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Improving property valuation accuracy: a comparison of hedonic pricing model and artificial neural network

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ABSTRACT

Inaccuracies in property valuation is a global problem. This could be attributed to the adoption of valuation approaches, with the hedonic pricing model (HPM) being an example, that are inaccurate and unreliable. As evidenced in the literature, the HPM approach has gained wide acceptance among real estate researchers, despite its shortcomings. Therefore, the present study set out to evaluate the predictive accuracy of HPM in comparison with the artificial neural network (ANN) technique in property valuation. Residential property transaction data were collected from registered real estate firms domiciled in the Lagos metropolis, Nigeria, and were fitted into the ANN model and HPM. The results showed that the ANN technique outperformed the HPM approach, in terms of accuracy in predicting property values with mean absolute percentage error (MAPE) values of 15.94 and 38.23%, respectively. The findings demonstrate the efficacy of the ANN technique in property valuation, and if all the preconditions of property value modeling are met, the ANN technique is a reliable valuation approach that could be used by both real estate researchers and professionals.

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Artificial neural network; hedonic pricing model; property valuation; valuation accuracy; predictive accuracy

Introduction

Property valuation estimations play a vital role in strategic decisions related to real estate investment. This is because real estate stakeholders (such as individuals, corporate organizations and government, among others) largely rely on property valuation estimates reported by valuers (Yalpir, 2014). The inaccuracy of such valuation estimates could cause an adverse effect on the investments of real estate stakeholders, which may eventually affect the economy of a nation, for instance, the 2007 global financial crisis (Jiang, Jin, & Liu, 2013). Also, several previous studies have demonstrated that the built environment industry is strongly linked to the economy (Chiang, Tao, & Wong, 2015). This clearly proves that the accuracy of property valuation estimation is important to all stakeholders.

In the real estate research domain, several methods have been used to estimate property values, and these methods which range from traditional to advanced valuation techniques (Pagourtzi, Assimakopoulos, Hatzichristos, & French, 2003). Studies have shown that

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traditional valuation approaches are unreliable and inaccurate (Zurada, Levitan, & Guan, 2006). Hence, this has led to a shift towards advanced valuation techniques, which tends to be more accurate and reliable, when compared with traditional methods (Gilbertson & Preston, 2005). Hedonic pricing model (HPM) is an advanced valuation method which has been used widely both in theory and in practice (Selim, 2008). However, despite its simplicity and straightforwardness in approach (Chin & Chau, 2002), it cannot effectively capture the nonlinear relationship that exist between property values and property attributes, it is subjective in nature, inaccurate and marred with functional form misspecification, amongst other shortcomings (Limsombunchai, Gan, & Lee, 2004; Lin & Mohan, 2011). In addressing the shortcomings of the HPM approach, the artificial neural network (ANN) technique, which has produced more accurate, reliable and comfortable predictions and forecasting estimates has been adopted in property valuation (Mora-Esperanza, 2004). A plausible reason for this is that the technique possesses high precision quality, it can handle the nonlinear relationship between property attributes and property values (Cechin, Souto, & Gonzalez, 2000), can handle data outliers (Mora-Esperanza, 2004), it is not subjective (Tay & Ho, 1992), user friendly (Borst, 1991), and so on.

Studies (Babawale & Ajayi, 2011; Adegoke, Olaleye, & Oloyede, 2013) focused on the Nigerian real estate industry have reported that the property valuation inaccuracy predominant in the domain is highly unacceptable based on international standards. This could be attributed to the adoption of inappropriate and unreliable property valuation approaches (Aluko, 2007). The HPM approach has been widely applied in the Nigerian property appraisal research (Abidoye & Chan, 2016a), and in the property valuation practice (Abidoye & Chan, 2016b). However, the application of the ANN technique in property valuation by researchers in developing countries, such as Nigeria, has been limited (Abidoye & Chan, 2016b). This may be accountable for the prevalence of property valuation inaccuracy observed both in practice and research in Nigeria (Ogunba & Ajayi, 1998). Considering the aforementioned, the present study seeks to evaluate the predictive accuracy of the ANN technique in comparison with the HPM approach in property valuation in Nigeria. The reliability of the developed models was assessed using established metrics of accuracy. To achieve this, both HPM and ANN model were developed with the same data set to compare their predictive accuracy in property valuation. The findings of this study would be useful to all real estate stakeholders, because the developed models could be used as a decision making tool for generating accurate property valuation estimates.

Literature review

Research into property valuation has a long history. The seminal study of Rosen (1974) provided a detailed explanation of HPM and the relationship that exist between an utility bearing commodity (here, real estate properties) and its attributes (here, property attributes). After this study, different property markets around the world have been modeled using the HPM approach to measure the contributive power of different classifications (locational, neighborhood and structural) of property attributes to property values determination (Chin & Chau, 2002). The HPM approach has been applied in Northern Ireland (Adair, Berry, & McGreal, 1996), United States of America (Cebula, 2009), Paris (Maurer, Pitzer, & Sebastian, 2004), Hong Kong (Hui, Chau, Pun, & Law, 2007), Ghana (Owusu-Ansah, 2012), Portugal

(Canavarro, Caridad, & Ceular, 2010), Nigeria (Famuyiwa & Babawale, 2014) and China (Jim & Chen, 2006), among other property markets.

