Performance Comparison of Artificial Neural Networks and Hedonic Pricing model in Predicting Residential Property prices in Lagos Metropolis, Nigeria

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Abstract

The search for techniques that can achieve better valuation estimates is a global issue, while much research has been done in the advanced countries, only a few researches are known to have been done in the area of adopting the advanced techniques in predicting property prices in Nigeria. The current paper compares the performance of the hedonic pricing model (HPM) and artificial neural networks (ANN) models in predicting the prices of residential properties in Lagos metropolis, Nigeria. Residential property prices and data for the variables affecting property prices were obtained from the databases of 53 firms of practicing Estate Surveyors and Valuers in the study area. A total of 3,079 datasets, encompassing property, neighborhood, and environmental-based features were gathered and employed in the research along with 19 explanatory factors. The entire dataset was split into training and testing at a ratio of 80% and 20% respectively to assess the prediction ability of the ANN and HPM. For both models, the performance evaluation metrics of R-squares, mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE) were computed and then compared. ANN model outperformed HPM model in predicting residential property prices in the Lagos metropolitan residential property market. The outcome of the research provides decision inputs for policymakers, investors in real estate, real estate professionals, and other stakeholders.

Key Words: *ANN, HPM, Valuation estimates, Prediction, Property Market*

1.0 Introduction

There have been growing needs for improved precision in property valuation estimates in Nigeria following the increasing dissatisfaction of valuation clients with the valuation estimates reported by property valuers. Valuation estimates accuracy plays crucial roles in the investment decision-making of industry, banks, insurance companies, institutional investors, purchasers, mortgages, and sellers among others.

The current situation in many nations is such that property value estimation is carried out either by using traditional methods (cost, investment, profit, residual) while advanced methods are also unusually engaged. Moreover, due to recent uncertainties and sophistication in the property market and the ineffectiveness of traditional methods leading to valuation inaccuracies, the traditional approach to valuation currently appears unpopular especially in the developing economy as it is known to overprice or underprice as the case may be in the property market, thus leading to loss of confidence in the competency of valuation professionals by real estate valuation clients. According to Małkowska and Uhruska, (2022), and Tien, et al. (2023), real estate valuation must provide a quantitative measure of the benefits and liabilities associated with real estate ownership. The conventional approach to estimating house price is typically based on cost and sale price comparison, but lacks standards and certification procedures (Stubnova et al, 2020).

In the quest for better valuation estimates, different techniques such as Hedonic Price Modelling (HPM), Artificial Neural Network (ANN) among others have been adopted in predicting property value estimates. A number of studies have adopted HPM and documented its strengths and weaknesses (Limsombunchi, 2005, Monson, 2009, Abidoye and Chan, 2018, & Setiowati, et al., 2023), while ANN, though promises to improve valuation accuracy but also suffered from black box syndrome (Limsombunchai, 2005, Ge, et al., 2021 &Alzain, et al., 2022). For example, Limsombunchair, (2004) and Abidoye & Chan, (2018) observed that HPM is convenient, trusted and frequently used for predicting real estate prices. Musser (2010) also stated that the method enables the sample determination of the contributions of asset attributes to the overall property value but studies like Moremo-Izquierdo et al, (2018) reported the negative implication of non-linearity, multicollinearity and heteroscedasticity as its main drawbacks. Nevertheless, it has continued to receive wide adoption in the property market across the countries of the world (Bohadur et al, 2022).

On the other hand, Markadiz (2019) expressed that ANN is gaining widespread acceptance in the property valuation process. Although, studies have alluded to the fact that ANN predicted more accurately than HPM (Worsala et al, 1998, Masias et al, 2016, Minrs et al, 2013 & Ge et al., 2021), its preference over HPM has been questioned, making absolute superiority of ANN over the predictive capacity of HPM yet inconclusive (Valier, 2020). For instance, the superiority assumption of ANN was made in relation to specific conditions of the dataset and the software employed (Stubnova et al, 2020), while in some other perspectives, the better accuracy claimed by ANN application is limited by its blackbox syndrome (Hassija, Chamola, Mahapatra, Singal, Goel, Huang, & Hussain, A. 2023). For a good balance, Ahmad et al., (2017) demonstrated that both models have comparable predictive power. Thus, it appears difficult to conclude which technique is best in all cases because the result tends to be data and market-specific.

