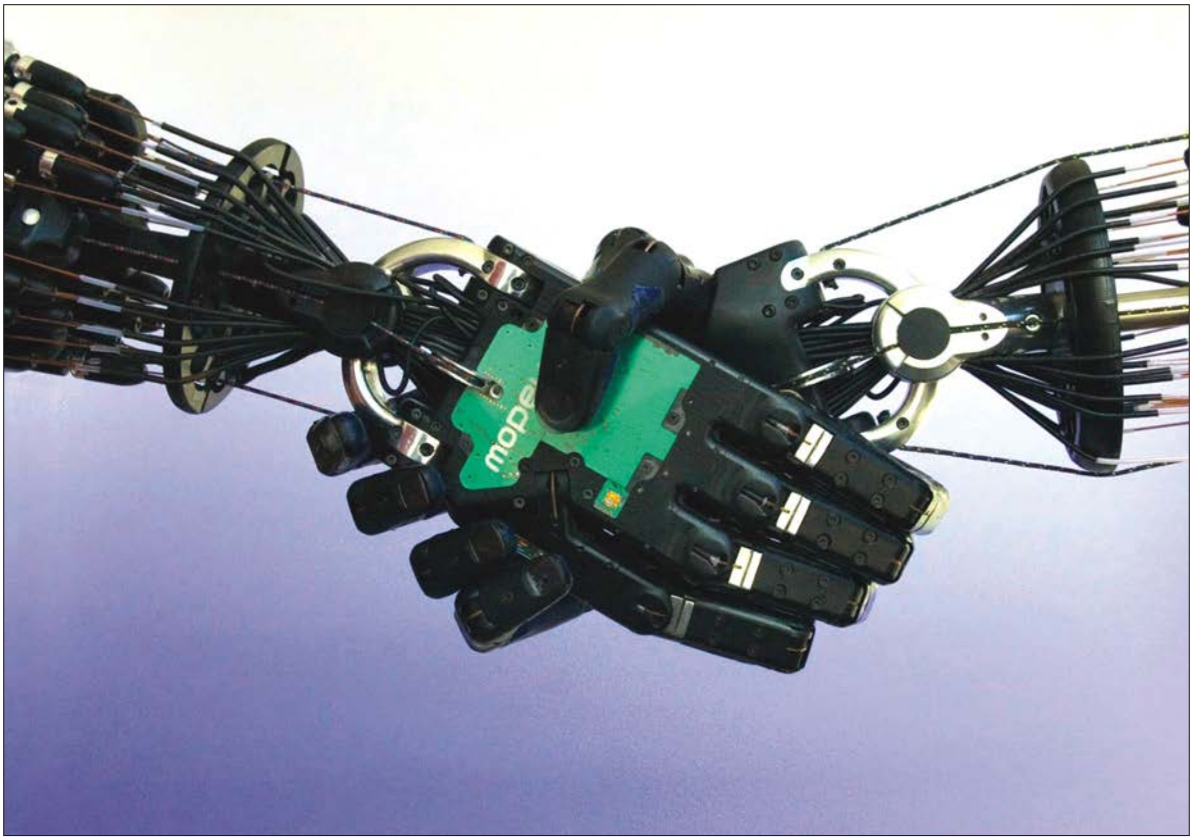

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Application of Neural Network in Evaluating Prices of Housing Units in Nigeria: A Preliminary Investigation*

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Abstract: The objective of the research is to compare the application of Brain Maker Neural Network (BMNN) and Multiple Regression Model (MRM) in the evaluation of housing unit prices in Nigeria when compared with the actual prices of sold houses in Nigeria between 1980 and 2001. The study revealed that Neural Network performed better than Multiple Regression Model in evaluating housing units in Nigeria. The research recommended that neural network should be used by stakeholders in the real estate sector in the evaluation and determination of housing unit prices in Nigeria in order to aid the fast emerging housing industry.