The processing of HPM is premised on the principle of the regression analysis (Selim, 2009). The regression analysis is of two types, namely the multiple regression and the simple regression (Montgomery, Peck, & Vining, 2015). Multiple regression analysis (MRA) explains the regression of a dependent variable over more than one independent variable. This makes it suitable for property price analysis, because property values are determined by more than one property attribute (Chin & Chau, 2002). Equation 1 shows the formal model of an MRA (Özkan, Yalpır, & Uygunol, 2007) which depicts that property value is a function of its independent variables.

$$y_i = \beta_0 + \beta_1 x_{i1} + \ldots\ldots\ldots + \beta_k x_{ik} + u_i \quad (1)$$

Where y_i is the property value (dependent variable), $x_{i1}, \ldots\ldots\ldots, x_{ik}$ are the property attributes (independent variables), u_i is the error term and $\beta_0, \ldots\ldots\ldots, \beta_k$ indicates the effect of the changes in one independent variable on the dependent variable.

The ANN technique on the other hand, was first applied in the real estate domain by Borst (1991). The study investigated the predictive accuracy of the ANN technique in property valuation. The findings of the study revealed that the ANN technique could produce reliable and accurate valuation estimates. This has led to a wide acceptance of the ANN technique in the real estate domain (Taffese, 2006). It has been used in modeling of property prices in the United States (Borst, 1995), Ireland (McCluskey, 1996), Hong Kong (Lam, Yu, & Lam, 2008), Spain (Tabales, Ocerin, & Carmona, 2013), Italy (Morano, Tajani, & Torre, 2015) and United Kingdom (Wilson, Paris, Ware, & Jenkins, 2002), among other countries.

The ANN model is developed based on a network architecture which is made up of three layers, namely the input, the hidden and the output layers. It is at the input layer that the variables to be inputted into the model are entered into the network, in this case, property variables. The mathematical processing takes place at the hidden layer, while the desired result is produced at the output layer (here, the property value). Figure 1 shows a typical ANN processing architecture.

Scholars have argued that the ANN technique was adapted to property valuation in order to address the shortcoming of the HPM approach (Do & Grudnitski, 1992; Amri & Tularam, 2012). In order to improve the predictions generated from the modeling processes, researchers seek to identify and develop techniques with improved predictive accuracy. This has resulted in a number of studies conducted in different property markets around the world

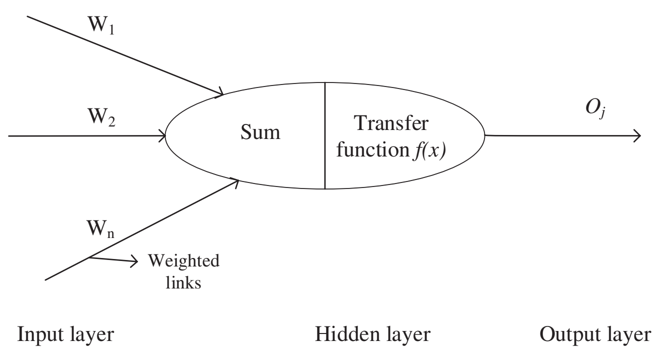

Figure 1. Artificial neural network architecture. Source: Adapted from: Lin and Mohan (2011, p. 226).

that have compared the predictive accuracy of HPM and the ANN technique (McGreal, Adair, McBurney, & Patterson, 1998). Abidoye and Chan (2017) reported that most of these studies emanated from developed countries, they were conducted by university scholars, and that the findings of these studies were mixed. However, in most cases, the ANN technique outperformed the HPM approach in terms of predictive accuracy. It should be noted that no valuation model fits all property valuation problems (Pagourtzi, Metaxiotis, Nikolopoulos, Giannelos, & Assimakopoulos, 2007), due to the fact that all valuation models possesses their respective pros and cons. The strengths and weaknesses of various property valuation techniques can be found in Lam et al. (2008) and Abidoye and Chan (2016b).

One of the early efforts to compare the predictive accuracy of ANN and HPM is the study of Do and Grudnitski (1992) that utilized property sales data collected in California, United States. The study showed that the ANN model produced forecasts which were twice better than HPM, in terms of the predictive accuracy of the property values. Do and Grudnitski (1992) posit that the ANN technique has great potential to produce accurate valuation estimates. Other studies have reported that the ANN technique is superior to the HPM approach. Some of these studies include Cechin et al. (2000), Selim (2009), Lin and Mohan (2011) and Kutasi and Badics (2016), among others.