It is noteworthy that, the prediction capacity of any technique can be enhanced by the number of variables, size of the dataset, condition of the market from where a dataset is drawn and the expected outcome of adopting the technique, this in essence gives room to the adoption of HPM in a specific way (Zhou, et al., 2018)

To enhance the predictive accuracy of the results produced by the modeling processes, researchers look for and create methods with higher predictive accuracy (Adewusi, 2021). Several studies have also contrasted the predictive accuracy of the ANN technique with that of HPM (McGreal, Adair, McBurney, & Patterson, 1998). Abidoye and Chan (2018) examined the prediction abilities of HPM and ANN using 230 datasets and with rather limited explanatory variables in the Lagos metropolis property market with the finding that ANN outperformed HPM in predicting the prices of residential properties, however, the authors noted that ANN may not always claim superiority over HPM as more work may still be done to further examine the conclusion.

Although the majority of these studies, according to Abidoye and Chan (2017) came from the advanced nations with largely inconsistent conclusions as per the predictive capacity of HPM and ANN, although, when it comes to prediction accuracy, the ANN technique generally performs better than the HPM approach. However, each valuation model has advantages and disadvantages of its own, thus, no valuation model can singularly handle all property valuation difficulties (Pagourtzi, Metaxiotis, Nikolopoulos, Giannelos, & Assimakopoulos, 2007). Abidoye & Chan (2016b) and Lam et al. (2008) discuss the advantages and disadvantages of several traditional property assessment methods. The conclusion of Abidoye and Chan (2018) that ANN is uniformly superior to HPM in predicting property prices may need re-examinations, especially as relatively small data and a limited number of predicting variables were used in the study. Arising from the foregoing and couple with the submission of Abidoye and Chan (2018) on the need for further studies with larger dataset and attributes, the current study assesses the performance of HPM and ANN in predicting the value estimates of residential properties in Lagos metropolitan market, Nigeria using three thousand and seventy-nine (3,079) datasets, covering all the income groups areas with 19 explanatory variables. The rest of the paper features literature review, methodology, results and discussion and concluding remarks.

2.0. Literature Review

Using property sales data gathered in California, USA, Do and Grudnitski's (1992) work is among the earliest attempts to compare the predicted accuracy of ANN and HPM. According to the study, the ANN model generated forecasts which doubled the predictive accuracy of the property values of the HPM model. According to Do and Grudnitski (1992), there is a lot of promise for the ANN approach to generate precise valuation estimations. The ANN technique is superior to HPM in property assessment, according to a number of researches, including Cechin et al. (2000), Selim (2009), Lin and Mohan (2011), and Kutasi and Badics (2016). Additionally, Tay and Ho (1992) used a sizable set of data from Singaporean residential unit buildings to evaluate the effectiveness of neural networks to conventional regression based analysis. The study discovered that ANN outperforms HPM in terms of mean absolute error. Peter (1997) conducted a comparative analysis of the Hedonic Pricing Model and Artificial Neural Networks for the purpose of residential property appraisal. Ten independent variables were employed in the evaluation of the models, which were trained on 223 sales data. ANN fared better in residential property value prediction than HPM, according to the findings, among other things. Comparative research on the use of the Multiple Regression Model (MRM) and the Brain Maker Neural Network (BMWN) to the analysis of housing unit prices in Nigeria between 1980 and 2001 was conducted by Peter and Ralph (2008). The study shows that the Neural Network performed better in valuing housing units in Nigeria than the Multiple Regression Model.

Steven (2012) used samples of 46,467 residential properties from 1999 to 2005 to compare the accuracy of artificial neural networks with linear hedonic pricing models. The study found that ANN outperformed HPM in terms of price precision. Further, Limsombunchai et al. (2004) evaluated the hedonic model and artificial neural network model with respect to their price predictive abilities. 200 homes in Christchurch, New Zealand were chosen at random from the Harcourt website as the sample. A lot of variables were taken into account, such as the house size, age, type, number of bedrooms, bathrooms, and garages, as well as its geographic location and surrounding facilities. Empirical results support the potential of Artificial Neural Networks on house price prediction, although previous studies have commented on its black box nature and achieved different conclusions exhibited especially amidst different software applications (Zurada, et al., 2011 & Ge, et al., 2021). According to Peterson and Flanagan (2009), ANN is thought to be a low-cost approach that produces more reliable results when it comes to model misspecification.

Regression-based techniques are among the most widely used in the real estate industry despite having significant non-linearity problems (Peterson and Flanagan, 2009). This assertion is supported by Steven, (2012), which discovered that this technique exhibits great prediction accuracy in performance when compared to linear hedonic pricing models. Aminuddin and Maimun (2021) demonstrates that the incorporation of artificial neural networks (ANNs) can surmount the inadequacies of the prevailing hedonic pricing model in the prediction of the housing price index. According to Zurada et al. (2011), the ANN also produces noticeably less pricing errors, has higher pricing precision out-sample, and performs better when extrapolating from more volatile pricing situations.

