Modeling Property Values in Nigeria using Artificial Neural Network

Abstract

Unreliable and inaccurate property valuation has been associated with techniques currently used in property valuation. A possible explanation for these findings may be due to the utilization of traditional valuation methods. In the current study, an artificial neural network (ANN) is applied to property valuation using the Lagos metropolis real estate market as a representative case. Property transactions data (11 property attributes and property value) were collected from registered real estate firms operating in Lagos, Nigeria. The result shows that the ANN model possesses a good predictive ability, implying that it is suitable and reliable for property valuation. The relative importance analysis conducted on the property attributes revealed that the number of servants' quarters is the most important attribute affecting property values. The findings suggest that the ANN model could be used as a tool by real estate stakeholders, especially, valuers and researchers for property valuation.

Keywords: artificial neural network, property valuation, valuation accuracy, property attributes, Lagos metropolis

1. Introduction

Property valuation estimates are usually needed for purposes which include mortgage, sales, purchases and taxation, amongst others. In these instances, the ultimate goal of the valuation report end-user is to be advised on the most accurate property value, which is usually relied on in making informed real estate investment decisions. Valuation inaccuracy may be completely unavoidable in property valuation due to the differences in the perception of appraisers (Shapiro et al., 2012). This has transformed the issue of valuation inaccuracy into an international debate (Crosby, 2000). Studies have been conducted to measure the level of valuation inaccuracy prevalent in different property markets around the world. Some scholars (for instance Hager & Lord, 1985; Mackmin, 1985) have argued that an error margin of ±5% of the property value is acceptable, while others (Hutchinson et al., 1996; Brown et al., 1998) posit that a range of ±5-10% is satisfactory.

In a more stable real estate market, these variations in estimates may be within a lesser range, but in unstable property markets, the reverse may be true (Shapiro et al., 2012). This may be attributed to why a high degree of valuation inaccuracy is rampant in a developing property market. The level of property valuation inaccuracy usually recorded in Nigeria is higher than what is acceptable in the international real estate appraisal practice (Babawale & Ajayi, 2011), and one of the main reasons is the adoption of traditional valuation methods in property valuation (Aluko, 2007). This is because, despite the simplicity in the application of these traditional methods, they are marred with imprecision and inaccuracy (Zurada et al., 2006).

Advanced valuation approaches have been adopted in the property valuation domain to address the shortcomings of the traditional approaches (Do & Grudnitski, 1992). An artificial neural network (ANN) model is one of such approaches that has been applied in real estate valuation around the world and has produced excellent results (Mora-Esperanza, 2004). Abidoye and Chan (2016b) found that a large proportion of Nigerian valuers are not aware of and do not use the ANN appraisal technique in practice. At the same time, the technique has not received attention from Nigerian real estate researchers. For the purpose of arriving at accurate and reliable valuation estimates, the adoption of an artificial intelligence (AI) technique such as the ANN technique for property valuation is important. In view of the aforementioned, this study aims to apply the ANN technique to property valuation in Nigeria using the Lagos metropolis as the study area and also to identify the most important property attribute(s) that influence property values. The outcome of this research will establish the suitability and viability of the application of ANN in the appraisal landscape of Nigeria and at the same time, serve as a pointer to the future direction of the Nigerian real estate research and practice.

The rest of this paper is divided into four sections. The first presents the previously discussed studies. This is followed by the description of the data adopted for the present study. The results and discussion of the data analysis are detailed in the third section. The fourth section which is the last, documents the conclusion of this study, the limitations and areas for further research.

2. Previous Related Studies

2.1 Artificial neural network in property appraisal research

The principle of the ANN model is designed to function like the human brain (Mora-Esperanza, 2004). It processes commands through the interplay of network neurons that mimic human brain neurons (Taffese, 2006). The network comprise three layers namely the input, hidden and output layers (Olden & Jackson, 2002). The property attributes are fed into the network at the input layer, the weight formation and transformation occurs in the hidden layer (Pagourtzi et al., 2007), while the expected predicted property value is produced at the output layer. The nonlinear relationship that exists between property prices and property attributes can be mapped by the ANN model (Cechin et al., 2000), and this has made it more suitable for property valuation when compared with other property appraisal techniques (Elhag, 2002).

In developing an ANN model, certain number of steps are involved. This process is iterative in nature (Ward, 1996). Kaastra and Boyd (1996) presented the process of developing an ANN model which can be summarized into eight steps listed below;

Step 1: The selection of the variables to be included in the model

Step 2: The collection of data from the study area

Step 3: Pre-processing of the collected data

Step 4: Division of the data set for training and testing of the model

Step 5: Neural network paradigm

- Determination of the number of hidden layers
- Determination of the number of hidden neurons
- Determination of the number of output neurons
- Selection of the transfer function

Step 6: Model evaluation criteria and accuracy measure

Step 7: Training of the ANN model

Step 8: Implementation

A detailed process of developing an ANN model for property valuation is presented in Pagourtzi et al. (2003) and Ge (2004).