On the other hand, the findings of a few studies are otherwise. For instance, Worzala, Lenk, and Silva (1995) investigated the predictive accuracy of HPM and ANN in property valuation by attempting to confirm the veracity of earlier studies, i.e. Borst (1991) and Do and Grudnitski (1992). Three models were constructed in the study; the first utilized the whole 288 sample data, the remaining two were developed using data set similar to the two previous studies under investigation. This was done in order to allow for a justifiable comparison. It was found that ANN produced a slightly different output compared with HPM. However, the authors suggested a note of warning in employing ANN in property valuation due to much effort not been put into the ANN technique principles at that time. This findings of Worzala et al. (1995) corroborates those of Lenk, Worzala, and Silva (1997), McGreal et al. (1998) and McCluskey, McCord, Davis, Haran, and McIlhatton (2013), that reported that the ANN technique is not actually superior to the HPM approach. The differences in the findings of the ANN property valuation studies could be attributed to the quality of the data available for use in each respective property market (Lenk et al., 1997), because this is an important requirement for developing robust property valuation models (Grover, 2016).

Research method

The data

Recent advances in artificial intelligence (AI) techniques have facilitated the several investigations targeted at evaluating its efficacy. This has resulted in the application of AI models to problems in different field of studies such as food processing (Cortez, Cerdeira, Almeida, Matos, & Reis, 2009), medicine (Lisboa & Taktak, 2006) and civil engineering (Hu, Lam, & Ng, 2005), among others. Hence, ANN, which is an AI modeling technique, was applied in property valuation. The output of the ANN model was compared to the baseline HPM. This served as a basis for evaluating the efficacy of the proposed ANN model.

The development of both HPM and the ANN model require the sales information of properties located in the property market under investigation. To this end, transaction data of residential properties were collected from registered real estate firms operating in the Lagos metropolis, Nigeria. This is because there is no centralized property sales databank in Nigeria (Adegoke et al., 2013). The collected information contained transaction details of residential properties located in the Lagos Island property market (Ikoyi, Lekki Peninsula Phase 1, Victoria Island, Victoria Garden City and other residential estates, on the Lekki - Epe Expressway corridor). The information of structural attributes of these residential properties were collected, as this seems to be the information that is retrievable from the real estate firms that have been involved in those sale transactions. This is not uncommon in the literature, such as in Lin and Mohan (2011) and Thanasi (2016), among others. The "presence of sea view" (neighborhood variable) and the "availability of security fence" were added as dummy variables in the development of the models.

The complete information on 321 property sales transaction were retrieved, and this represent the data used for this study. The information contained 11 independent variables and one dependent variable (i.e. property price). The collected data were of properties sold between 2010 and 2016. However, in order to factor in the effect of inflation on the property prices, the sale prices of the properties were inflation adjusted to current values before the analyses. This is common in the literature, for instance, see Zurada et al. (2006) and McCluskey, Davis, Haran, McCord, and McIlhatton (2012). The descriptive statistics of the collected data are presented in Table 1.

Model specification: hedonic pricing model

The multicollinearity test was conducted to remove correlated variables (if any). This revealed that all the variables are not correlated, except for the number of bathroom and the number of toilets in a property that had a correlation coefficient of .965. Hence, the

Table 1. Descriptive statistics of the variables.

Variable	Minimum	Maximum	Mean	Standard deviation	Definition of the variables
Price	14500000	1182844000	149769541.60	199367090.90	Naira (Nigerian currency)
Number of bedrooms	1	10	3.49	1.26	Numerical value of 1,2,34, …….
Number of toilets	1	7	4.28	1.37	Numerical value of 1,2,34, …….
Number of bathrooms	1	7	3.38	1.25	Numerical value of 1,2,34, …….
Property type	1	6	3.87	1.45	The design structure of the property
Number of boys' quarters	0	8	1.08	1.36	Numerical value of 0,1,2,34, …….
Parking space	0	20	3.27	2.45	Numerical value of 0,1,2,34, …….
Age of building	0	42	3.30	4.97	Years of existence in numerical value
Number of floors	1	16	2.83	2.19	Numerical value of 1,2,34, …….
Availability of security fence	0	1	.98	.14	1 if available, 0 if not available
Availability of sea view	0	1	.05	.22	1 if available, 0 if not available
Location of property	1	5	3.36	1.70	The neighbourhood which the property is situated

number of toilets variable was removed from the list of independent variables. Therefore, 10 independent variables were included in the HPM development. The testing for heteroscedasticity on the data set was performed by conducting the White test (White, 1980). This test revealed that there is no form of heteroscedasticity amongst the variables in the data set. A linear relationship between property prices and the independent variables was investigated using the scatter plot approach. This investigation shows that there is a linear relationship between property prices and the independent variables and the relationship recorder here does not violate model assumptions (Janssen, Söderberg, & Zhou, 2001). The linear regression was developed using the Statistical Package for the Social Sciences (SPSS) software version 21.0. The choice of the linear functional form in this study stem from the fact that it is easy to compute by users, and its parameters are easy to interpret for prediction purposes (Lin & Mohan, 2011).