However, the findings of some studies contradict the notion that ANN is better than HPM in predicting property price. In order to verify the assertions of Borst (1991) and Do and Grudnitski (1992) that the predictive performance of ANN is consistently better than HPM, Worzala, Lenk, and Silva (1995) examined the prediction accuracy of HPM and ANN in property valuations. However, it was discovered that ANN and HPM produced rather distinct outputs. Worzala et al. (1995) found similar results as Lenk, Worzala, and Silva (1997), McGreal et al. (1998), and McCluskey, McCord, Davis, Haran, and McIlhatton (2013), who claimed that ANN model is not always superior to HPM model in terms of prediction, the discrepancies in the results of the ANN property valuation studies may be explained by the type of the data that is accessible for usage in each individual real estate market (Lenk et al., 1997, Grover, 2016).

In a similar vein, a study by Worzala, Lenk, and Silva (1995) examined neural networks and their applicability to real estate appraisal. The results of the study, which was based on the sales of 288 homes in Fort Collins, Colorado, contradict the notion that neural network is a better tool for appraisal analysis. Furthermore, Worzala et al. (1995) discovered that significant difficulties were faced when implementing neural networks, including inconsistent results within packages, incoherent results between runs of the same package, and lengthy runs.

2.1 Hedonic Pricing Model

Property valuation research has a long history incorporating various approaches and advancements. A thorough description of HPM and the relationship between a utility-bearing commodity (in this case, real estate properties) and its qualities (property attributes) was given in the landmark work of Rosen (1974). Following this study, the HPM approach was used to model various real estate markets globally in order to assess the relative contribution of several property attribute classifications (structural, neighborhood, and locational) to the determination of property values (Chin & Chau, 2002).

HPM approach has used by several property markets across nations in the world: Ghana (Owusu-Ansah, 2012), Nigeria (Famuyiwa & Babawale, 2014), China (Jim & Chen, 2006), Hong Kong (Hui, Chau, Pun, & Law, 2007), the United States of America (Cebula, 2009), Northern Ireland (Adair, Berry, & McGreal, 1996), and Portugal (Canavarro, Caridad, & Ceular, 2010). Regression analysis is the foundation for HPM processing (Selim, 2009). The regression of a dependent variable over multiple independent variables is explained by multiple regression analysis as property values are influenced by multiple property attributes, this makes it appropriate for property price analysis (Chin & Chau, 2002).

The mathematical definitions of simple and multiple regression are provided in equations 1 and 2, respectively;

$$Y_i = \beta_0 + \beta_1 X_{li} + \varepsilon_i \qquad (1)$$

$$Y_i = \beta_0 + \beta_1 X_{li} + \beta_2\, X_{2i} + \cdots \ldots\ldots\ldots\ldots\ldots \beta_k X_{ki} + \varepsilon_i \qquad (2)$$

Where Y_i = predicted value β_0 regression constant

$\beta_1 \beta_2 \beta_3, , , \ldots\ldots\ldots \beta_k$, are referred to as the regression coefficients.

ε_i = random error

2.2 Artificial Neural Networks

A massively parallel collection of tiny processing units called an artificial neural network (ANN) may gather information from its surroundings and stores it in its connections. Additionally, Rojas (1996) and Gurney (2003) define ANN as Processing Elements (PE) and the learning method. An artificial neural network, according to Worzala, Lenk, and Silva (1995) is a model of artificial intelligence that mimics the way the human brain learns. In this model, the neutrons in the brain serve as the fundamental processing units that receive and transfer sensory data to numerous nervous system channels throughout the processing time.

Artificial Neural Networks (ANN) is an extremely sophisticated modeling technique that allows projection of high-level functions (Alzain, et al., 2022). A wide range of human activities can benefit from the application of artificial neural networks, particularly real estate valuation, where solutions for classification, control, and prediction are required (Limsombunchai, 2004, Ge, et al., 2021, Zhou, et al., 2018).

In a study comparing artificial neural networks and fuzzy logic techniques, Gowd, Jayasree, and Hegde (2018) state that an ANN is a computer model that is built based on biological neural networks. A group of artificial neurons that can communicate with one another is called an artificial neural network (ANN). Typically, an ANN modifies its structure based on the data it receives. An ANN must be created by adhering to a set of methodical procedures called learning rules.

There are three main components to these models:

i. The input data layer;
ii. The hidden layer(s), also known as the "black box"; and
iii. The output measure(s) layer, which contains the estimated values (s).

The hidden layer(s) contains both the transformation functions and the weighted summation functions. These two functions relate values to output measures (the sales price) from the input data (property qualities, number of bathrooms, house age, lot size, basement space, total area, number of fireplaces, and number of garages, for example). The weighted summation function in a feed-forward/back propagation neural network model is summarized in equation 3 and picture 1;

$$Y_j = \sum_j^n X_i W_{ij} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

For each of the j hidden layer nodes, X i is the input values, and W ij is the weights allocated to the input values.