Key words: Neural network, predicting, real estate, housing units

INTRODUCTION

In the last decade, neural network, which is an area in artificial intelligence, has drawn the attention of researchers and analysts. Neural network has been used successfully in developed economies in predicting stock price movement and investment banking (Leung *et al*., 2001). The application has found its way into information theory, business, management, finance and real estate appraisal in most developed countries. Many studies in these countries have found encouraging results in its potential functions (Mackay, 2003; Waters *et al*., 2005) Specifically, the technique is now being used to appraise sales of property in the real estate industry in developed economy (Mackay, 2003). To the best of our knowledge, neural network has not been used in Nigeria before to appraise real estate properties. It will therefore be interesting to examine its relative predictive performance in evaluating real estate properties in Nigeria in the midst of high cost of housing units in Nigeria.

The main objective of this study is to test the predictive ability of neural network against the traditional method of regression analysis in the evaluation of real estate properties in Nigeria. The study focused on the major housing estates in Nigeria. They are: the housing estate in Abuja, Port Harcourt and Lagos where developers are concentrated. Abuja is located at the heart of Nigeria. The choice of Abuja is informed by the new status of the city. It is the new Federal capital of Nigeria. All the embassies in Nigeria are located in Abuja. It is a cosmopolitan city. All the Federal Ministries and the 36 States of the Federation have their liaison offices in Abuja. Abuja has an international airport, a world-class stadium. Indeed, it is one of the mega cities in Africa. Lagos was once the Federal Capital of Nigeria. It is a seaport and has an international Airport. It is still the economic nerve center of Nigeria. It is located in the South West of the country. Port Harcourt is an oil city and has a sea port. It is located in the Southern part of Nigeria, in the Niger Delta area of the country. Port Harcourt has assumed a new status and has witnessed an inflow of investors in the housing industry because of its

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relative peace and, away from the heat of the Niger-Delta crisis. It now houses multinational firms in the oil industry. The study covers the housing units built from January 1980 to December 2001. The period is considered enough periods to establish a pattern of valuation of real estate property in Nigeria.

MATERIALS AND METHODS

Data were collected from six major housing estate managers (realtors) in Abuja, three in Port Harcourt and three in Lagos. In all, the data were collected from twelve out of sixteen realtors in Nigeria. In all, 94 housing units were used for the study. Out of the 94 housing units, 50 housing units were from Abuja. The 50 housing units are made up of 20 4-bedroom units, 10 three-bedroom units and 10 two-bedroom units and 10 one-bedroom units.

Twenty-four housing units were used in Lagos, out of which are: 10 four-bedroom, 8 three-bedroom, 3 two-bedroom and 3 one-bedroom. In Port Harcourt we used 20 housing units in all, out of this are: 10 four-bedroom, 4 three-bedroom, 3 two-bedroom and 3 one-bedroom.

A total of 1,316 observations of the residential properties from the 94 housing units from the three cities were used for the study. The period covered is from 1980 to 2001. The property attributes available in the files of the realtors and used for the study are: the year the house was built, month the house was sold, land size (in square meters) availability of boreholes facilities, whether fenced, boy's quarters (Bq), neighborhood group (whether it is high density, medium density or low density), accessibility of property, number of masters bedroom, number of other rooms, number of bathrooms, recreation room, condition/desirability/usefulness (CDU), plumbing features and actual sales (in Naira). These are the attributes that the realtors used in arriving at their housing values. The value for each of the attributes is continuous except for boreholes, boy's quarters, whether fenced, neighborhood and accessibility. These five inputs were assigned values of 1 where the facilities exist and 0 where the facilities do not exist. And in the case of neighborhood, the values assigned are 1, where it is high density, 0.50, where it is medium density and 0 for low density.

The BMNN was used to train, test and run the data. It was used specifically because of its abilities and facilities to display network testing, training and change network size. From the connection menu, it gives the required number of hidden neurons of the inputs and the outputs. It allows the user to set the tolerance level and activate progress display. Above all, the BMNN is ideal for what if by changing values for the inputs and observing the change to predict output. The BMNN has a methodological approach to choosing the best settings. The BMNN has overcome the problems associated with the determination of data representation, model specification, number of hidden neurons and layers, number of neurons of each hidden layers, learning rate and number of training cycles, which evidently are needed to be able to obtain the best results in other nets.