Model specification: artificial neural network

The development of an ANN model entails the determination of the number of input neurons, hidden layers (and hidden neurons) and the output neurons at first (Kaastra & Boyd, 1996). The input layer is usually one, and the number of neurons in this layer is subject to the number of independent variables to be used in developing the model. The number of hidden layer(s) in a model could vary. However, one hidden layer has been proven to be sufficient for the modeling of property prices (McCluskey et al., 2012). As to the number of hidden neurons to be included in the hidden layer, there is no consensus in the literature (Cechin et al., 2000). A three-layered ANN model was constructed using the R programming software and rminer package (R CoreTeam, 2016), by adopting the backpropagation learning algorithm which is commonly used in previous studies (Sampathkumar, Santhi, & Vanjinathan, 2015). In the present study, the number of neurons in the hidden layer was automatically determined by the R programming software, by optimizing the network architecture that best fit the data using the grid search, using the default parameters in terms of learning rate, stopping criteria and weight decay. A detailed process of the application of the ANN technique in property valuation can be found in Abidoye and Chan (2017). Table 2 shows the details of the ANN model developed in this study.

Model evaluation metrics

The same data set was used to develop both HPM and ANN model. This was done so as to have a common basis for comparison. The data set was randomly divided into two parts. A portion (80%) of the data set was used for the development of both models, while the rest (20%) was used for the testing of the models, as commonly done in previous studies

Table 2. Details of the ANN model.

Parameters	Details
Network architecture	Three-layer (11-5-1)
Algorithm	Backpropagation
Training and testing ratio	80:20
Dataset	321
Validation	10-fold cross-validation

(see Wilson et al., 2002; Lam et al., 2008; Morano et al., 2015, amongst others). The testing of the models was conducted in order to estimate the predictive accuracy of the models. In doing this, the holdout sample was used to predict the actual property prices and any difference between the predicted values and the actual values (if any) amounts to an error in estimation.

There exists a number of accuracy measures in the literature. However, only a few have been commonly adopted in previous related studies. These measures include the root mean square error (RMSE), the mean absolute percentage error (MAPE), the mean absolute error (MAE) and the coefficient of determination (r^2) (McCluskey et al., 2013). A lower value of these accuracy measures depicts a good model with a satisfactory predictive accuracy (Zurada, Levitan, & Guan, 2011), with the exception of r^2 which a value closer to 1 depicts as good model fit (Lin & Mohan, 2011).

In addition to the accuracy measures adopted for the evaluation of the accuracy of the models developed, the percentage of the predicted property values that had margin of error that fell within the international acceptable margin of ± 0 and 10% (see Brown, Matysiak, & Shepherd, 1998), and those that fell beyond this margin were established. This is to ascertain how suitable each of the model can satisfy international standards in the appraisal domain.

Results and discussion

Table 3 shows the results of the regression analysis. Almost all the variables had the expected sign except the number of bathrooms, the availability of security fence in a property and the location of a property that had a negative sign.

A visual examination of the predicted property prices shows that some were beyond reasonable range, hence, the removal of such properties sales. Consequently, a holdout sample of 30 observations were used for the model testing. This is not uncommon in previous studies, see for instance, Worzala et al. (1995) and McCluskey (1996).

The evaluation of the developed HPM and ANN model are presented in Table 4. On the basis of the r^2 values of the models, ANN produced a r^2 of .81. This is higher than that of HPM which is .77. Since the r^2 only explains the relationship between the dependent variable and the independent variables and not the quality of the predictions generated by the models (Willmott, 1981; Sincich, 1996), the evaluation of the models based on MAE, RMSE and MAPE is necessary. In the same vein, the ANN model produced MAE and RMSE values lower than that of HPM. This depicts that the ANN could predict property

Table 3. Result of the regression analysis.

Independent variables	Coefficient	*t*-ratio
Number of bedrooms	8664822.596	.738
Number of bathrooms	−20051336.870	−1.448
Property type	8076944.769	1.144
Number of boys' quarters	102816020.589	15.151
Parking space	9526774.351	2.615
Age of building	−1635743.326	−1.068
Number of floors	4539570.089	1.455
Availability of security fence	−10789691.840	−.229
Availability of sea view	154767562.522	4.832
Location of property	−26885403.503	−6.176
Constant	98778305.063	1.396

Table 4. Predictive ability of the models.

Models	r^2	MAE	RMSE	MAPE (%)
HPM	.77	61,408,856	103,370,573	38.23
ANN	.81	28,492,514	41,814,564	15.94

Table 5. Valuation accuracy of the HPM and the ANN models prediction.