Borst (1991) was the first to apply the ANN approach in the real estate industry. The study looked into the predicted accuracy of ANN technique in real estate appraisal. The study demonstrated that the ANN technique could generate trustworthy and accurate valuation estimations, which has contributed to its widespread adoption in the real estate industry (Taffese, 2006). Worldwide, it has been applied to property price modeling, e.g., in the US (Borst, 1995), UK (Wilson, Paris, Ware, & Jenkins, 2002), Ireland (McCluskey, 1996), Hong Kong (Lam, Yu, & Lam, 2008), Spain (Tabales, Ocerin, & Carmona, 2013), Italy (Morano, Tajani, & Torre, 2015), and so on.

Additionally, researchers contend that in order to overcome the drawbacks of the HPM approach, the ANN technique was developed for use in property assessment (Do & Grudnitski, 1992; Amri & Tularam, 2012).

3.0 Methodology

3.1 Input Variables and Data Samples

Nineteen (19) input variables were chosen for this study as factors that determine the value of residential properties. The variables were chosen based on data collected from previous researches and the criteria for tenant selection usually in practice by practicing estate surveying and valuation firms to determine the value of residential properties. The size, number of bedrooms, number of bathrooms, types of properties, number of floors, number of buildings, number of boy quarters, age, security, location, state of the property, accessibility, finishes, type of ceiling, type of window, type of paint, and type of roof were among the details gathered.

As a result, 3,079 records were retrieved from the database of estate surveyors and valuers. Nine (9) neighborhoods—Abule-Egba, Amuwo-Odofin, Egbeda, Agege, Lekki, Ikeja, Ikoyi, Ajah, and Victoria Island—were the areas from which the data was gathered. The author was able to gather sufficient information about completed property values even though the majority of the firms do not have operational property databanks. Four thousand pieces of data were obtained in all, but first, they were cleaned and pre-processed to remove any incomplete or missing information. 3.079 property information in total were deemed appropriate for analysis

The variables consist of numeric and nominal data as indicated in table 5;

3.2 Operationalization of Variables

The following variables have been identified for this study:

Table 5: Operationalization of variable

Variable	Variable Code	Measurement
Dependent Variable		
Market Value	*Mktval*	Actual Market Value of property in #
Independent Variable		
Property Size	*Pptysize*	Actual in square meters
Number of Bedroom	*Nobed*	Actual Number
Number of Toilet	*Notoilet*	Actual Number
Property Type	*Pptytype*	1- Detached: 2- Semi Detached, 3 – Duplex, 4 – Flat
Number of Floors	*Nofloors*	Actual Number
Number of Buildings	*Nobuild*	Actual Number
Number of Boys Quarters	*Boysq*	1 – Present; 0 – Not Present
Car park	*Carpark*	1- No car park; 2_ 1-2 Park; 3 – 3-4 Park
Age of Property	*PPTYAge*	Actual in Years
Security	*Sect*	1-Gates Estate: 2- Street Gate: 3-Private Security; 4 – None
Location	*Loctn*	1- High Income; 2- Medium Income: 3- Low Income
Condition of Property	*Condt*	1 – Poor; 2- Fair; 3- Good
Availability of facilities	*Faclt*	1 – Poor; 2- Fair; 3- Good
Proximity	*Proxmt*	1 – Close to main road; 2- Close to Bus stop; 3- Far Inside
Type of Finishes	*Finsh*	1 – Tiles; 2- Wooden Floor; 3- Granite/ Marble
Type of Ceiling	*Ceilg*	1 – POP; 2- Ceiling Boards; 3- PVC
Type of Window	*Windw*	1 – Glazed Aluminium; 2- Wooden; 3- Metal
Type of Painting	*Paintg*	1 – Satin; 2- Emulsion; 3- Textcote
Type of Roof	*Roff*	1 – Longspan; 2- Asbestors; 3- Corrugated iron

3.3 Model Development and Specification

The obtained dataset is divided into training and testing sets during the evaluation of the network in supervised training, a process also referred to as cross-validation (Arlot & Celisse, 2010).

3.1.1 Training Data

Weights and biases are updated based on targets and network output values using a training data set. The training data is used to build the model, and test/validation or holdout data is used to determine the accuracy of the model after it has been fitted. The network learns from historical data during the training phase (Khumprom & Yodo, 2019). The system can identify the kinds of correlations between the input data and the outputs, in this case, the features and attributes of residential properties form the inputs. It builds and executes a model that includes the relationship between the features and the output labels after the training phase. Based on distinct criteria, the trained network comprises mixed sorts of residential property types. To create a strong model in this study, 80% of the dataset was set aside for training.

