extremely useful alternative to the market-based approach in valuing real estate in its classic variant, namely the market grid. ANN would largely eliminate the subjectivity of valuation and minimize the working time of evaluators who would apply it, as well as of report users and auditors (auditors, members of the Romanian Chamber of Auditors - CAFR) and reviewers of those reports (specialized valuators from the National Association of Valuators in Romania - ANEVAR). It should also be noted that ANN is useful for certain purposes of property valuation, namely valuation to secure loans and valuation to determine the tax base of companies' assets.

2. Theoretical background. The logic of Artificial Neuronal Network (ANN) model

In the field of property evaluation, various statistical-mathematical models (let's call them econometric) have been applied and tested, sometimes accompanied by computer applications. We think of hedonic models (linear regression model, multiple regression), artificial intelligence models (neuronal network model, fuzzy neural network) and various combinations between them (neural network models, linear regression associated with the geographical model, network model associated with the geographical model) and extensions for their improvement. The neural network model (ANN) is extremely debated today, for which the literature has mixed results above the superiority over other models, such as the regression models (Borst, 1991; Tay and Ho, 1992; Worzala et al., 1995; McCluskey et al., 1996; Wilson et al, 2002; Limsombunchai et al., 2004; Mora-Esperanza, 2004; Peterson and Flanagan, 2009; Lin and Mohan, 2011; McCluskey, 2013). Initially, the ANN model was used in medical research, and then it was taken over in various fields, observing its pliability and efficiency. In the economic field, the ANN model was used to make predictions for economic variables, including transaction prices (market values, selling prices) and rental prices for real estate, generally residential (Kauko et al., 2002; Wilkowski and Budzyński, 2006; Pontus N., 2019).

Artificial neural networks mimic the learning process of the human brain (Lin and Mohan, 2011). The process of conducting the information that needs to be processed is done similarly to the human neuronal cell. In the human cell, the information goes by snaps from the dendrite to another neuronal cell. In ANN communication is done with the help of weights and functions. They make possible the interaction between the three components of the model, and hence the self-learning process takes place, as illustrated in Figure 1. An ANN model consists of three layers: the first layer is the input data units, the second is the hidden layer, being the data processing unit and the third layer is the output layer. The last layer is the unit responsible for emitting the result expressed by the model. Each system is treated separately in order to understand how it works in an ANN model.

Figure no. 1. Components and function of the artificial neural network model



Source: adapted after Lenk et al., 1997, p. 19

The input layer is the first layer, shown in Figure 1. Here the database is entered into the model. In the case of real estate appraisals, the data entered represent variables denoted by X1, X2, Xn which describe the characteristics of real estate (Limsombunchai et al., 2004; Curry et al., 2002; Lin and Mohan, 2011). Each variable corresponds to an artificial neural network that makes connections to the next layer through synapses. The power of conducting information through synapses is due to the weights, called in the literature weight, noted in the figure above with W1, W2, and Wn. They enable the learning activity. Neural networks calculate the total weights entered and the level of stimuli on the connection that is created between the two layers. Each neuron contains a thousand values, which explains the power of information transmission, note Wilkowski and Budzyński (2006). The information that reaches the second layer is called the hidden layer, or can we name the black box.

It is the layer in which countless connections take place to find solutions following the processed data. The following formula illustrates this logic:

$$u = W * X + b$$

Where, u = unit of calculation (linear combination), W = weight (weights of synapses), X = input vector (represented by variables), and b = unit of displacement, the scientific term being bias (Lenk et al., 1997)