	Hedonic pricing model		Artificial neural network	
Accuracy range	Frequency	Percentage	Frequency	Percentage
± 0–10%	8	26.67	10	33.33
± 11–19%	4	13.33	13	43.33
> ± 20%	18	60.00	7	23.33

values more accurately than HPM. On the MAPE values of the models, the ANN model produced a MAPE value of 15.94%. This suggests that the average absolute error that could be recorded in predicting property values using the ANN technique is about 15%. This figure is in the range of what is obtainable in the literature (Pagourtzi et al., 2007 (31.6%); Kutasi & Badics, 2016 (15.93%), amongst others).

The MAPE value that the HPM approach generated is 38.23%, meaning that the absolute error using HPM could be higher than 30%. This results show that the ANN technique could predict accurately two times better than the HPM approach. This corroborates the findings of Do and Grudnitski (1992, p. 44) that reported that "the ANN's estimates of residential property values are nearly twice as accurate as those of a multiple regression model", based on the MAPE values of both models. This also substantiates the findings of Ogunba (2004) that the valuation inaccuracy that is common in Nigeria could be as high as between 22 and 67%, probably due to the adoption of unreliable valuation approaches. This indicates that other nonlinear valuation approach such as ANN could produce better results than HPM. This is because the prediction error generated with the use of the HPM approach could be unacceptable by any rational real estate investor. This supports the findings of previous studies that have reported the better predictive accuracy of the ANN technique above the HPM approach (Wong, So, & Hung, 2002; Lin & Mohan, 2011, amongst others).

The accuracy performance of both models were also evaluated based on the number of predicted property values that had an absolute error range that are within the industry acceptable standard. The information in Table 5 shows that 26.67% of the predicted values of HPM have an error of between ± 0 and 10%, whereas the ANN model had 33.33% of its predictions within the same range. This same trend was evident for the rest of the accuracy range, with the ANN model predictions having a lower number of values with an error rate of greater than ± 20%, when compared with HPM. About two-third (60%) of HPM predictions had an error margin of over ± 20%. This could be responsible for the loss of confidence property valuation clients have in the profession and the professionals in Nigeria (Adegoke et al., 2013), because such a high margin of error may render a real estate investor/stakeholder to go bankrupt.

The predicted property values produced by both HPM and the ANN model were plotted against the actual property values as shown in Figure 2. This visual evaluation shows that the ANN model predicted property values are much closer to the actual property values when compared with the HPM predicted values. Wider disparities exist between the HPM

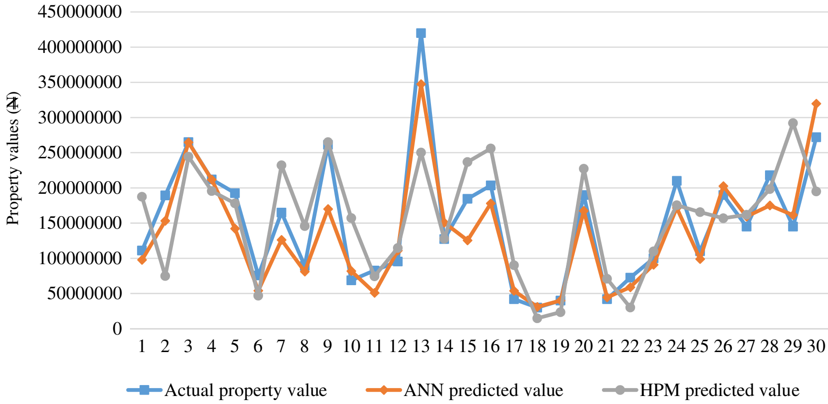

Figure 2. Actual property values and HPM and the ANN model predicted values.

predictions and the actual property values which suggest that HPM could not produce reliable and accurate property valuation estimates.

Overall, the findings of the present study vividly show that the ANN model could predict more accurate and reliable valuation estimates when compared with the HPM approach. These results support the findings established in different property markets around the world that have reported the greater predictive accuracy of the ANN technique over the HPM approach in property valuation. For instance, the studies of Lin and Mohan (2011) in the United States, Selim (2009) in Turkey, Wong et al. (2002) in Hong Kong, Limsombunchai et al. (2004) in New Zealand, and Amri and Tularam (2012) in Australia, amongst other property markets around the world. This study is an exploration of the ANN technique in property valuation in a developing nation, which its property market is not transparent and immature (Dugeri, 2011). However, the credibility of the models could be improved by the use of more robust and quality data (Grover, 2016). When this is in place, as obtainable in most developed nations (Hofmann, 2003), accurate property valuation estimates could be achieved. This will in turn reduce the high property valuation inaccuracy prevalent in such emerging markets. Subsequently, AI property modeling techniques could be introduced in the property valuation practice of emerging property markets as obtainable in some developed property markets (Mora-Esperanza, 2004; Grover, 2016).