The ANN technique was first applied in the field of mathematics. McCulloch and Pitts (1943) developed an ANN model known as the “threshold logic model” in this seminal study. After this ground-breaking study, scholars in different research areas have adopted this novel technique for prediction, pattern recognition, classification and non-linear mapping (Paliwal & Kumar, 2009), in solving real-life problems. The technique gained the attention of real estate scholars in the early 1990s. The original study of Borst (1991) examined the accurate predictive ability of the ANN technique under four cases using different network architecture. Borst (1991) concluded that the forecasting accuracy produced by ANN is reliable and with more research effort towards the application of ANN to real estate appraisal, the model would produce outstanding estimates. Different real estate markets around the world had been and are still being modeled using this technique. A summary of some of these studies are presented in Table 1.

Table 1. ANN property valuation studies.

Author(s)	Country of origin	Sample size	Summary of finding
Do and Grudnitski (1992)	United States	163	ANN performed two times better than other approaches
Tay and Ho (1992)	Singapore	1055	ANN is easy to apply and serves as an alternative to other appraisal models
Worzala et al. (1995)	United States	288	ANN not better than other approaches, caution should be taken in applying ANN in property valuation
McCluskey (1996)	Northern Ireland	416	ANN produced reliable and acceptable estimates
Rossini (1997)	South Australia	334	The finding is not conclusive, but optimistic on the prospects of ANN in property valuation
Jenkins et al. (1999)	United Kingdom	990	The ANN has promising prospects to enhance valuation accuracy
Cechin et al. (2000)	Brazil	1600	Error of ANN estimates is three times less than others
Wong et al. (2002)	Hong Kong	251	ANN is a good alternative appraisal technique to traditional approaches
Mora-Esperanza (2004)	Spain	100	ANN can handle the nonlinear and complex relationship between property value and property attributes
Limsombunchai et al. (2004)	New Zealand	200	ANN performs better than other appraisal techniques
Sarip (2005)	Malaysia	138	ANN produces accurate valuation estimates
Xie and Hu (2007)	China	200	ANN appraisal technique is superior to some others techniques
Özkan et al. (2007)	Turkey	170	ANN estimates are close to actual market values
Pagourtzi et al. (2007)	Greece	141	ANN technique produces accurate estimate
Mousa and Saadeh (2010)	Jordan	891	ANN is a promising appraisal technique
Kontrimas and Verikas (2011)	Lithuania	100	ANN is not better than other appraisal techniques
Lai (2011)	Taiwan	2471	ANN performs better than other valuation approaches
Sampathkumar et al. (2015)	India	252	ANN estimates are more accurate

From Table 1, it can be seen that the outstanding performance of the ANN technique in property valuation was reported by various scholars. Although some cited a note of warning in the application of ANN in property valuation, continuous research efforts are being invested in improving the predictive performance of the ANN technique (McCluskey et al., 2012).

The ANN model has been widely accepted in the real estate appraisal domain for its ability to outperform the traditional methods of valuation (Borst, 1991); it produces model outputs quickly and it is also simple to operate (Ge, 2004). A priori theory is not needed for the development of an ANN model (Worzala et al., 1995). This allows it to address the subjectivity attributed to the traditional methods of valuation (Yacim & Boshoff, 2014). The ANN model is referred to as a "black-box" model, implying that it may be difficult to understand what happens in the internal structure of the network (Jenkins, 2000; Amri & Tularam, 2012). It has also been termed as a data hungry model (Lam et al., 2008) and the determination of the size and structure of the network could be problematic (Taffese, 2006). Scholars (Limsombunchai et al., 2004; Lin & Mohan, 2011) have argued that the process of determining the best network architecture which is based on "trial" and "error" may limit the predictive quality of the ANN model. However, the continuing development of different ANN software has been efficient at handling these shortcomings (McCluskey, 1996).

2.2 The Nigerian Property Market

The evolution and growth of the Nigerian property market is not well documented in literature. Dugeri (2011) attributed this to the lack of interest by international property investors when compared with the European and Asian property markets. Another plausible reason could be linked to the lack of a centralized database for the storage of property transactions information (Aluko, 2007). The emergence of big data analysis has led to improvements in practice related to property valuation, investment analysis and portfolio management, among other aspects of real estate practice (Du et al., 2014). However, Ogunba and Ajayi (2007) acknowledged that the reverse is the case in property markets of developing countries, such as Nigeria.

