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Property Rental Value Classification Model: A Case of Osogbo, Osun State, Nigeria

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Abstract: Residential property rental value forecasting has an impact on property investment decision. This necessitates the need for a study to forecast residential property rental value considering all associated variables including presence of cultural sites in the study area. Data for the study were gathered from the record of recent lettings in the study area. For the purpose of precision, this study adopted three artificial intelligence models. These are artificial neural network, logistic regression and support vector machine as models of classifying the rental value of residential property in Osogbo. The study considered relevant input variables among which are distance to cultural site, age of building, state of exterior/interior of building. Findings from the study revealed that the three adopted forecasting models had over 80% of the forecasted properties correctly classified thus making the residential property rental forecasting very reliable. Also, it was established that, in the study area, distance from cultural site is the property attribute with the highest negative impact on rental value.

1. Introduction

Residential subsector of the real estate markets contributes significantly to national economy. This assertion was corroborated by Wilson et al. (2002) who established that real estate markets contributes significantly to the United Kingdom national economy. Previous studies have shown that a relationship exists between the property market and the economy (Dang and Low; 2011; Peng et al., 2008). In addition, empirical evidence has also demonstrated that changes in macro-economy have significant impact on residential property rental values and housing supply (Baharoglu, 1996; Zheng et al. 2012). However, though statistical data on the contribution of the Nigerian real estate market to national economy is lacking; there is no evidence to suggest that this sector is one of the main pillars of the economy.

Fluctuations in residential property rental values have an impact on investment decisions in new construction projects and the economy. This assertion was corroborated by Jiang et al. (2013) who linked the global financial crisis experienced in the 2000s to problems in the real estate sector. The cyclical behaviour of residential property rental value creates a negative impact on the economy as it leads to job losses, failure of construction business organisations and loss of productive capacity in the construction sector (Ofori et al., 1996; Lam and Oshodi, 2015; Liang and Cao, 2007). Chaphalkar and Sandbhor (2013) and Morano, Tajani and Torre (2014) reiterated the need for accurate residential property rental value prediction models hence, it has become increasing important to develop models that can accurately and reliably predict residential property rental value. This is vital for forward planning decision that can reduce uncertainties associated with residential property rental values.

Several academic studies focused on developing predictive models for residential property rental value. Stevenson and Mcgarth (2003),Tsolacos (2006) and Lam et al., (2008) are examples of such studies. Previous studies on residential property rental value forecasting can be categorized into two groups. These are property value by Lam et al., (2008) and rental price by Donovan and Butry (2011). The ability to reliably and accurately predict residential property rental value is important for real estate investors, government and relevant stakeholders. For instance, the real estate investors need reliable models so as to be able to evaluate investments in new purchases or development of new residential properties. In this study, three artificial intelligence modeling techniques, namely artificial neural network, regression and support vector machine were used to predict classifications of residential property rental values.

2. Literature Review

(i) Property attributes affecting residential *property rent*

Different scholars had adopted different property attributes for predicting rent. Abidoye and Chan (2017) adopting Artificial Neural Network considered the following property attributes in predicting residential property rental values in Lagos: number of bedrooms, number of toilets, number of bathrooms, property type, number of boys quarters, number or parking lots, age of building, number of floors, availability of security fence, availability of sea view and location of property. The study established that the predicting ability of the Artificial intelligence model is higher than other traditional valuation models.

Li and Li (1996) adopting Analytical Rent Model and Neural Network considered rent passing, number of bedrooms, cooking facilities, parking facilities, security, privacy, dwelling appearance, landscaping, outdoor lighting and support services, as attributes for consideration in rental forecast model in Townsville, Australia. The scholars adopted different intrinsic and extrinsic variables for developing property price, rental and value models.

Tabales, Ocerin and Carmona (2013) conducted research on property price forecasting in a medium sized city in South of Spain. The scholars classified property attributes considered in the study into internal and external attributes. The internal attributes were further classified into: basics, general, orientation and economics. The basic attributes are: area, bedrooms, bathrooms, complimentary bathroom, terrace, communications, wardrobes, garage, storage room and climatization. The general attributes are: number of floors, type of window, interior, kitchen furniture and reformation. The external attributes are classified into: general, extras and location. The general classifications are: building year, lift and laundry and the extras are: pool, tennis and garden. Location is all about the zone. The scholars considered large number of attributes, some of which are numerical.