Conclusion

Property valuation inaccuracy has been on the international debate for a while, whereas the level of prevalence in the Nigeria property valuation landscape is highly unacceptable (Babawale & Ajayi, 2011; Adegoke et al., 2013). This has warranted this study which aimed at recommending a property valuation model that is more reliable and accurate for property valuation. Data of residential properties collected from real estate firms operating in the Lagos metropolis was used to develop both HPM and the ANN model. The evaluation of the predictive accuracy of both models shows that the ANN model outperformed the HPM approach in terms of a higher r^2, lower MAE, RMSE, MAPE, and also a higher percentage of predicted property values that has an absolute prediction error of between ± 0 and 10% of the actual property values. This depicts that if the ANN technique is applied in an immature property market, it could still produce more accurate and reliable valuation estimates when compared with the HPM approach. Most of the Nigerian property valuers are not aware of and do not use the ANN valuation technique in practice, but mostly adopt traditional methods of valuation (Abidoye & Chan, 2016b). Whereas, if the pre-conditions for property value modeling (robust and quality databank, appropriate training of valuers and transparent property market, amongst others) (Grover, 2016) are in place, property valuation inaccuracy could be reduced to a barest minimum in the property valuation domain. The data set used for this study was collected from property firms operating in the study area, and hence, the use of a small sample size. Also, structural property attributes were mainly used for the development of the models. Other categories of property attributes that influence property values were not retrievable. The ANN technique has been termed as a "black-box" model (McCluskey et al., 2013); however this is being addressed through the continuous development in the ANN model theory (Olden & Jackson, 2002). The comparison of the predictive accuracy of property valuation model was limited to HPM and the ANN model due to the lack of sufficient data. Therefore, other modeling techniques such as the fuzzy logic system (FLS) and Support Vector Machine (SVM), amongst others, that have been adopted in different property markets around the world, could be subsequently compared with the ANN technique in Nigerian and in other developing property markets around the world, in order to achieve sustainable property valuation practice.

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References

Abidoye, R. B., & Chan, A. P. C. (2016a). *A review of the application of hedonic pricing model in the Nigerian real estate market* Paper presented at the CRIOCM 21st International Conference on Advancement of Construction Management and Real Estate, Hong Kong, 14–17 December.
Abidoye, R. B., & Chan, A. P. C. (2016b). A survey of property valuation approaches in Nigeria. *Property Management, 34*(5), 364–380.
Abidoye, R. B., & Chan, A. P. C. (2017). Artificial neural network in property valuation: Application framework and research trend. *Property Management, 35*(5), 554–571.
Adair, A. S., Berry, J. N., & McGreal, W. S. (1996). Hedonic modelling, housing submarkets and residential valuation. *Journal of Property Research, 13*(1), 67–83.
Adegoke, O., Olaleye, A., & Oloyede, S. (2013). A study of valuation clients perception on mortgage valuation reliability. *African Journal of Environmental Science and Technology, 7*(7), 585–590.
Aluko, B. T. (2007). Examining valuer's judgement in residential property valuations in metropolitan Lagos, Nigeria. *Property Management, 25*(1), 98–107.

Amri, S., & Tularam, G. A. (2012). Performance of mulitple linear regression and nonlinear neural networks and fuzzy logic techniques in modelling house prices. *Journal of Mathematics and Statistics, 8*(4), 419–434.

Babawale, G. K., & Ajayi, C. A. (2011). Variance in residential property valuation in Lagos, Nigeria. *Property Management, 29*(3), 222–237.

Borst, R. A. (1991). Artificial neural networks: The next modelling/calibration technology for the assessment community. *Property Tax Journal, 10*(1), 69–94.

Borst, R. A. (1995). Artificial neural networks in mass appraisal. *Journal of Property Tax Assessment & Administration, 1*(2), 5–15.

Brown, G. R., Matysiak, G. A., & Shepherd, M. (1998). Valuation uncertainty and the Mallinson Report. *Journal of Property Research, 15*(1), 1–13.

Canavarro, C., Caridad, J. M., & Ceular, N. (2010). *Hedonic methodologies in the real estate valuation.* Paper presented at the Mathematical Methods in Engineering International Symposium, Coimbra, 21–24 October.

Cebula, R. J. (2009). The hedonic pricing model applied to the housing market of the city of Savannah and its Savannah historic landmark district. *The Review of Regional Studies, 39*(1), 9–22.

Cechin, A., Souto, A., & Gonzalez, A. M. (2000). *Real estate value at Porto Alegre city using artificial neural networks.* Paper presented at the 6th Brazilian Symposium on Neural Networks, Rio de Janeiro, Brazil, 22–25 November.

Chiang, Y., Tao, L., & Wong, F. K. (2015). Causal relationship between construction activities, employment and GDP: The case of Hong Kong. *Habitat International, 46*(1), 1–12.

Chin, T. L., & Chau, K. W. (2002). A critical review of literature on the hedonic price model. *International Journal for Housing Science and Its Applications, 27*(2), 145–165.