3.1.2 Test Data

Can et al. (2019) state that the performance of the trained ANN and HPM is assessed using the test data. It is used to forecast the network's future performance and offers an unbiased way to measure performance using random indices. Test data are also utilized to evaluate the model's predicted accuracy. Performance indices must be computed using a test data set that was not used in the modeling in order to produce a trustworthy estimate of model performance with minimal variation (Ayouche et al., 2011). It is important to note that test data sizes differ among authors, with most academics classifying 10% to 20% of all data as test data and others noting that test data sizes can approach 25% (Ward Group, 1995). According to Kutner et al. (2005), the size and intended use of the model should be taken into consideration while selecting the testing sample. Thus, the test data for this study is 20% of the entire dataset. Additionally, a three-layer feedforward network was used to create the ANN model, and back propagation (BP), a commonly used training approach, was used to train the network (Mimis et al., 2013). The network implementation process made use of Phyton 3.5 version.

3.4 Methods of Measuring Accuracy

There is no single, most reliable way to gauge model forecast accuracy. Nonetheless, this study employed several commonly used metrics from the literature, including the Root Mean Square Error (RMSE), Coefficient of Determination (r2), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) (Zurada et al., 2011; McCluskey, McCord, Davis, Haran, & McIlhatton, 2013). Equations 4,5, 6, and 7 provide the formulae for estimating r2, MAE, MAPE, and RMSE, which have been found in the literature (Limsombunchai et al., 2004; Lin & Mohan, 2011).

$$r^2 = 1 - \frac{\sum_{i=1}^{n}(P_i - \acute{P}_i)^2}{\sum_{i=1}^{n}(P_i - \acute{P}_i)^2} \quad \text{...(4)}$$

$$MAE = \frac{1}{n}\sum_{i=1}(P_i - \acute{P}_i) \quad \text{..(5)}$$

$$MAPE = \frac{\sum_{i=1}^{n}\left(\frac{P_i - \acute{P}_i}{P_i}\right)}{n} \, x\, 100 \quad \text{...(6)}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}\left(P_i - \acute{P}_i\right)^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(7)$$

where n is the number of observations, Pi denotes the actual property price, Pi denotes the model's predicted property price, and P denotes the sample mean of the property prices.

4.0 Results and Discussions

The descriptive statistics of the characteristics of residential properties is presented in Table 2;

Table 2: Descriptive Statistics of The Characteristics of Residential Properties

Variable	Minimum	Maximum	Mean	Std. deviation
Market Value	4350000	98000000	29090475	19255011
size(sqm)	131.44	990.56	676.24	187.05
NoBed	2	6	3.05	0.3
Notoilet	2	7	3.17	0.45
ppty type	1	5	2.01	0.95
No of floors	1	3	1.95	0.46
No of buildings	1	3	1.82	0.66
Boys Quarters	1	2	1.75	0.43
car park	1	1	1	0
age of property	1	23	9.52	3.81
Security	1	3	2.34	0.72
Condition	1	3	2.56	0.51
availability of facilities	1	3	2.8	0.4
proximity	1	3	1.19	0.46
Finishes	1	2	1.09	0.28
Ceiling	1	3	1.79	0.94
Windows	2	2	2	0
Painting	0	3	1.11	0.33
Roof	1	2	1.95	0.22
Abule Egba	0	1	0.1	0.3
Amuwo Odofin	0	1	0.09	0.29
Egbeda	0	1	0.1	0.3
Agege	0	1	0.11	0.31
Lekki	0	1	0.11	0.31
Ikeja	0	1	0.12	0.33
Ikoyi	0	1	0.1	0.31
Ajah	0	1	0.09	0.28
Victoria Island	0	1	0.1	0.3

The outcomes of descriptive statistics for the characteristics of residential properties utilized in the Hedonic model are displayed in Table 2. After the missing data were eliminated, 3,079 observations remained, which were then used in the study. These 3,079 data, which included property assessment information, were taken from the files of estate surveying and valuation companies in the Lagos metropolis.

With respect to the market values of properties that were retrieved from nine (9) distinct locations in Lagos State—Abule-Egba, Amuwo-Odofin, Egbeda, Agege, Lekki, Ikeja, Ikoyi, Ajah, and Victoria Island—it was determined that the mean market value of residential property was N29,090,475 and that the minimum market value was N 4,350,000. The standard deviation is 19255011. The properties range in size from 131.44 square meters at the minimum to 990.56 square meters at the maximum, with a mean size of 676.24 square meters and a standard deviation of 187.05.