Rossini (2000),in a study on residential property rental value forecasting in Australia, adopted land area, equivalent area, year built, sale date, zone, wall, roof, style, rooms, condition and improvements as attributes necessary for predicting residential property rental values. The scholar classified the attributes into major value determinant and value adjustment. The major value determinants are: land area, equivalent building area, year of construction and building style. Also, the value adjustment attributes are: land area, equivalent area, year built and conventional. The study revealed how practitioners can adopt property attributes for residential property rental value forecasting.

(ii) Residential property rental value prediction: A review of modelling techniques

Different forecasting models have been developed to forecast the property market. However, Hepsen and Vatansever (2011) broadly categorized forecasting models into multivariate forecasting models and univariate forecasting models. Multivariate forecasting models try to explain changes in a variable by references to the movements in the current or past values of other explanatory variables. Whereas, univariate forecasting models constitute a class of specifications in which one attempt to model or predict time series variables using only information contained in their own past values and current and possibly, past values of an error term(Brooks and Tsolacos, 2010; Bonner, 2009). Multi-variate forecasting models can be described as the resultant effect of all property attributes on property value. Univariate forecasting models are structured around trend analysis. Examples of uni-variate forecasting model are ARIMA models and SESMA models. Also examples of multi-variate models are: Artificial neural network, support vector machine and logistic regression.

Peng and So (2002) posited that Logistic regression is well suited for studying the relationship between a categorical or qualitative outcome variable and one or more variables. The scholars asserted further that logistic regression does not require that data be drawn from multivariate normal distribution with equal variances and co-variances for all variables hence it is less restrictive than linear discriminant function analysis for modelling categorical outcomes. The model can also be used for estimation, classification and forecasting.

NunezTabales, Caridad and Rey (2013) emphasized the usefulness of Artificial Neural Networkwhere there is enough statistical information. The scholars forecasted residential property value in a medium sized city in southern Spain using exogenous variables which include each dwelling's external and internal data (both numerical and qualitative) and its surrounding. Alternative models were estimated for several time intervals, enabling the comparison of the effects of the rising prices during the bull market over the last decade. Sensitivity analysis of the model allows the evaluation of the influence of each exogenous variable considered in the study. Building area was identified as the most important variable that influenced value, followed by location index and common expenses.

Lam, Yu and Lam (2008) established that integration of entropy and artificial neural network can give desirable result in housing price forecasting. The study reviewed micro and macro factors that affect housing price. Also, an entropy-based rating and weighting model was presented with the aim of providing objectives and reasonable weighting of the considered variables. Then based on the key variables, the predictive ability of artificial neural network (ANNs) was examined. Various networks were designed to examine the performance of ANN towards different parameters. Different sample sizes and different sets of input variables, together with different net structures and net types were undertaken to test the accuracy of ANN. From the comparison of the results of the R squared, as well as the mean absolute errors, the authors found that ANN performed well in forecasting with smaller sample size and standard net type. Also, the overall result of the research revealed that integration of Entropy and Artificial Neural Network can serve as a desirable function in house price forecasting.

Al-Marwani (2014) forecasted residential property price considering types of residential properties. The study applied Geographical Information System (GIS) and socio-economic modelling and the study revealed that higher property prices were awarded to real estate with more green spaces, residents with higher disposable incomes, lower council tax bands, fewer tax benefits claimants, and better health services.

Jadevicius and Houston (2015), in a study that compared simple and complex property market forecasting models, asserted that vector auto-regression was among the best fitting models out of the five forecasting models considered. However, the study revealed that the accuracy of the model to forecast out-of-sample data was poorer than some less complex models and that the adoption of a model is not a function of types of data available, quality of data, expertise on adopted tools and the precision level of the tools.