Hidden nodes are activated or replaced by a flexible process depending on the signals received (Curry et al., 2000). Thus, data processing takes place on the principle of non-linearity (Curry et al., 2000; Din et al., 2001, Gracía et al., 2008). Details of the data processing cannot be known, which is why it is called a black box. The hidden layer works on the basis of two functions. The first function is related to the sums of weights, and the second function is that of transformation (Lenk et al., 1997). Both applications process the initial values and information (attributes of real estate) after which the result of the values is transmitted (estimating the selling price/market value). The function for weighting sums is used in the network model for the so-called feed-forward or back-propagation (BP) drive procedure. Mathematically, the idea can be represented as follows:

$$Y_j = \sum_{j}^{n} X_i \, W_{ij}$$

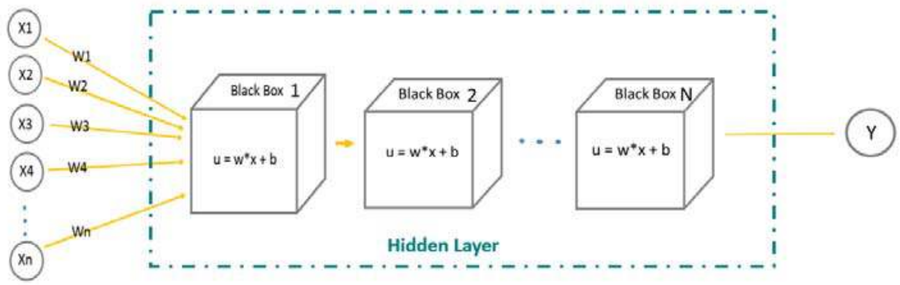
Where Xi = the values entered, Wij = weights for each value entered according to a node j in the hidden layer.

The result of the calculations performed is the market value or Yj denoted in the above equation. In the model, it is not mandatory to use the same function for all layers of the neural network. For example, García et al. (2008) used the linear function for activation, and for the hidden layer and the output, the layer used the sigmoid activation function. The most used function for the model is the sigmoid (regular sigmoid transformation function). It looks like this:

$$T_T = \frac{1}{1 + e^{-y}}$$

Researchers' preference for this function is due to continuity, lack of variation, lack of linearity, and differences in properties (Borst, 1991; Trippi and Turban, 1992). A preference for feed-forward or back-programming was observed. Curry et al. (2002) applied another algorithm, called the Polytope algorithm, but this has a disadvantage for the model by extending the working time as opposed to using the usual algorithms (feed-forward or back-programming). The model starts data processing by randomly selecting or by grouping which assigns according to the same weights for the hidden layer (hidden network). For each new topic introduced, the ANN model will estimate the property price. Then the model compares the introduced price with the estimated one. If there are differences between the results, then the program resumes the calculation and fixes the node weights so as to minimize the error prediction. Of note is the similarity of the network model through its way of processing data with the traditional method from the approaches applied by evaluators on adjustment. During testing, ANN goes through this adjustment step in order to minimize errors when introducing each new real estate subject or in the process of learning. Running of the model will stop when the best results are obtained and that means the lowest error. The lack of the calculated error threshold for the tested sample implies only the effective memorization of the processing or simply the running of the model and thus the result would tend towards a significantly erroneous prediction for any new property introduced in the model. The optimal internal error threshold, the choice of the fixed number of neural nodes and/or the optimal number of nodes to be included for each hidden layer, and the impossibility to penetrate the visualization of the model applied in the hidden layer (black box) are the minuses raised by most researchers (Trippi and Turban, 1992). Unlike any of the component layers of the network, the hidden layer is the only permissive layer in choosing the number of hidden layers depending on the need of the approximation property of the model. A model of artificial neural networks can have at least one hidden layer. For example, Curry et al. (2002) ran neural networks with two hidden layers, and Din et al. (2001) used a three-layer hidden network. García et al. (2008) applied five hidden layers, and the results were satisfactory. Therefore, the increase in hidden layers can be translated as equal to the increase in the complexity of network processing (Curry et al., 2002). Curry et al. (2002) point out that a single-layer hidden model cannot have the same accuracy as a multi-layer model. This is due to the infinite number of nodes in the hidden layer that forms in the black box. This is the reason on the one hand for which in numerous studies there are highlights by which it is noted the inclusion of another hidden layer as opposed to the number of layers with which the run began. Thus the output of one layer can become input for the next layer (Lenk et al., 1997). And on the other hand, a single hidden layer can be used to mention the number of nodes on the basis of which the run is made. In figure no. 2 a network model is illustrated for which N number of hidden layers was chosen, the layer being represented by the number of black boxes.