The bedroom count indicates that there are a minimum of 2 bedrooms and a maximum of 6 bedrooms, with a mean of 3.05 bedrooms. As a result, the number of toilets revealed that the minimum was two, the maximum was seven, and the mean was 3.17. The building's floor count ranged from 1 at the lowest to 3 at the highest, with a mean of 1.95. The table also revealed a mean of 1.82.

Reliability Test

Reliability and multicollinearity tests were performed to make sure the dataset was consistent and stable. Reliability is a measure of an instrument's degree of measurement accuracy (Grinnell, 2015). To ensure that there were no possible errors, every instrument was assessed prior to its official administration. Since the Cronbach Alpha Coefficient (ά) helps establish and demonstrate the consistency of respondents' responses with regard to each study concept, it was used in this study to ensure reliability or internal consistency.

According to Hair et al. (2010), genuine reliability is shown by a Cronbach Alpha number better than 0.70. The instrument utilized has a Cronbach Alpha value of 0.924, which is higher than the 0.70 acceptable level. This implies that the data acquired allows for the drawing of reliable conclusions.

The coefficient of determination, t value, probability and effect values are presented in Table 3;

Table 3: Standardized coefficients (Market Value)

Source	Value	T	Pr > |t|	Effect (exp(coeff.)
		Locational and Environmental Attributes		
size(sqm)	0.26	17.44	**< 0.0001*** **	1.29
NoBed	-0.02	-0.88	0.38	0.98
Notoilet	0.01	0.57	0.57	1.01
ppty type	-0.02	-1.87	**0.06***	**0.98**
No of floors	-0.01	-0.73	0.47	0.99
No of buildings	-0.02	-2.11	**0.04****	**0.98**
Boys Quarters	0.02	1.62	0.11	1.02
age of property	-0.01	-0.48	0.63	0.99
Security	**0.03**	**2.07**	**0.04****	**1.03**
Condition	-0.02	-1.49	0.14	0.98

availability of facilities	-0.01	-0.5	0.62	0.99
Proximity	0.01	0.64	0.52	1.01
Finishes	-0.01	-0.48	0.63	0.99
Ceiling	0	0.29	0.77	1.00
Painting	-0.01	-0.75	0.45	0.99
Roof	0.01	1.12	0.26	1.01
		LOCATION		
Abule Egba	-0.25	-48.36	**< 0.0001*** **	**0.77**
Amuwo Odofin	0.23	29.87	**< 0.0001*** **	**1.25**
Egbeda	-0.21	-34.25	**< 0.0001*** **	**0.81**
Agege	-0.21	-35.79	**< 0.0001*** **	**0.81**
Lekki	0.29	25.81	**< 0.0001*** **	**1.34**
Ikeja	0.47	41.21	**< 0.0001*** **	**1.60**
Ikoyi	0.06	1.73	**0.08***	**1.06**
Ajah	0.1	18.11	**< 0.0001*** **	**1.11**
Victoria Island	-0.07	-8.06	**< 0.0001*** **	**0.93**

As shown in Table 3, property size, property type, number of buildings, security have significant effects on the market prices of residential properties which indicates that a unit increase or decrease in these attributes will affect the prices of properties. Also, in Table 3 and figure 2, all the areas considered under location are statistically significant with properties located in Ikeja having a higher effect on market prices than other areas such as Abule Egba, Egbeda, Amuwo-Odofin, Agege, Lekki, Ikoyi, Ajah and Victoria Island. The effect of location on the prices of residential properties in Ikeja is more significant than other areas under review because Ikeja is the Capital city of Lagos State and central economic nerve of Lagos (Adegoke, 2013)