Nigeria is made up 36 states and a federal capital territory - Abuja (The World Bank, 2014). The Nigerian property market can be categorized into primary (characterized with high rental and capital values) and secondary markets (characterized with low rental and capital values), with the primary markets being the most active in Nigeria (Olaleye, 2008). The primary markets are the Lagos, Abuja and Port-Harcourt property markets and these three markets account for about 60% of the real estate transactions completed in Nigeria (Olaleye, 2008).

The Lagos metropolis is the most active property market in Nigeria due to the high number of sophisticated real estate stakeholders that interact in the metropolis (Oni, 2010). Also a large percentage of the multinational companies operating in Nigeria are domiciled in Lagos and over 90 percent of the commercial banks and financial companies operating in Nigeria have their head offices in Lagos (Central Bank of Nigeria, 2015). This is because the Lagos metropolis is the commercial nerve center of Nigeria (Aluko, 2007), corroborating why more than 50 percent of the Nigerian registered real estate professionals practice in the Lagos metropolis property market (Ibiyemi & Tella, 2013).

Dugeri (2011) evaluated the maturity of the Nigerian property market based on six parameters which include openness, property profession, capital liquidity, state of information and market transparency. It was found that the property market is still at its infancy state. It should be noted that the Nigerian property market has the potential to grow and mature into the one of the most advanced within the African continent. However, there is a need to address several pertinent issues (see Dugeri, 2011), so that the property market can grow in a sustainable manner.

2.3 Property value determinants

Scholars have investigated the marginal contribution of residential property attributes to property values determination in different property markets around the world. These attributes have been categorised into three classifications, namely neighbourhood, locational and structural attributes (Chin & Chau, 2002). Different attributes have been found to significantly affect property values. For instance the number of bedrooms (Ge & Du, 2007; Selim, 2008), the number of bathrooms and toilets (Zietz et al., 2008; Pozo, 2009), the property location (Ge & Du, 2007; Anim-Odame et al., 2009), the availability of public transport (Mbachu & Lenono, 2005; Choy et al., 2007), the property size (Choy et al., 2007; Sanjari, 2012) and the availability of security fence (Mbachu & Lenono, 2005), amongst other attributes, have a significant impact on property value.

With regard to the Lagos metropolis property market, authors have conducted similar studies. Babawale et al. (2012) reported that the number of bedrooms, the number of bathrooms, the size of bedroom and the security fencing significantly affect property values. Similarly, Ajide and Kareem (2010) found that the number of bedrooms, the toilets and bedrooms are the major property value determinants. Bello and Bello (2007) established that the age of a property and the property location contribute significantly to property value estimation in the Lagos metropolis property market. Olayiwola et al. (2005) found public transport system facilities to be an important property value determinant. All these studies and others have adopted analysis techniques that range from the hedonic pricing model (HPM), descriptive statistical analysis and correlation analysis, amongst other techniques, that cannot adequately capture the nonlinear relationship that exists between property values and property attributes (Limsombunchai et al., 2004). Therefore, this study intends to explore the use of the ANN technique by establishing the relative importance (RI) of the property attributes of the Lagos metropolis residential properties. The ANN technique can capture the underlying nonlinear relationship between property attributes and property values (Cechin et al., 2000), and it is expected to produce reliable findings, owning to its reliability and accuracy quality (Paliwal & Kumar, 2009).

3. Research Method

3.1. The Data

Nigeria is a developing country and its real estate market is still evolving (Dugeri, 2011). This may be attributed to the lack of a centralised database of properties bought or sold in the property market (Ajibola, 2010). This necessitated the gathering of sales and purchases information of residential properties in different high-income neighbourhoods in the Lagos Island property market. Real estate properties located within the high-income neighbourhoods where the data was collected (i.e. Ikoyi, Victoria Island, Victoria Garden City (VGC), Lekki Peninsula Phase 1 and other high-income neighbourhoods on the Lekki – Epe corridor (between Lekki Peninsula Phase 1 and Abraham Adesanya Estate)) command higher values when compared with other locations in the Lagos metropolis (Famuyiwa & Babawale, 2014). The data were collected from registered real estate firms operating in Lagos. The authors intended to retrieve information of completed sale transactions as far back as possible, in order to retrieve a sizable sample data. Unfortunately, the firms do not maintain a property sales database. However, they were able to provide details of recent transactions (2010-2016). At the end of the data collection exercise, which lasted for four months (March 2016-June 2016), data on 370 completed transactions were retrieved. The data were pre-processed and after the cleaning process aimed at excluding entries with missing/incomplete records, 321 observations remained and were subjected to analysis.