Figure no. 2. The artificial neural network model with multi hidden layers (black boxes).



Source: adapted after Lenk et al., 1997, p. 19

The output layer results from the processing of the entered data. Figure no 1. Illustrates the transition from the black box layer to the output layer, where the result is given by the following formula: Y = ϕ (u). Y is the estimation of the market value of the building and ϕ represents the activation function of the neuron model for “u” (the unit of calculation) from the black box (Lenk et al., 1997). The most used function for activating the calculation mode is the sigmoid function (Curry et al., 2002). Each run of the model issues a value for the validation error. The best result must be the lowest value for the validation error. As a starting duration of the learning (supervision) of neural networks has the database and the optimization of weights based on the difference between the resulting market value and the comparison market value. A disadvantage of the ANN model is the need to run it manually to optimize the best result, or it takes time (Curry et al., 2002).

The neural network model runs the data introduced from the first layer to the second where various calculations are made, and we are provided with a single result, which is for us the market price of real estate (Curry et al., 2002). Each user of the neural network model has the possibility to make his own design of the model structure depending on the available data and the purpose of use. Here are some examples of the structure of artificial neural networks used in the evaluation. Worzala et al. (1995) tried to choose the right number of nodes for the hidden layer. Thus, in the first case, it had two structures for networks: 7 - 1: 8 - 1, the input layer consisted of 7 independent variables with a hidden layer with 8 nodes and a network in the output layer, represented by the independent variable which is the estimated price for residential property. This structure was used for the informatics model @Brain, and for NeuroShall the following structure was used: 7 - 1: 5 - 1. The results were similar. Also, Worzala et al. (1995) used for the second case the structure 7 - 1: 3 - 1 (@Brain and NeurShall) and for the third group is was 7 - 1: 9 - 1 for @Brain and 7 - 1: 5 - 1 for NeuroShall. García et al. (2008) used the following simplified structure, 14-5-1: 1. As a way of interpretation, we observe the three structures of the model. In the first layer, 14 variables were introduced, and the second layer of the model ran with five hidden layers. The input later, noted in the 1: 1 structure, symbolizes selection for a single answer. 82 - 1 - 1: 1 is the structure of the network model used by Lin and Mohan (2011). Morano et al. (2015) have an ANN model with an 8 - 13 - 1 structure.

3. Research methodology

Worzala (2003) is an example of studies conducted for review of real estate literature. Also, Abidoye et al. (2016) used a systematic review approach to develop a reliable knowledge-based on the ANN model. Similar to these studies, we applied for a historical literature review and critical analysis of the literature on ANN model content and utility as a tool to apply market approach for real estate valuation. The article's sources for analysis are platforms such as Web of Science and Scopus. The keywords used for searches where artificial neural network model, real estate, market value, accuracy, and appraisal. As a type of articles, we privileged those published in prestigious journals but also used (fewer) articles published in conference papers, books, or even papers of various universities in the case of studies conducted for emerging countries, less explored. Since the information has been gathered together, we concluded with an ANN model applying guide in real estate valuation.

4. Debates on the accuracy of ANN in property valuation

Representative for our paper is the works of literature that tested the superiority of ANN over traditional regression models. These include Do and Grudnitsky (1992), Worzala et al. (1995), Rossini (1997), Din et al. (2001), Curry et al. (2002), Limsombunchai et al. (2004), Lin and Mohan (2011). Their results are mixed, with a preference for the ANN model. Do and Grudnitski (1992) obtained, for a sample of residential properties, a price prediction percentage of 40% for ANN, and for the regression model 20%. Worzala et al. (1995) used ANN to test their accuracy, but the results were inconclusive and indicated caution regarding the applicability of ANN. Din et al. (2001) argued that ANN is superior to the simple linear regression (OLS) model developed with a geographic system, having the best performance by obtaining the result closest to the selling price. Lin and Mohan (2011) compared for ANN model the performance with two types of traditional regressions, and the results indicated similar performance on estimating the market price of the three models, associated with an affordable cost. In such studies, to verifying the model performance, the comparison of the percentage of prediction with a statistically relevant threshold is considered, which, the larger it is, the better is the prediction. Another element of comparison is the mean absolute error (MAE), where the lowest value suggests the best performance (Worzala et al., 1995). Lin and Mohan (2011) also introduced other verification benchmarks such as the root mean squared error (RMSE), the mean absolute error MAE, and the Theil's U statistic.