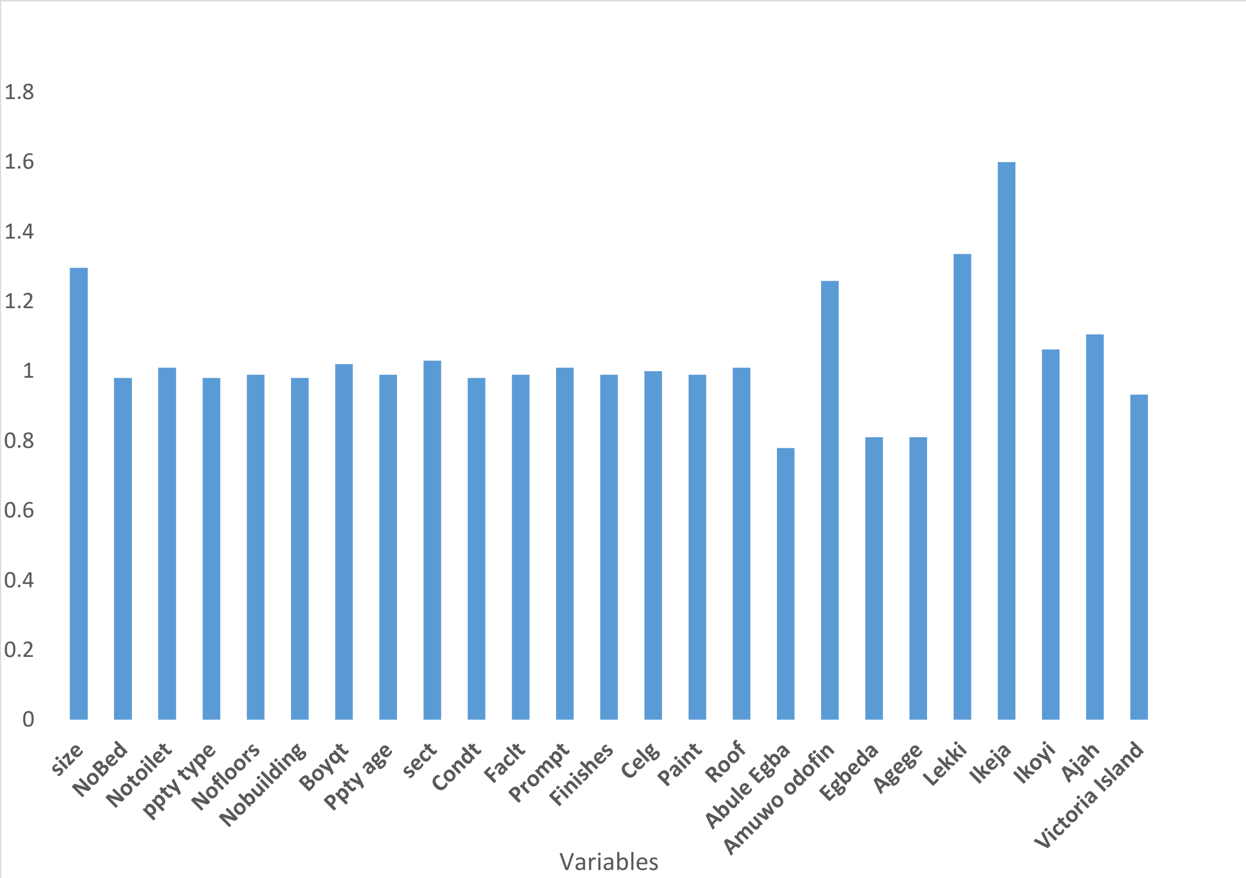

Figure 2: Contributions of Variables to Residential Properties Prices

*Where;**Size** is size of the building, **nobed** is number of bedroom, **notoilet** is number of toilet. **Ppty type** is property type, **nofloors** is number of floors, **nobuilding** is number of buildings, **boyqt** is boys quarters, **sect** is security, **condt** is condition of the property, **fadt** is facility available, **prompt** is proximity, **finishes** is type of finishes, **celg** is type of ceiling, **paint** is type of paint, and **roof** is type of roof.*

Several accuracy measurements are found in the literature (McCluskey et al., 2013). Only a handful of them, nevertheless, have been extensively employed in previous studies of a similar nature. These metrics include the coefficient of determination (r^2), mean absolute percentage error (MAPE), mean absolute error (MAE), and root mean square error (RMSE) (McCluskey et al., 2013). A lower value of these accuracy metrics indicates a solid model with outstanding predictive accuracy, with the exception of r2, which has a value closer to 1 (Zurada et al., 2011).

Table 4 presents a comparison of the training and testing performances of the ANN and HPM models, which were assessed using R^2, RMSE, MAPE, and MAE. The R^2 value that the ANN model generated using the testing dataset is 89%, which is more than the value generated by the HPM model. The degree of model fitness resulting from the change in property prices explained by the explanatory variables for the predictive performance of the two models is indicated by the R^2 value, which does not, however, represent the predictive power of the model (Adewusi and Oguntokun, 2021). MAE, RMSE and MAPE were equally used as shown in the table 4 to evaluate the predictive performance of the two models, ANN produces MAE value of 277, 896.35 and RMSE value of 689,982.39 which are lower than the one produced by HPM which indicates that ANN model generates lower error than HPM pointing to the conclusion that ANN model appears more reliable in predicting property prices. Even the MAPE value is higher in ANN when compared to HPM. The finding is in line with studies by Mimics et al. (2013) and Ge and Runeson (2004) which show that ANN models have a reliable predictive accuracy. Nonetheless, the results of McCluskey et al. (2013) and Worzala et al. (1997) are contrary to the conclusion of the present investigation.

Table 4: Comparative Performance of ANN and HPM in Residential Property Pricing.

