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Forecasting Rental Values of Residential Properties: A Neural Network Model Approach

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Abstract. The current study intends to use the neural network (NN) algorithm for modelling and forecasting of rental values of residential properties located in Cape Town, South Africa. Data relating to property attributes and its rental value were collected. Neural network algorithm was applied in this study. The collected data was divided into two parts. The first part was used for the development of the model. Subsequently, the developed model was used to generate the forecast of rental values of residential properties. For the second part of the data, the accuracy of the model was evaluated by comparing the predicted class and actual class. Experimental results gave an accuracy of 66.67% for the test dataset. It was also found that floor area has the most significant impact on the rental value of residential properties within the study area. This study demonstrates that the neural network algorithm could be applied to real-world investigations focused on prediction of rental values of residential properties.

Keywords: Classification, Forecasting, Modelling, Property economics, Rental value

1 Introduction

The importance of prediction of rental values of residential properties has been a subject of several investigations in the field of property economics. The significance of property values stems from the fact that it influences decisions related to real estate investment [1]. However, inaccuracies in property values have been widely reported in the literature, and it is a subject of international debates [2] Also, Jiang et al. [3] assert that the global financial crisis of 2007 has been linked to the events in the US property market. Based on the information presented previously, it is evident that the reliability of the estimate of the value of a property is essential to all stakeholders (private investors and government, among others).

In a bid to develop reliable models for forecasting of the rental value of residential properties, several investigations have been carried out. The modelling techniques used to generate the forecast of the value of residential properties include traditional multiple regression, neural network and support vector machine, among others [1],[4] Comparative analysis has shown that non-linear models (such as neural network and support vector machine) tend to outperform linear models (multiple regression) when considering predictive accuracy and reliability of forecasts [1], [5]. This finding reported in previous research has led to calls for a shift in methods used for estimating property values.

Several studies have evaluated the effects of several variables on values of properties in the South African real estate market. Du Preez and Sale [6] used regression to examine the impact of proximity to low-cost housing development on property values in Nelson Mandela Bay. It was found that the presence of railway stations had a positive influence on the values of commercial properties [7]. Yacim and Boshoff [8] developed models for prediction of the sale value of residential properties using the neural network and regression models. It is now well established that property attributes (location, structural and neighbourhood) have an impact on the value of properties [1], [9]. However, the influence of these attributes on rental values of residential properties in South Africa has remained unclear. The current study seeks to develop models for forecasting of the rental value of residential properties in South African using the neural network algorithm. To achieve this aim, the study addresses two primary objectives: (1) To examine the efficacy of using neural network algorithm for modelling and forecasting of rental values of residential properties and (2) To evaluate the impact of attributes of residential properties on its value.

2 Literature Review

A considerable amount of literature has been published on modelling and forecasting of rental values of residential properties. These studies have majorly examined the impact of property attributes on its value. These attributes have been classified by Chin and Chau [10] into three main groups namely neighbourhood, locational and structural. Forecast models have been developed to understand the effect of these attributes on the rental value of residential properties in different parts of the world. For example, Zambrano-Monserrate [11] demonstrated that the type of water supply, distance to central park and waste disposal have an impact on rental values of residential buildings in Ecuador. Similarly, Also, Hoshino and Kuriyama [12] reported that the distance to green areas has an impact on rental values of single-room dwellings in Tokyo, Japan. However, it has a negative impact if the building is within a radius of 1,000 meters. Flood risks have a significant impact on rental values of residential properties in Germany [13]. The findings from these studies show that the impact of these attributes on rental prices of residential properties varies from country to country. Therefore, the study reported in this paper aims to develop a model for forecasting of rental values of residential properties in Cape Town, South Africa. Also, sensitivity analysis would be used to examine the impact of the attributes of residential properties on its rental value.

3 Research Methodology

3.1 Overview

In the past, researchers have utilised the hedonic price model (i.e. regression) to predict the value of residential properties [5] [11]. However, the results of recent studies have shown that nonlinear models (such as Neural Network) tend to generate a better forecast of property value when compared with linear regression model [1]. One advantage of the neural network algorithm is that it can capture the nonlinear relationship which exists between residential property and its attributes. Thus, this study adopted the neural network algorithm in modelling and forecasting of the rental value of residential homes in Cape Town, South Africa.

3.2 Results

Data mining models (such as a neural network) are applied to two types of forecasting problems: (i) regression and (ii) classification. Classification problems refer to cases where the output variable is categorical. In contrast, the output variable is continuous for predicting problems referred to as regression. In the present study, the output variable (i.e. rent paid on a monthly basis) is partitioned into three groups (less than 15000 South African Rands, between 15,001 and 30,000 South African Rands, and Over 30,001 South African Rands). Classification models have been widely used in various disciplines, such as medicine [14] and finance [14] among others. The effectiveness of classification models is rarely exploited in the field of property economics. The neural network model utilised in this study is described in the next section.