Cortez, P., Cerdeira, A., Almeida, F., Matos, T., & Reis, J. (2009). Modeling wine preferences by data mining from physicochemical properties. *Decision Support Systems, 47*(4), 547–553.

Do, A. Q., & Grudnitski, G. (1992). A neural network approach to residential property appraisal. *The Real Estate Appraiser, 58*(3), 38–45.

Dugeri, T. T. (2011). *An evaluation of the maturity of the Nigerian property market* (Doctoral dissertation). University of Lagos, Lagos, Nigeria. Retrieved from http://www.afrer.org/docs/pdf/dugeri.pdf

Famuyiwa, F., & Babawale, G. K. (2014). Hedonic values of physical infrastructure in house rentals. *Journal of Facilities Management, 12*(3), 211–230.

Gilbertson, B., & Preston, D. (2005). A vision for valuation. *Journal of Property Investment & Finance, 23*(2), 123–140.

Grover, R. (2016). Mass valuations. *Journal of Property Investment & Finance, 34*(2), 191–204.

Hofmann, B. (2003). Bank lending and property prices: Some international evidence. *Working Paper No. 22* (pp. 1–20). Hong Kong: Hong Kong Institute for Monetary Research.

Hu, T., Lam, K., & Ng, S. T. (2005). A modified neural network for improving river flow prediction. *Hydrological Sciences Journal, 50*(2), 299–318.

Hui, E. C., Chau, C., Pun, L., & Law, M. (2007). Measuring the neighboring and environmental effects on residential property value: Using spatial weighting matrix. *Building and Environment, 42*(6), 2333–2343.

Janssen, C., Söderberg, B., & Zhou, J. (2001). Robust estimation of hedonic models of price and income for investment property. *Journal of Property Investment & Finance, 19*(4), 342–360.

Jiang, H., Jin, X.-H., & Liu, C. (2013). The effects of the late 2000s global financial crisis on Australia's construction demand. *Australasian Journal of Construction Economics and Building, 13*(3), 65–79.

Jim, C., & Chen, W. Y. (2006). Impacts of urban environmental elements on residential housing prices in Guangzhou (China). *Landscape and Urban Planning, 78*(4), 422–434.

Kaastra, I., & Boyd, M. (1996). Designing a neural network for forecasting financial and economic time series. *Neurocomputing, 10*(3), 215–236.

Kutasi, D., & Badics, M. C. (2016). Valuation methods for the housing market: Evidence from Budapest. *Acta Oeconomica, 66*(3), 527–546.

Lam, K. C., Yu, C. Y., & Lam, K. Y. (2008). An artificial neural network and entropy model for residential property price forecasting in Hong Kong. *Journal of Property Research, 25*(4), 321–342.

Lenk, M. M., Worzala, E. M., & Silva, A. (1997). High-tech valuation: Should artificial neural networks bypass the human valuer? *Journal of Property Valuation and Investment, 15*(1), 8–26.

Limsombunchai, V., Gan, C., & Lee, M. (2004). House price prediction: Hedonic price model vs. artificial neural network. *American Journal of Applied Sciences, 1*(3), 193–201.

Lin, C. C., & Mohan, S. B. (2011). Effectiveness comparison of the residential property mass appraisal methodologies in the USA. *International Journal of Housing Markets and Analysis, 4*(3), 224–243.

Lisboa, P. J., & Taktak, A. F. (2006). The use of artificial neural networks in decision support in cancer: A systematic review. *Neural Networks, 19*(4), 408–415.

Maurer, R., Pitzer, M., & Sebastian, S. (2004). Hedonic price indices for the Paris housing market. *Allgemeines Statistisches Archiv, 88*(3), 303–326.

McCluskey, W. (1996). Predictive accuracy of machine learning models for the mass appraisal of residential property. *New Zealand Valuers Journal, 16*(1), 41–47.

McCluskey, W., Davis, P., Haran, M., McCord, M., & McIlhatton, D. (2012). The potential of artificial neural networks in mass appraisal: The case revisited. *Journal of Financial Management of Property and Construction, 17*(3), 274–292.

McCluskey, W. J., McCord, M., Davis, P., Haran, M., & McIlhatton, D. (2013). Prediction accuracy in mass appraisal: A comparison of modern approaches. *Journal of Property Research, 30*(4), 239–265.

McGreal, S., Adair, A., McBurney, D., & Patterson, D. (1998). Neural networks: The prediction of residential values. *Journal of Property Valuation and Investment, 16*(1), 57–70.

Montgomery, D. C., Peck, E. A., & Vining, G. G. (2015). *Introduction to linear regression analysis* (5th ed.). Hoboken, NJ: Wiley.

Mora-Esperanza, J. G. (2004). Artificial intelligence applied to real estate valuation: An example for the appraisal of Madrid. *CATASTRO, April.* (1), 255–265.