Significance of residential property rental value prediction model

Property price forecasting has been at point of extensive research and empirical analysis over the decades (Chaplin 1998; 1999, Stevenson and Mcgarth, 2003; Tsolacos, 2006). Barras (2009) posited that it primarily developed within the academia before it was adopted by the practitioners. Rinclumphi et al., (2012) found that property price usually comprises of physical, economic, location, environment and branding characteristics. The scholars explained further that these characteristics and many more make it cumbersome to evaluate the exact value of properties using conventional methods. However, residential property rental price prediction model makes it possible to forecast the impact of each of these characteristics on residential property value and consequently make property valuation less cumbersome.

Chaphalkar and Sandbhor (2013) emphasized the need for prediction models as a means of reducing the inaccuracies that characterized the traditional methods of valuation. The scholars also attributed the development of property price prediction models to the level of sophistication expected from users of property valuation. Studies (Ogunba, 1997; Babawale, 2008; Ayedun, 2009 and Oyedeji and Sodiya, 2016) in Nigeria have shown high level of inaccuracy in property valuation thus confirming the need for innovative valuation techniques to reduce valuation inaccuracy and variance in assets' valuation in Nigeria.
Previous studies have been identified artificial intelligence as innovative valuation models with high accuracy. Do and Grudnitski (1992) in a study conducted in United State of America established that ANN performs two times better than other valuation methods. Wong, So, and Hung (2002), in a study conducted in Hong Kong, posited that artificial intelligence models are good alternative appraisal techniques to the traditional approaches. Özkan, Yalpır, and Uygunol (2007) in a study conducted in Turkey, established that estimates from artificial intelligence models are close to actual market value of property. Lai (2011), in a study conducted in Taiwan, posited that Artificial Neural Network performs better than other appraisal techniques.

Methodology

A review of past studies on the built environment related problems identified the use of survey, experiment, literature survey, case-study, modelling, archival research and grounded theory (Laryea and Leiringer, 2012). Wing et al., (1998) affirmed that the choice of research method largely depended on the problem addressed by the study. In addressing the objectives of this study, two AI models: artificial neural network (ANN) and support vector machine (SVM) were compared with multiple ordinal logistic regressions (MOLR). The variable to be included in an Artificial Intelligence (AI) model are rarely known beforehand. However, because the present research is focused on how close a property is to a tourist site influence annual rental property value, the variables included in the model are limited to those related to property attributes as identified in literature (Lam et al., 2009). Measures of accuracy were used to evaluate and compare the predictive power of AI with other conventional models. The dataset used in development of the model were gathered from Oshogbo, Osun State, Nigeria.

Artificial Neural Network (ANN) – is a computational model based on the structure and functions of biological neural networks. Information that flows through the network affects the structure of ANN. ANNs is a non-linear statistical data modeling tools where the complex relationships between inputs and outputs are modeled. It has many advantages but one of the most recognised of these is the fact that it can actually learn from observing data sets.

Support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall. In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

Logistic regression is a statistical method for analysing a dataset in which there are one or more independent variables that determine an outcome. The outcome is measured with a dichotomous variable (in which there are only two possible outcomes). The goal of logistic regression is to find the best fitting (yet biologically reasonable) model to describe the relationship between the dichotomous characteristic of interest (dependent variable = response or outcome variable) and a set of independent (predictor or explanatory) variables. Logistic regression generates the coefficients (and its standard errors and significance levels) of a formula to predict a *logit transformation* of the probability of presence of the characteristic of interest.

Modeling Development Process

The first stage of the study involved identification of a list of property attributes often associated theoretically with residential property rental values. This phase of the study was carried out using a comprehensive literature search. Data on these property attributes were collected from property owners in the study area. This is because the property rental market in Osogbo, Osun State is largely controlled by the informal sector. These data were collected and stored in a computer for further analysis. The property attributes served as input and independent variables for the AI and MOLR models respectively. The use of similar input in the three models ensured that the predictive accuracy of the models was compared. At the second stage, the collected data was divided into training and test data sets. The independent dataset was used to evaluate the forecast accuracy. This means that the predictive capability of the three models was tested on a dataset that was not used during the model training process. Finally, the computation of the prediction error of the three models was carried out thus allowing for the comparison of the forecasting accuracy of the developed model.