Eleven independent variables and one dependent variable (i.e. property price) were identified in the present study. The independent variables are structural attributes with the exception of the location of the property and the presence of a sea view. Property structural characteristics have a significant influence on real estate property value when compared with locational and neighbourhood variables (Wen et al., 2005) and are commonly used in similar studies (see Do & Grudnitski, 1992; Lin & Mohan, 2011; McCluskey et al., 2012). The independent variables used in this study were selected based on the data availability, knowledge of the real estate market under investigation and their RI to the formation of property values in the study area (see Abidoye & Chan, 2016a). The variables include the number of bedrooms, the number of bathrooms, the number of toilets, the age of the building, the number of floors, the number of parking lots for cars, the property type, the number of servants' quarters and the availability of security fencing. The descriptive statistics of the collected data is presented in Table 2.

Table 2. Descriptive statistics of the variables.

Variable	Mean	Standard Deviation	Minimum	Maximum
Dependent				
Price (₦)	149769541.60	199367090.90	14500000	1182844000
Independent				
Number of bedrooms (0-10)	3.49	1.26	1	10
Number of toilets (0-10)	4.28	1.37	1	7
Number of bathrooms (0-10)	3.38	1.25	1	7
Property type	3.87	1.45	1	6
Number of boys' quarters (0-10)	1.08	1.36	0	8
Number of parking lots (0-10)	3.27	2.45	0	20
Age of building (Years)	3.30	4.97	0	42
Number of floors (1-10)	2.83	2.19	1	16
Availability of security fence (Yes/No)	0.98	0.14	0	1
Availability of sea view (Yes/No)	0.05	0.22	0	1
Location of property	3.36	1.70	1	5

Note – ₦ is naira (Nigerian currency). For the property type, each was represented with a number ranging from 1-6. They are presented in that order in Table 3.

The frequency distributions that describes the collected data are presented in Table 3. It is evident that about 57 percent of the properties were sold for less than ₦100,000,000, while only 15 properties were sold above ₦500,000,000 (see Table 3). It can be said that most of the properties were either three-, four- or five-bedroom properties, with the properties having a corresponding number of bathrooms. Most of the properties had about four, five and above five toilets, suggesting that most properties had extra toilets when compared to the number of bathrooms in a building. The extra toilet facility could be for guest use. It is worth noting that this feature is highly priced in the Lagos metropolis property market. Flat, detached and terrace buildings are common in the study area as seen in Table 3. One servants' quarters (usually referred to as boys' quarters [BQ] in the Nigerian environment) is attached to about half (44.2 percent) of the properties. Although some properties do not have BQ, these are probably one bedroom properties and in these cases the occupants may not need their domestic staff to live with them. The properties used for this study have at least one parking lot for the use of the occupants. Twenty-one of the properties were recently constructed and sold at the time of data collection. However, the information in Table 3 shows that most of the properties were either constructed between one to three years ago, suggesting that properties in the study areas are relatively new. Almost all (98.1 percent) the properties included in this study have security fences erected around their perimeter boundaries. On the other hand, the sea cannot be viewed from most (94.7 percent) of the properties. In terms of the location of the properties, about a quarter are located in Ikoyi, 16.5 percent are located in Lekki Peninsula Phase 1, while about half (46.7 percent) are located in other areas such as Northern Foreshore, Nicon Town, Oniru Estate and Chevy View Estate, amongst other high-income neighbourhoods in the study area. It should be noted that the 'location of property' variable was included as a dummy variable that describes the geographical position of the property. The actual address of each property used in this study could not be retrieved from the real estate firms. This is not uncommon in the literature (for instance Selim, 2009; Kontrimas & Verikas, 2011; Tabales et al., 2013).

Table 3. Frequencies of the variables.

Variable	Frequency	Percentage (%)
Price		
0-50,000,000	111	34.6
50,000,001 – 100,000,000	73	22.7
100,000,001 – 200,000,000	66	20.6
200,000,001 – 500,000,000	56	17.4
Above 500,000,000	15	4.7
Number of bedrooms		
1	29	9.0
2	31	9.7
3	95	29.6
4	94	29.3
5	69	21.5
Above 5	3	0.9
Number of bathrooms		
1	29	9.0
2	50	15.6
3	83	25.9
4	92	28.7
5	64	19.9
Above 5	3	0.9
Number of toilets		
1	19	5.9
2	11	3.4
3	52	16.2
4	84	26.2
5	92	28.7
Above 5	63	19.6
Property type		
Duplex	12	3.7
Detached House	71	22.1
Semi Detached House	36	11.2

Terrace	67	20.9
Flat	98	30.5
Others	37	11.5
Number of BQ		
0	105	32.7
1	142	44.2
2	61	19.0
3	3	0.9
4	1	0.3
5	1	0.3
Above 5	8	2.5
Number of parking lots		
0	3	.9
1	46	14.3
2	121	37.7
3	45	14.0
4	34	10.6
5	28	8.7
Above 5	44	13.7
Age of building		
0	21	6.5
1	119	37.1
2	54	16.8
3	53	16.5
4	14	4.4
5	19	5.9
Above 5	41	12.8
Number of floors		
1	34	10.6
2	169	52.6
3	44	13.7
4	57	17.8
5	1	0.3
Above 5	16	5.0
Availability of security fence		
Yes	315	98.1
No	6	1.9
Availability of sea view		
Yes	17	5.3
No	304	94.7
Location of property		
Ikoyi	82	25.5
VI	28	8.7
Lekki 1	53	16.5
VGC	8	2.5
Others	150	46.7