3.3 Model Validation

In this study, a three-layer feedforward neural network (NN) model was applied to forecasting of the rental value of residential properties. NN model is inspired by the human brain. The NN model is made up of interconnected neurons whose functioning is similar to the human brain. The neurons in the NN model are calibrated during the learning phase. The final forecast computed by the model is mainly dependent on the initial weights of the neurons. To reduce the variations in the final forecast from the NN model due to randomisation, an ensemble of NNs was applied in this study. The final prediction from each NN model was averaged following the suggestion of Hastie et al. [16]. The architecture of the NN model is 12-H-1. The input layer has 12 neurons (i.e. 12 independent variables). The number of nodes in the hidden layer (H) is the only parameter of the artificial neural network (ANN) model that was tuned using the grid search algorithm. The output layer (neuron) of the NN model is rental value.

The predictive experiments were carried out using the R-programming [17] and rminer package, which facilitates application of artificial intelligence models (such as ANN) to real-world problems [18]. The process of developing predictive models entails two important phases: model estimation and model validation. The NN model was estimated by capturing the relationship between the 10 independent variables and rental value. To validate the model, the collected data was divided into two groups (i.e. training and test data set). Zhang, Patuwo, and Hu [19] mentioned that the ratio for training and test data set in previous studies include 90:10; 80:20 and 70:30, respectively. For this study, the collected data were randomly divided into two groups based on 70% and 30%. Thus, 70% of the data was used to develop the neural network model, while the remaining 30% was used to evaluate the predictive accuracy of the developed model.

3.4 Data Collection and Pre-processing

Evidence shows that the listing prices of residential properties tend to provide a realistic estimate of its value [20] when compared to transaction data. In this study, listed rental values were retrieved from a reliable source (www.property24.com). At the end of the data collection phase, data on 225 rental values of residential properties in Cape Town was retrieved. The data was pre-processed and cleaned to ensure that incomplete entries were excluded. At the end of the cleaning process, 101 observations remained, and this data was used for the development of the neural network model.

Table 1. Table captions should be placed above the tables

VN	Variable	Definition of variable
BE	Number of bedrooms	Numeric values of 1, 2, 3, 4, …
BA	Number of bathrooms	Numeric values of 1, 2, 3, 4, …
PA	Parking type	Classified into three groups (covered, open, none)
PA_S	Number of car park space	Numeric values of 0,1, 2, 3, …
D	Dining room	Numeric values of 0,1, 2, 3, …
L	Lounge	Numeric values of 0,1, 2, 3, …
B	Balcony	Binary values of 0 and 1
K	Kitchen	Binary values of 0 and 1
PO	Swimming pool	Binary values of 0 and 1
FA	Floor area (in Sq. meters	Numeric values of 0,1, 2, 3, …
F	Furnished	Classified into two groups (yes and no)
S	Services	Classified into two groups (yes and no)
	Output variable	
R	Monthly rental value (in South African Rands)	Classified into three groups (less than 15000, between 15,001 and 30,000, and Over 30,001)

Note: VN = Variable name

4 Model Performance and Sensitivity Analysis

4.1 Model performance

The neural network model was used for forecasting of the categorical rental values of residential properties in Cape Town, South Africa. For the computational experiment, the neural network model was developed using the 71 data set (i.e. training data). The test data set (30 observations) was then used to verify and evaluate the predictive performance of the developed neural network model. For classification problems, the predictive performance of the developed model is evaluated based on the percentage of "correctly classified" and "incorrectly classified". This value ranges between 0% and 100% [21]. Generally, a value close to 100% indicates that the model can correctly classify all the test data set.

The results from model validation (i.e. prediction of the test dataset using the trained neural network model) are summarised and presented in Table 4.1. The overall predictive accuracy of the neural network model is 66.67%. Also, 50% of A class were incorrectly predicted as B (6 out of the 12 cases were incorrect).

Table 2: Summary of model validation

Observed	Predicted			Accuracy (%)
	A	B	C	
A	6	6	0	50.00
B	1	12	2	80.00
C	0	1	2	66.67
			Overall	66.67

4.2 Sensitivity Analysis

The output of the ANN models does not contain coefficients or t-values like the hedonic price model. This outcome makes it difficult to establish the impact of each attribute of a residential property on its rental value. Based on this, neural network models are often referred to as "black box" techniques. Cortez and Embrechts [22] developed sensitivity analysis as a technique to be used for visualising the impact of independent variables on a predicted variable in black box models. In the present study, a sensitivity analysis was used to evaluate the influence of property attributes on its rental value. Figure 4.1 shows the relative importance of the 12 attributes used in developing the neural network model. As can be seen from Figure 4.1, floor area (FA), balcony (B) and a number of bedrooms (BE) are the significant attributes affecting the rental value of residential properties in Cape Town, South Africa.