A subcategory of studies in the category of those testing ANN's superiority investigated nuances the idea of ANN's superiority over classical models. Several discussions relate to the appearance that the ANN model is dependent as a predictor on the specificity of the data set. Other difficulties in applying the ANN model and which have provoked debates are the period of time covered by the empirical data used in the model, the model tolerance, the number of hidden nodes, or the number of hidden layers.

Regarding *the ideal number of independent variables*, it differs from one study to another. Worzala et al. (1995) had 7 independent variables as opposed to Kuburic et al. (2012) which had a long list of independent variables that referred to the internal and external description (natural, social, and economic descriptions) of real estate. It has been observed that the higher the number of variables, the longer the data run time.

The size of the tested sample is one of the other discussing issues. Some studies highlighted the performance of ANN for a small database. Do and Grudnitski (1992) ran two models (the regression model and ANN) on 105 database real estate properties. The results highlighted the superior performance of the ANN model over the regression model. Worzala et al. (1995) had a sample of 288 real estate properties for which they ran ANN in two different computer programs, creating three samples. The best network performance was for the 83-property sample versus the other two samples whit 218-property and 137-property samples. Rossini (1997) researching 334 subjects. He highlighted the performance of ANN with a small number of subjects. Din et al. (2001) ran the network model on a sample of 285 subjects. Although ANN obtained better results with $R = 0.87$ than $R = 0.84$ for linear regression, the authors emphasized the need to apply ANN on a larger sample, a conclusion contrary to the other research mentioned above. Other studies have used a much larger database. Tay and Ho (1992) applied the ANN model on a large database of 1,055 subjects, and the results were good. By removing the outliers subjects from the data sat, an improvement of the network performance was observed. Lin and Mohan (2011) had a database collected from New York with 33,342 residential properties, and the predictions for ANN were as good as those for the multiple regression model. The achievement of Sweden results noted by Pontus (2019) mentioned the changing of results by the number of the running sample and highlighted that the most relevant results were for the sample with the lowest number of subjects. We conclude that the database should have a relevant size, but not necessarily a massive volume.

It seems that *ANN is time-consuming*. Rossini (1997) points out that data processing increases time with the number of subjects. Moreover Worzala et al. (1995) noted that time processing differs from the computer program performance used to run the model. The time-consuming can belong to find the appropriate structure of the neural network and to find the optimal result (Worzala et al., 1995).

ANN excels in some results comparatively whit other less credible results. For the most part, ANN is considered by researchers a possible model in real estate and acclaim being used with great care (Worzala et al., 1995; Rossini, 1997). For example, Worzala et al. (1995) observed a difference in results when running networks in the two different computer programs @Brain and NeuroShall. The database was divided into three particular cases. In the first two cases, @Brain had better results besides the NeuroShall software. Another result noted by Worzala was related to the different results of the three cases studied though the same database was used. The linear regression was more performant than ANN for the first two cases. However for the third case ANN was the best performing.

There is *some missing information* on how neural networks work, particularly related to the black box. For instance, is discussed the non-linear character and flexibility of the ANN model (Rossini, 1997; Din et al., 2001; García et al., 2008). Another element related to the black box is the need for an ideal number of the hidden layers (Trippi and Turban, 1992; Curry et al., 2002). Similarly, Worzala et al. (1995) encountered problems in choosing the optimal number of hidden layers and the number of nodes that these layers should contain. To reach the final structure of the model, there were numerous tests of structures of model construction, with two-three hidden layers and three-nine nodes for the hidden layers. The final choice was a network with one hidden layer.