The composite consumer price index (CPI) which is available from the National Bureau of Statistics (see National Bureau of Statistics, 2016) was used to deflate the current property prices to constant prices. This adjustment ensured that the effect of inflation on property values was removed. The process for adjusting the values can be mathematically expressed as presented in Equation 1. This formula was adopted from McCluskey et al. (2012).

$$\text{Current property price} = \text{Base year price} \times \frac{\text{Current CPI}}{\text{Base year CPI}} \quad (1)$$

3.2. Model specification

The ANN model was developed using a three-layer feedforward network. Mora-Esperanza (2004) suggests that the number of hidden layers in an ANN model can range between half and double the number of the input variables. However, the use of one hidden layer is considered adequate for handling complex real-life prediction for ANN models (Masters, 1993; McCluskey et al., 2012). There is no agreement in the literature as regards the number of hidden neurons an ANN model should have (Cechin et al., 2000). Mathematically, the number of neurons to be included in a model could be determined by adopting the expression in Equation 2 as presented by Ward (1996). However, in the present study, the number of neurons in the hidden layer was automatically determined by the software.

$$N_h = \frac{N_{in} + N_{out}}{2} + \sqrt{N_s} \quad (2)$$

Where N_h is the number of neurons of hidden layer, N_{in} is input layer, N_{out} is output layer and N_s is the number of training samples.

The development of an ANN model is based on a trial and error experimentation to attain the best model (Limsombunchai et al., 2004). The iteration process is usually performed in order to construct the best ANN model that fits the data. This is unlike the approach of other techniques such as the hedonic pricing model (HPM) where the analysts will have to subjectively identify the functional form that best explains the relationship between the dependent and independent variables (Do & Grudnitski, 1992). After the iteration, an ANN architecture of 11-5-1 (11 input variables, 1 hidden layer with 5 neurons and 1 output) generated by the software was found to be the best network in this study. Figure 1 shows the topology of the ANN architecture generated in this study.