	Metrics	ANN	HPM
	R^2	0.9996	0.6474
	MAE	163,172.35	3,824,665.67
	RMSE	298,276.02	11,411,795.16
Training	MAPE	0.51	12.59

	Metrics	ANN	HPM
	R^2	0.9986	0.6509
	MAE	227,896.35	4,031,581.08
	RMSE	689,982.39	11,430,383.18
Testing	MAPE	0.85	12.83

In addition to the accuracy metrics used in Table 4, margin of errors generated by each model was assessed. Hager and Lord (1985) and Hutchinson *et. al*. (1996), among others scholars, posited that a property valuation margin of error of between ± 5 and 10% of the actual property value is acceptable and that any error beyond this could be attributed to the values' negligence. The paper evaluated and compared the predicted estimates of the two models with the actual property values to see if there is a difference between the actual values and the predicted values of the models, this is done to assess how well each model satisfies international standards in the appraisal sector. It is important to remember that the valuation clients will accept an error margin of plus or minus 10% and within the range of plus or minus zero (Abidoye & Chan, 2018). Based on the results presented in Table 5 and figure 3, the ANN model predicted that 98.9% of the property values fall within the acceptable range of ±1 and ±10. In contrast, 69.6% (approximately 70%) of the HPM predicted values fall within the error range of ±1 and ±10. According to the results, the ANN model seems to be a more effective substitute method for HPM in property appraisal. This current finding is in line with the findings of Ge and Runeson (2004) and Mimics et al. (2013), whose reports assert that the ANN model can handle property valuation more reliably and accurately.

However, a few studies, including McCluskey et al. (2002) and Kontrinas and Verikas (2011), concluded that the ANN model does not consistently outperform HPM. It is important to note that the predictive power of HPM in this study is somewhat different to that of similar studies conducted in the same area (Lagos metropolis) by Abidoye and Chan (2018) and Ogunba (2014), the former found that the majority of the predicted property values of HPM are within plus or minus 20 and above and also claim that only 16.33% of the predicted property values have an error margin of plus or minus 1 and plus or minus 5 percent. While the latter study asserted that the results of the predictive ability of HPM indicated that approximately 67% of Nigerian valuations were inaccurate. In contrast, the current study which was carried out in the same Lagos metropolis show contrast results, as indicated in table 5 that about 70 percent of the HPM predicted property values fall within the industry accepted standard error margin of plus or minus 1 and plus or minus 10 percent (Brown et al., 1998). The possible reason for contrast in result from the same study area could be connected to the fact that larger dataset and variables were adopted in the current study than the ones used in the previous studies. HPM predictive ability may become more acceptable if larger dataset and more independent variables are used in the analysis (Abidoye and Chan, 2018).

Table 5: Valuation Accuracy Level Achieved by ANN and HPM Models

Range	**ANN**	**HPM**
± 1- ±5%	97.51	46.94
±6 - ± 10%	1.30	22.45
± 11- ±19%	0.33	14.29
± 20% and above	0.87	16.33
Total	100	100

Figure 3: Valuation Accuracy Achieved by ANN and HPM Models

5.0 Conclusion

The study assesses the comparative performance of ANN and HPM model in predicting residential property prices in the Lagos metropolitan residential property market. A total of 3,079 datasets encompassing property, neighborhood, and environmental-based attributes were obtained from the databases of 53 firms of Estate Surveyors and Valuers practicing in Lagos using 19 explanatory variables. For training and testing purposes, the dataset was split into 80% and 20% respectively. R^2, MAE, RMSE, and MAPE are among the performance measures adopted to determine the respective accuracy of the models. The results show that ANN model performed better than the HPM model. Also, based on the valuation accuracy achieved by the two models, the ANN model predicts property prices with 98 percent accuracy within the margin error range of ± 0 and ±10%, which is higher than about 70% (69.9%) achieved by HPM model. It is important to note that, contrary to claims made by Abidoye and Chan (2018) and Ogunba (2007), that 70% of HPM predictions for property values fell within ±20 and above margin of error making HPM not acceptable to valuation clients. The current study finds no evidence for the appallingly low performance of HPM. Naturally, its performance is likely to improve with improvements in data size and number of attributes (variables) . The finding of the study is limited by the data obtained for analysis in the study area in view of absence of databank for some real estate firms. According to Akinbogun (2014) Abidoye and Chan (2018), and Shridhur and Sathyanathans (2022), it might be challenging obtaining reliable data required for analysis in developing nations because the real estate market is opaque and primarily unstructured. Large-quality data may improve the models' performance in subsequent studies.

The predictive capacity techniques like Random Forest, gradient boosting, and regression-based models in predicting property prices may be examined in future researches. At large, the model provides information that can aid real estate professionals, investors, policymakers, and other stakeholders in decision making.

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