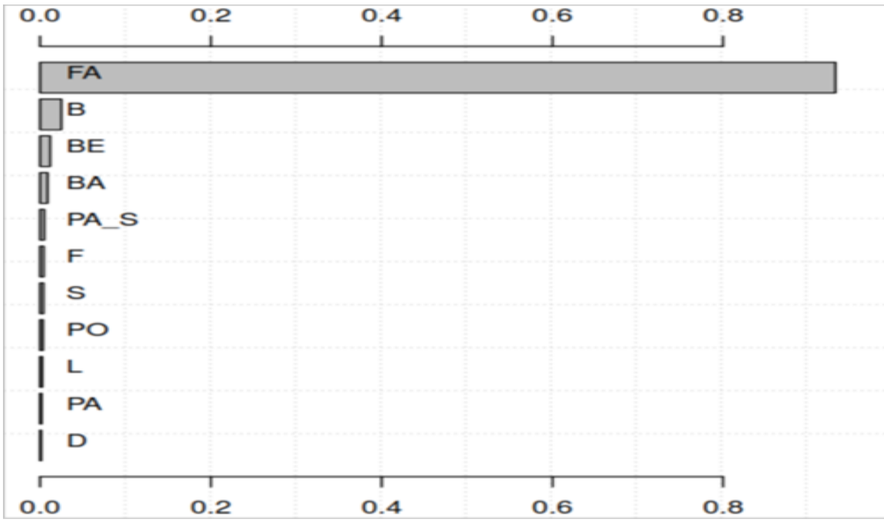

Fig. 1. Relative Importance of the Attributes of Residential Properties

5 Discussion

As mentioned in the literature review, the impact of attributes of a residential property on its value tends to vary from country to country. With respect to the first research question, it was found that the neural network model can be used for prediction of rental values of residential properties. Also, floor area has a significant impact on the rental value of residential properties located within the study area. The result of this study shows that the presence of kitchen did not affect the rental value of residential properties. A possible explanation for this finding could be attributed to the availability of kitchen in all the residential properties sampled in this study.

Consistent with the literature, this research found that the attributes of the residential property are good predictors of its value [1], [5] Abidoye and Chan [22] found that numbers of boy's quarters, number of bedrooms, sea view are important attributes that influence the value of residential properties in Lagos, Nigeria. Access to air conditioning, number of bedrooms, pool facilities, closeness to the beach, golf facilities and marketing to upscale travellers are significant on rental values of villas and cottages in Barbados [24] . However, it must be noted that the most critical attribute influencing the value of residential properties vary from market to market. For example, the number of rooms in the boys' quarters is reported as the most important attribute affecting the value of residential properties in Nigeria [23]

These findings suggest that the value of residential properties can be predicted using its attributes. Also, floor area remains as the main factor affecting the value of residential properties. These findings may help stakeholders (property developers, property economist, government and investors) to gain an understanding of attributes influencing the value of residential properties located in Cape Town, South Africa. Although the results of the predictions are disappointing, it is known that the size of datasets affects the forecasts generated by neural network models. A further study with a larger dataset is needed to validate the findings reported in this study.

6 Conclusion

The aim of this study was to use the neural network algorithm for modelling and forecasting of the rental value of residential properties. Floor area, balcony, and the number of bedrooms emerged as the most critical attributes affecting the rental value of residential properties in Cape Town, South Africa. In general, the findings of this investigation show that the neural network algorithm is a good modelling technique for forecasting the rental value of residential properties. These findings contribute in several ways to knowledge in the field of property economics concerning rental value of residential properties.

Despite the contribution of the findings of this study to the body of existing knowledge in property economic, the results are subject to certain limitations. For instance, the dataset used to develop the neural network model is considered to be small. Shin et al. [25] affirm that the quality of forecast generated by the neural network model depends on the size of data used for its development. However, it is important to reiterate that unavailability of data remains a challenge faced by researchers in the field of construction economics and property economics. Also, the scope of this study was limited to Cape Town, South Africa. In spite of these limitations, the study adds to the current knowledge on the impact of attributes of residential properties on its rental value. Alos, this South African study can be used to predict residential prices in other similar developing countries. Further work needs to be done to establish the influence of proximity to green areas (such as parks) on the rental value of residential properties. Also, future studies could be conducted to determine the effectiveness of using a neural network model for forecasting of rental values of commercial properties.

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