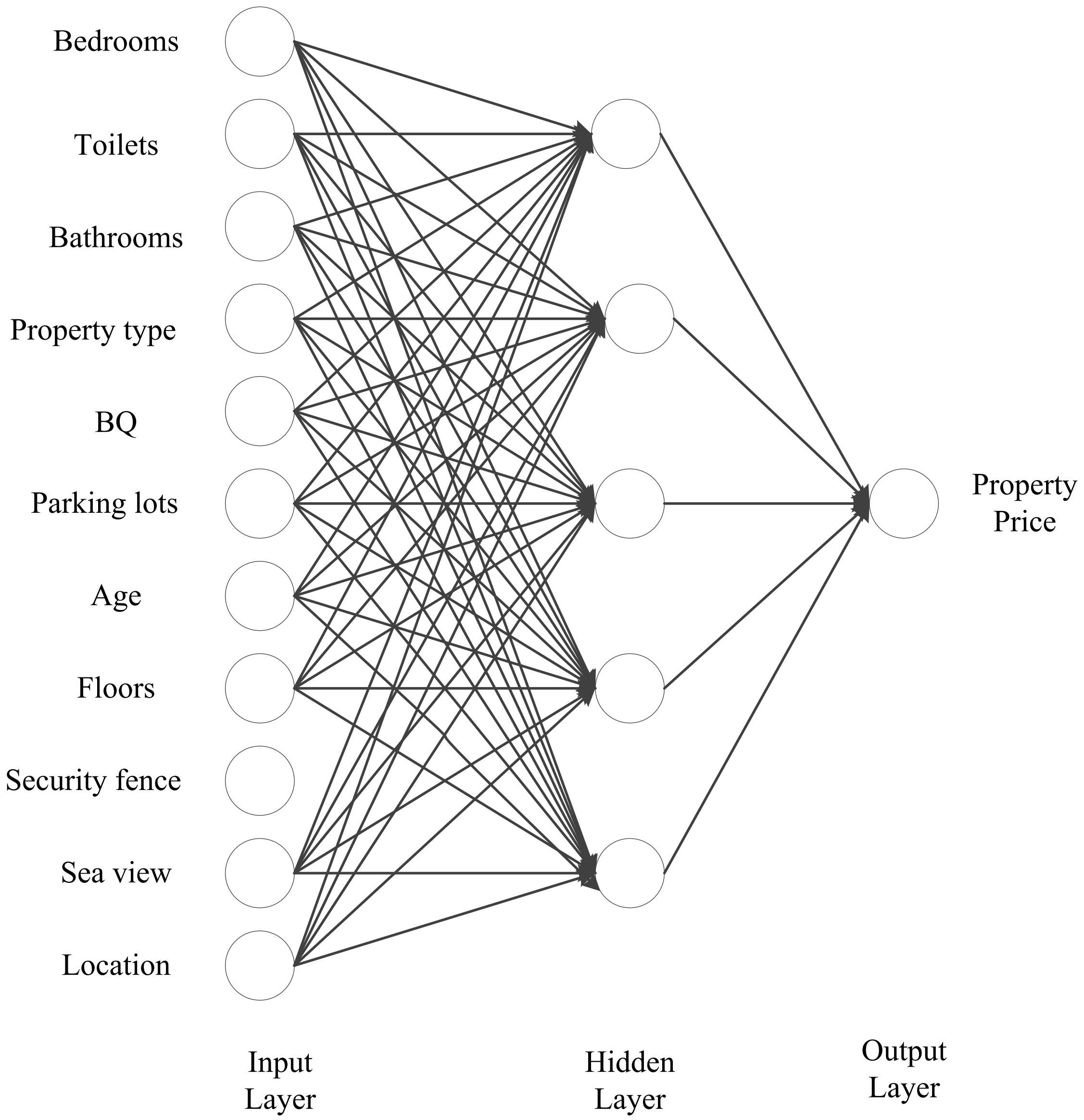

Figure 1. The ANN architecture.

As mentioned, the ANN model presented in the present study was developed using the R programming software (R CoreTeam, 2016) and the Rminer package (Cortez, 2010). The backpropagation learning algorithm which is widely adopted in the literature (Mimis et al., 2013) was adopted for this study. Backpropagation (BP) is based on multilayer perception (MLP) that ensures that the neurons in the models are arranged in interconnected layers (input, hidden and output). In developing an ANN model, the available data set is to be divided into two, i.e. for training and testing of the model (Wilson et al., 2002). The training data set is used to develop the model by determining the arc weights, while testing is the process of evaluating the predictive and generalization ability of the developed model (Lam et al., 2008). There is little or no guidance in the literature on the division ratio for the training and testing of the model (Cechin et al., 2000). Although ratio 90:10, 80:20 and 70:30 for training and testing, respectively, have been widely adopted in the literature because the model testing can be performed with small data set (Zhang et al., 1998). This suggests that the analyst's discretion is required in determining the ratio based on what is obtainable in the literature. For this study, the collected data were randomly shared into two sets i.e. for training and testing with a ratio of 80 percent and 20 percent, respectively. This amounted to 256 samples for training and 65 holdout samples for the testing of the predictive ability of the ANN model. In estimating the error rate of this model, a cross-validation was used and the standard approach is a 10-fold cross-validation (Witten & Frank, 2005). Through this, the model will average all the 10 error estimates generated in order to arrive at an unbiased and minimum error measure (Murat & Ceylan, 2006). In this study, a 10-fold cross-validation was used as obtainable in previous studies (see for instance Zurada et al., 2011; McCluskey et al., 2012).

3.3. Accuracy measures

Although there is no consensus on the most appropriate model predictive accuracy measure, the root mean square error (RMSE), the coefficient of determination (r^2), the mean absolute error (MAE) and the mean absolute percentage error (MAPE) that are widely adopted in the literature (Zurada et al., 2011; McCluskey et al., 2013) were adopted in this study. The formula for estimating r^2, MAE, MAPE and RMSE are presented in Equations 3, 4, 5 and 6, respectively, as found in the literature (Limsombunchai et al., 2004; Lin & Mohan, 2011).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(P_i - \hat{P}_i\right)^2}{\sum_{i=1}^{n}\left(P_i - \overline{P}\right)^2} \qquad (3)$$

$$MAE = \frac{1}{n}\sum_{i=1}\left(P_i - \hat{P}_i\right) \quad (4)$$

$$MAPE = \frac{\sum_{i=1}^{n}\left(\frac{P_i - \hat{P}_i}{\hat{P}_i}\right)}{n} \times 100 \quad (5)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(P_i - \hat{P}_i\right)^2} \quad (6)$$

Where n is the number of observations, P_i is the actual property price and $\hat{P}_i$ is the estimated/predicted property price from the model.