The property attributes that influence the rental value of residential real estate properties have been identified in several studies (Li and Li, 1996 and Lam, Yu and Lam, 2008). Previous studies showed that the determinant of residential property values vary from one country to another (Li et al., 2011). Since the determinant of property values are unique and location specific, DFCS-Distance From Cultural Site, House Types, Age of Building, State of exterior, State of interior, Availability of water, Road Network, Availability of neighbourhood security and Rent p.a. were considered as the property attributes for the purpose of this study. The models were utilized to capture the relationship between these indicators and rental property values (output). The rental values of the residential properties have been classified into four groups (less than ₦50,000 p.a.; between ₦51,000 and ₦100,000 p.a.; between ₦101,000 and ₦200,000 p. a.; and between ₦201,000 and ₦300,000 p.a.).

Results and Discussion

Table 1: Showing property price classification by AI models

AI Models	Correctly classified %	Correctly Classified Frequency	Incorrectly Classified %	Incorrectly Classified Frequency	RMSE
ANN	89	148	10.30	17	0.1875
SVM(C1)	87.27	144	12.73	21	0.3284
SVM(C2)	89.70	148	10.30	17	0.3253
Logistic Regression	86.06	142	13.94	23	0.2112

Source: Artificial Intelligence models analysis

(i) The application of Artificial Neural Network showed that 89.70% of the analysed data were correctly classified which translates into 148 correctly classified data with 17 incorrectly analysed data. The Root Mean Square Error (RMSE) of the Artificial Neural Network model was 0.1875 thus translating into 18.75%

(ii) Support Vector Machine with a Slack variable of C = 1 has 87.27% of the analysed data correctly classified. This translates into 144 correctly classified data with 21 incorrectly classified data. The RMSE of Support Vector Machine with Slack variable of C=1 as 0.3284 translates into 32.84%.

(iii) Support Vector Machine with a Slack variable of C= 2 has 89.70% of the analysed data correctly classified. This also translates into 148 correctly classified data with 17 incorrectly classified data. The RMSE of Support Vector Machine with Slack Variable C= 2 is 0.3253 which translates into 32.53%.

(iv) The Logistic Regression has 86.06% correctly classified data translating into 142 correctly classified data with 23 incorrectly classified data. The RMSE of Logistic Regression is 0.2112 which translates into 21.12%.

The study showed that the errors associated with classifications are relatively low except the RMSE of the Support Vector Machine that is above 30%. These classifications can therefore be adopted for predicting residential rental property value in the study area. Also, ANN has the highest predictive capability among the three artificial intelligence models.

Confusion matrix of the artificial intelligence models

(a) Confusion Matrix of ANN of this study is:

a	b	c	d	
57	4	0	0	a
2	52	1	0	b
0	2	28	3	c
0	0	5	11	d

Based on the ANN classifications, 61 houses fell within the zero to ₦50, 000 annual rental value range. Out of these 61 houses, rental values of 57 houses were correctly classified. Also, 55 houses were within the ₦51,000 and ₦100,000 annual rental value group, out of which 52 houses were correctly classified. Furthermore, 33 houses fell within the rental price range of ₦101,000 and ₦200,000 p.a. out of which 28 houses were correctly classified in terms of rental value. Finally, 16 houses were categorized in the ₦201,000 and ₦300,000 annual rental value range, out of which 11 houses were correctly classified. It can therefore be inferred, that based on the property attributes considered, the incorrectly classified houses had their rental values either overvalued or undervalued by the landlords or their estate agents.