Morano, P., Tajani, F., & Torre, C. M. (2015). Artificial intelligence in property valuations an application of artificial neural networks to housing appraisal. Retrieved September 9, 2015, from Advances in Environmental Science and Energy Planning, http://www.wseas.us/e-library/conferences/2015/Tenerife/ENVIR/ENVIR-02.pdf

Ogunba, O. (2004). *The demand for accuracy in valuations: The case of Nigeria.* Paper presented at the CIB International Symposium on Globalization and Construction, Bangkok, Thailand, 17–19 November.

Ogunba, O., & Ajayi, C. (1998). An assessment of the accuracy of valuations in the residential property market of Lagos. *The Estate Surveyor and Valuer, 21*(2), 19–23.

Olden, J. D., & Jackson, D. A. (2002). Illuminating the "black box": A randomization approach for understanding variable contributions in artificial neural networks. *Ecological Modelling, 154*(1), 135–150.

Owusu-Ansah, A. (2012). Examination of the determinants of housing values in urban Ghana and implications for policy makers. *Journal of African Real Estate Research, 2*(1), 58–85.

Özkan, G., Yalpır, Ş., & Uygunol, O. (2007). *An investigation on the price estimation of residable real-estates by using artificial neural network and regression methods.* Paper presented at the 12th Applied Stochastic Models and Data Analysis International conference (ASMDA), Crete, Greece. May 29–June 1.

Pagourtzi, E., Assimakopoulos, V., Hatzichristos, T., & French, N. (2003). Real estate appraisal: A review of valuation methods. *Journal of Property Investment & Finance, 21*(4), 383–401.

Pagourtzi, E., Metaxiotis, K., Nikolopoulos, K., Giannelos, K., & Assimakopoulos, V. (2007). Real estate valuation with artificial intelligence approaches. *International Journal of Intelligent Systems Technologies and Applications, 2*(1), 50–57.

R CoreTeam. (2016). R: A language and environment for statistical computing. Retrieved July 19, 2016, from R Foundation for Statistical Computing, https://www.R-project.org/

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy, 82*(1), 34–55.

Sampathkumar, V., Santhi, M. H., & Vanjinathan, J. (2015). Evaluation of the trend of land price using regression and neural network models. *Asian Journal of Scientific Research, 8*(2), 182–194.

Selim, H. (2009). Determinants of house prices in Turkey: Hedonic regression versus artificial neural network. *Expert Systems with Applications, 36*(2), 2843–2852.

Selim, S. (2008). Determinants of house prices in Turkey: A hedonic regression model. *Doğuş Üniversitesi Dergisi, 9*(1), 65–76.
Sincich, T. (1996). *Business statistics by example* (5th ed.). Upper Saddle River, NJ: Prentice Hall Englewood.
Tabales, J. N. M., Ocerin, C. J. M., & Carmona, F. J. R. (2013). Artificial neural networks for predicting real estate prices. *Revista de Metodos Cuantitativos para la Economia y la Empresa, 15*, 29–44.
Taffese, W. Z. (2006). *A survey on application of artificial intelligence in real estate industry*. Paper presented at the 3rd International Conference on Artificial Intelligence in Engineering and Technology, Kota Kinabalu, Malaysia.
Tay, D. P., & Ho, D. K. (1992). Artificial intelligence and the mass appraisal of residential apartments. *Journal of Property Valuation and Investment, 10*(2), 525–540.
Thanasi, M. (2016). Hedonic appraisal of apartments in Tirana. *International Journal of Housing Markets and Analysis, 9*(2), 239–255.
White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica, 48*(4), 817–838.
Willmott, C. J. (1981). On the validation of models. *Physical geography, 2*(2), 184–194.
Wilson, I. D., Paris, S. D., Ware, J. A., & Jenkins, D. H. (2002). Residential property price time series forecasting with neural networks. *Knowledge-Based Systems, 15*(5), 335–341.
Wong, K., So, A. T., & Hung, Y. (2002). Neural network vs. hedonic price model: Appraisal of high-density condominiums. In K. Wang & M. L. Wolverton (Eds.), *Real estate valuation theory* (pp. 181–198). New York, NY: Springer.
Worzala, E., Lenk, M., & Silva, A. (1995). An exploration of neural networks and its application to real estate valuation. *Journal of Real Estate Research, 10*(2), 185–201.
Yalpir, S. (2014). *Forecasting residential real estate values with AHP method and integrated GIS*. Paper presented at the People, Buildings and Environment Conference, an International Scientific Conference, Kroměříž, Czech Republic. 15–17 October.
Zurada, J., Levitan, A., & Guan, J. (2011). A comparison of regression and artificial intelligence methods in a mass appraisal context. *Journal of Real Estate Research, 33*(3), 349–387.
Zurada, J. M., Levitan, A. S., & Guan, J. (2006). Non-conventional approaches to property value assessment. *Journal of Applied Business Research, 22*(3), 1–14.