4. Results and Discussion

4.1. Model performance

After the construction of the model, the r^2 value of the ANN model is 0.81. This connotes that the model explains 81 percent of the variance in the data set. The r^2 value range between 0 and 1, and a value close to 1 shows a perfect performance (Limsombunchai et al., 2004). Hence, the ANN model can be said to have performed satisfactorily. The MAPE of the model is 15.94 percent, the MAE value is ₦28,492,514 while the RMSE is ₦41,814,564 (see Table 4). According to Lin and Mohan (2011), an MAE value of a model that tends towards 0 depicts a goodness of fit, a low RMSE value connotes a superlative model (Limsombunchai et al., 2004), while the MAPE measures the error of prediction in terms of percentage (Zurada et al., 2011). The MAPE, MAE and RMSE figures recorded here suggests that the output of the ANN model are encouraging, considering that the valuation inaccuracy being experienced in the Lagos metropolis property market could be as high as 67.91 percentage (Ogunba, 2004).

Table 4. Predictive accuracy of the ANN model.

Measure of accuracy	ANN model
r^2	0.81
MAPE	15.94
MAE	28,492,514
RMSE	41,814,564

The validation of the model developed was performed on the holdout data sample. Through this, the holdout sample data was predicted using the ANN model developed with the training samples. These predicted estimates were compared with the expected values in order to establish the difference (if any) between the expected values and predicted values. Figure 2 shows the plot of the relationship between the expected property values and the ones predicted by the ANN model. The scatterplot shows that the ANN model produced a good prediction for almost all the holdout samples ($r^2 = 0.81$), with just few that were far from the line of fit. The ANN model can handle data sets that contains outliers and still produce precise outputs (Mora-Esperanza, 2004). This has been proven in previous studies where the ANN model produced good fit with and without the inclusion of outliers in the data set (see for instance Cole et al., 1986; Tay & Ho, 1992).

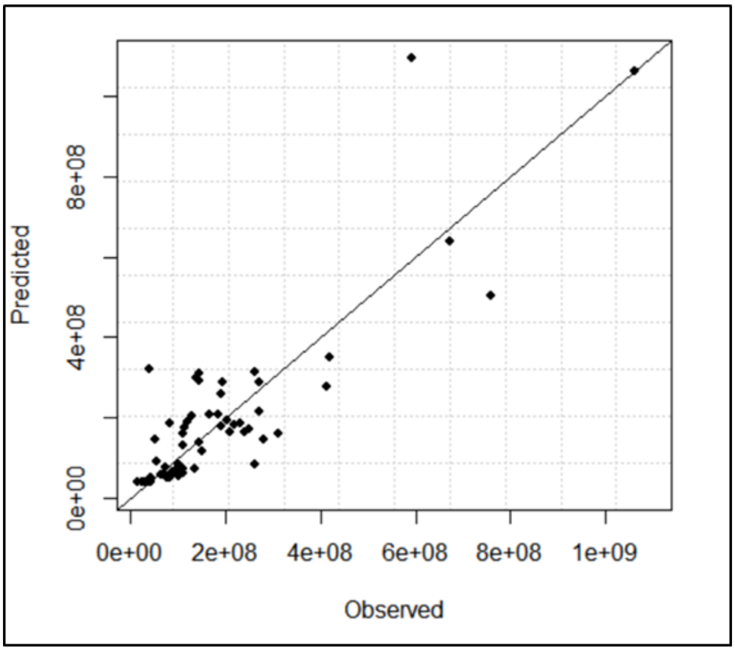

Figure 2. Expected values against predicted values.

These results are similar to the findings of Ge and Runeson (2004), Mimis et al. (2013) and Cechin et al. (2000), amongst other studies, all of which reported that the ANN technique possesses a reliable predictive ability that can address the nonlinearity of property values and property attributes. Even though a few studies (for instance Kontrimas & Verikas, 2011; McCluskey et al., 2012) conclude that the ANN may not be a reliable predictive technique for property valuation. The inconclusiveness of the findings of previous studies could be attributed to the quality of the data sample used for these studies, as this may have an effect on the ANN output (Lenk et al., 1997). The ANN model should not be seen as a replacement for the valuer in a valuation exercise; it is a tool to achieving the end result. This has translated into "various countries having included the ANN in their real estate valuation computer system, as a help tool for their valuators" (Mora-Esperanza, 2004, p. 260). Hence, the valuer's sound knowledge of the property market under investigation may also affect the quality of the ANN predicted estimate.

4.2. Relative importance of the attributes

The output of the ANN model does not contain the coefficients or *t*-values of the property attributes like in the HPM, however, its output can establish the RI of the variables (McCluskey et al., 2012). Figure 3 shows the RI of the 11 attributes used in developing the ANN model. The RI value ranges between 0.0 and 0.5, where a 0.0 value indicates that the attribute has no effect on property value formation, while 0.5 connotes a highly significant contribution to property value estimation. The most important attribute is the number of BQ in a building, which recorded an RI value of 0.49 out of the 0.50 benchmark (see Figure 3), implying a high significant contribution to the value of properties in the study area. A BQ is an adjoining room normally constructed outside of the main building for the accommodation of domestic and other personal staff. Being that the study area is a high-income residential neighbourhood, it is safe to suggest that home buyers or tenants will firstly consider the numbers of BQ rooms available in a building before negotiating further. This property attribute may be uncommon in the real estate literature, probably because in other real estate markets, servants' quarters are within the main building. However, Basu and Thibodeau (1998) found that the presence of servants' quarters has an insignificant influence on property prices in Dallas, United States.