(b) Confusion Matrix of SVM 1 C = 1

a	b	c	d	
55	6	0	0	a
4	51	0	0	b
0	2	26	5	c
0	0	4	12	d

Based on SVM1 with Slacked variable C=1, rental values of 61 houses were within the zero and ₦50,000 range with 55 houses being correctly classified. Also, 55 houses were categorized between the ₦51,000 and ₦100,000 annual rental value range, out of which 51 houses had their rental value correctly classified and 4 houses have their rental value incorrectly classified. Furthermore, within ₦101,000 and ₦200,000 annual rental value range, 26 houses have their rents correctly classified, and 7 houses have their rents incorrectly classified. Finally, 16 houses falls within the ₦201, 000 and ₦300, 000 rental value range with 12 houses correctly classified and 4 houses incorrectly classified.

(c) Confusion Matrix of SVM 2 C = 2

a	b	c	d	
57	4	0	0	a
4	51	0	0	b
0	2	27	4	c
0	0	3	13	d

From the SVM2 with Slacked variable = 2, 61 houses fell within Confusion Matrix of zero and ₦50,000 annual rental value range, out of which 57 houses were correctly classified and 4 houses are incorrectly classified. Also, 55 houses were classified in the ₦51, 000 and ₦100, 000 annual rental value range and 51 houses were correctly classified and 4 houses were incorrectly classified. Furthermore, 33 houses were within the ₦101, 000 and ₦200, 000 annual rental value range, out of which 6 houses have their rental values incorrectly classified. Finally, 16 houses were classified within the ₦201, 000 and ₦300, 000 annual rental value ranges. 3 houses out of the 16 are incorrectly classified and 13 houses are correctly classified.

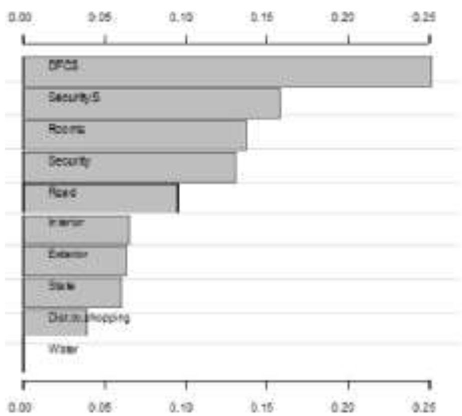
(d) Confusion Matrix of Logistic Regression

a	b	c	d	
57	4	0	0	a
6	46	3	0	b
0	1	27	5	c
0	0	4	12	d

From the logistic regression, 61 houses fell within the zero and₦51, 000 rental value p.a., 57 houses out of these 61 are correctly classified. Also, 49 houses fells within the ₦51, 000 and ₦100, 000 price range p.a., 46 houses out the 49 are correctly classified. Furthermore, 33 houses were within annual rental price range of ₦101, 000 and ₦200, 000 with 27 houses out of these 33 correctly classified. Finally, 16 houses were within the price range of ₦201, 000 and ₦300, 000 p.a. with 4 out of the 16 houses incorrectly classified.

Sensitivity Analysis of Property Attributes

Fig 1: Importance of property attributes in the artificial intteligence models



After using the three artificial intelligence models (Artificial Neural Network, Support Vehicle Machine and Logistic Regression) to classify residential property rental value according to property attributes developed for prediction, a sensitivity analysis was carried out. Sensitivity analysis is a technique used to extract additional information on the importance of each independent variable in predicting the dependent variable in machine-learning models (Cortez, Cerdeira, Almeida, Matos & Reis, 2009; Tinoco, Correia & Cortez, 2011). Figure 1 shows the importance attributed by the property attributes considered in the study. As can be seen from the figure, it is evident that the most influential input property attributes is distance from cultural site, followed by neighbourhood security. The neighbourhood security attribute can also be linked to the ritualistic activities going on in the cultural site. The sensitivity analysis revealed that distance from the cultural site is the most important property attribute that influence residential property value in the study area.

Conclusion

In the face of uncertainty that characterises property price forecast, it becomes imperative to adopt different advanced forecasting tools to predict annual property rentals hence the adoption of the three artificial intelligence models for the forecast of annual residential property rental value in Osogbo in this study. The study showed that adopting the three models would ensure that a larger percentage of the considered variables would be correctly classified. In addition, the sensitivity analysis of the property attributes employed in the study revealed that distance from cultural site has the highest impact on residential property rental value.

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