One other thing is *the vulnerability of ANN related to the correct sampling methodology* (Rossini, 1997). Din et al. (2001) divided the apartments from 258 samples into three groups, the first being 60% of the observation sample, the second is 30% of the test sample, and the third 10% of the sample to validate the results (60:30:10). Lin and Mohan (2011) divided a database of 33,342 residential homes in two 80:20 samples. Thus, they had a sample for validation of 6,668 subjects and for testing 26,674 subjects. The results obtained were satisfactory. Accordingly, to the different results, we conclude that accurate results can be obtained with samples under 1000 subjects.

Finally, another issue raised is *how to know when to stop running the model* (Trippi and Turban, 1992; Rossini, 1997). If ANN is prolonged run can lead to better results for the test sample, hence for the working sample, it leads to significant errors, and not all computer models know when to stop regularly (Worzala et al., 1995; Rossini, 1997). Despite all these uncertainties of the model, the researchers mentioned several methods used for solving the problem evoked. For example, Lin and Mohan (2011) recalled the need of training by running the ANN model until the network error is reduced. After the ANN stored the data set in the testing sample, the Bayesian regularization technique had been used to prevent excessive running. Another example is that of Worzala et al. (1995) which suggested that it should be tracked the network error and applied the judgment of the user of the ANN model for the optimal choice of the number of hidden layers and the number of nodes.

5. Proposing a model adapted to the Romanian market

Based on the literature review and the discussion of various points of view, we appreciate that running an ANN model for the Romanian market is opportune and possible. As research model design for the creation of an appropriate model we see the following coordinates as justified:

a) taking into account that the real estate market and its prices are sensitive in time and differentiate in space, hence a specific geographical context, and a period of 6 months as the age of the model entry data being needed;

b) building a sample of approximately 1,000 apartments with 1 to 4 rooms to ensure the standardization of the type of property and the possibility of obtaining homogeneous data, in a reasonable volume;

c) selecting quantitative independent quantitative but also qualitative variables, in a number as large as possible, when it comes to the relation to the complexity of the databases to be used and to the possibilities of verification/completion of some data by the researcher;

d) running ANN compared to Generalized Linear Model regression using a single application, to avoid replicates with different accuracy;

e) for the construction of the ANN model, using a feed-forward / backpropagation neural network software package, Multilayer Perceptron

f) using up to 30 input nodes as predictors, 1 hidden layer with up to 8 nodes (because there is no theoretical ground for the number of hidden layers and also having in mind to not provoke overfitting of the network), and 1 output node, the estimated selling price of the real estate;

g) as models performance indicators, using the mean absolute error between the predicted sales price and the current prices in the sample, and the percentage of properties whose absolute error was less than 5% of the current sales price, being the most used indicators in the studies that have attempted to demonstrate the superiority of ANN.

6. Conclusions

Above all, as many studies asserted, ANN is not easy to use. Supplementary, it is a goal for testing the model in emerging markets. Designing an econometric model such as the ANN model for the Romanian market of valuations provides the basic needs for practical exercises to be applied by researchers and practitioners in real estate valuation. Creating an ANN model for the Romanian mass appraisal, following the example of market-based economies, would be useful in terms of cost-benefit, and all of those reasons would increase the accuracy of market value estimates. Also, ANN would facilitate the verification of valuation reports, by third parties and profession itself. So, the ANN model it's a promising tool for ANEVAR recent specialization, Verification of valuations. Because of the utility of weighs generated by an accurate ANN model, as well as the predictions of selling prices, ANN would be useful for the mass appraisal (such as those for setting taxes) or for guaranteeing loans. We also believe that an ANN model could help to validate the correctness of the valuation reports required in judicial expertise reports. Often we observe, depending on the number of experts involved in litigation, significantly different values, which create suspicions about the accuracy of values.

Of course, the performance of the ANN model must be improved. As we have shown from the literature review, the ANN model has some imperfections that can be counteracted to some extent. However, some researchers and appraisers wonder if the human brain thinking (*i.e.* professional thinking) and the design of every real estate report is going to be replaced with the ANN model performance. We believe that the diversity of properties, the purpose of using the reports, the display of the amounts of information, and other features do not allow the replacement of professional premise. So we plead for the continued involvement of the judgment of a professional, and for ANN to become only helpful tool in real estate valuation that can be verifiable through various coherence tests.

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