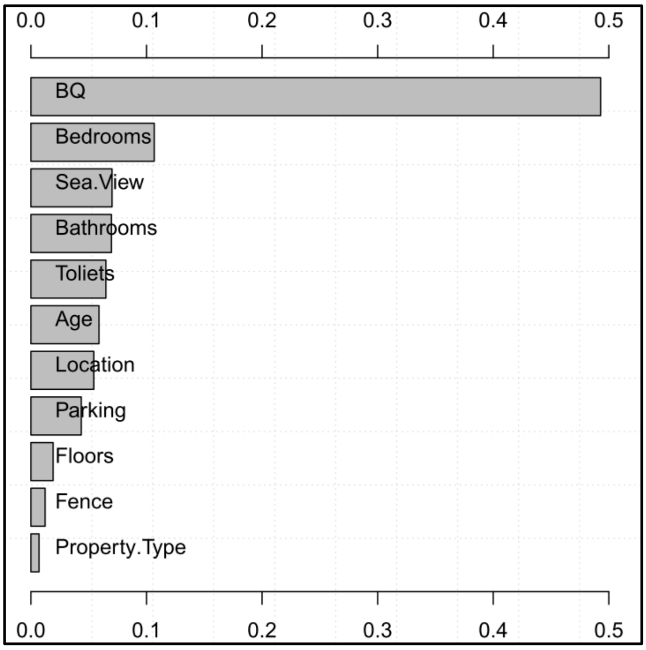

Figure 3. The relative importance of the attributes.

The second most important attribute is the number of bedrooms in a building, which translates that the higher the number of bedrooms in a building, the higher the property value. This corroborates the findings in other property markets around the world (Mbachu & Lenono, 2005; Ge & Du, 2007; Selim, 2008). The presence of a sea view in a building was found to be the third most important attribute in the present study. The study area where data was collected for this research is surrounded by the sea and lagoon, so this may be attributed to it being a high-income neighbourhood that is dominated mostly by expatriates and high-income earners. This result corroborates the studies of Tse (2002); Choy et al. (2007) Hui et al. (2007) and Michael et al. (2002) who reported that the presence of a sea view significantly influence the value of a property. The least important attribute is property type. Generally, the study area is characterized with property types associated with high-income earners such as duplexes, detached houses, terraces and others. So, it is understandable that property values in this property market are not highly determined by this factor.

5. Conclusion

The predictive ability of the ANN model was investigated in this study using the Lagos metropolis property market as the study area. Transactions data collected from registered real estate firms in the Lagos metropolis was processed and used to develop a three-layer ANN model. The predictive ability of the model developed based on its satisfactory r^2, MAE, MAPE and RMSE values, suggests that the ANN appraisal technique can be both feasibly applied and produce satisfactory predictive accurate and reliable valuation estimates in the Lagos metropolis property market. In addition, it was found that the number of BQ rooms has the most significant impact on property values in the property market. Taken together, these results suggest that the developed ANN model can be used as a tool for generating accurate property valuation figures. This conforms to the knowledge gleaned from the previous literature which suggests that artificial intelligence models can generate accurate and reliable property valuation estimates (see Borst, 1991; Nguyen & Cripps, 2001; Mora-Esperanza, 2004; Selim, 2009). This implies that the adoption of the ANN technique in property valuation could reduce the valuation inaccuracy in property value estimation. Also the information on the number of BQ rooms available in a building should be considered during the conception/design phase of a new residential development for high-income earners in the Lagos metropolis. To date in Nigeria, there is no centrally managed property sales and purchases information database. This current situation warranted the door-to-door collection of property sales and purchases information from real estate firms operating in the Lagos metropolis. This resulted in the retrieval of 370 transaction observations for this study. In order to develop a more robust model with the dataset available, a cross-validation process was adopted in training the ANN model. However, the real estate practice regulatory professional bodies in Nigeria should as a matter of urgency, embark on maintaining a property transactions databank, in order to make big data available to aid real estate market research in Nigeria. Data used in this study was collected from high-income neighbourhoods, conversely, data from other neighbourhoods could produce different findings. Also, other macro-economic variables (such as interest rates, gross domestic product (GDP) and exchange rate, amongst others), locational and neighbourhood variables that could affect property values, were not added to the model. With the results of this research, continuing research is necessary so as to improve the desirable performance of the model. The applicability of the ANN model in other property markets within Nigeria and the predictive ability of the ANN model compared with other traditional valuation methods will be investigated in further researches.

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