We have used Microfit 4.0 by Pesaran and Pesaran (1997), an econometric software, to carry out the Multiple Regression Analysis (MRA) to predict the housing unit prices and generate the errors. Microfit is ideal to take care of the log of age and square footage of the housing units and perform the Ordinary Least Square Regression and correct for autocorrelation of the variables used for the study. We used the single equation static forecast model in using the housing data for the MRM. Both the prediction error values of the MRM and the predicted error values of BMNN are in the appendix. Forecast accuracy was estimated for the two models and compared with the actual sales errors, using Eviews, 4.1 (a Quantitative Micro Software, 2004). The result is reported in the results section.

Previous studies have shown the superiority of Neural Network (NN) over the naïve models like the rule of thumb and Multiple Regression Analysis (MRA) in predicting housing values (Do and

Grudnitski, 1992; Tsukuda and Baba, 1990; Huang *et al*., 1994; Lawrence, 1994). Other studies however, argued that NNs are not necessarily superior (Allen and Zumwalt, 1994; Worzala *et al*., 1995).

However, a major contention of the proponents of the use of the NN is in its applications in financial field and economics, where data-involving variables in non-linear relations are common. Granger (1991), for example, maintains that in financial and economics data, non-linear relationships are more likely to occur than linear relationships. Researchers have examined the application of neural network to financial market, where the non-linear properties of financial data create too many difficulties for traditional methods of analysis (Ormerod *et al*., 1991; Grudnitski and Osburn, 1993; Altman *et al*., 1994; Michie *et al*., 1994; Kaastra and Boyd, 1995; Swanson and White, 1995). Researchers have found for example, that age and square footage of living area has non-linear relationship with housing values (Grether and Mieskowszki, 1974; Jones *et al*., 1981; Do and Grudnitski, 1992; Goodman and Thibodeau, 1995) tested the accuracy of forecast produced by both multiple regression and neural network models. They used ten different out-of-sample data sets and analyzed the forecasting errors of each of the models. They found that the neural network outperformed the conventional methods in all cases.

Similar studies have been carried out to test the predictive ability of the neural network in business management and risk control (Brockett *et al*., 1994), in industrial management and production (Davis *et al*., 1994; Satake *et al*., 1994; Eberts and Habibi, 1995); in forecasting of stock price indexes and derivative securities (Hutchinson *et al*., 1994; Li, 1994; Shachmurove and Witkosha, 2001); in prediction of exchange rates (Kuan and Liu, 1995) and in discriminant analysis in predicting future bonds (Surkan and Singleton, 1990). Donalson *et al*. (1993) found that neural network models outperformed many traditional models, including the Autoregressive Conditionally Heteroskedastic, (ARCH) model, in removing leptokurtosis and symmetric and asymmetric heteroskedasticity from stock index data (Shachmurove and Witkosha, 2001). All these allow the neural network models to be utilized confidently as a deterministic tool in business and finance. The neural network models are revolutionalising statistic computing in many fields because of their ability, not only to learn autonomously, but also their ability to notice non-linear relationship in data (Rummelhart and McClellend, 1986; Wasserman, 1989; Maren *et al*., 1990; Hoptroff, 1993).

These studies generally support the use of neural network in various aspects of business finance and investment, including determining housing values.

However, there are other studies that do not support the claim of superiority of NN over MRA (Worzala *et al*., 1995). There are also other studies that were inconclusive. In the area of housing values, many studies have identified ways to improve the functional specifications of the MRA in predicting housing values. These studies used quadratic, cubic and quartic value for age and square footage in order to overcome the non-linearity relationship between housing values and these two variables (Grether and Mieszkowski, 1974; Jones *et al*., 1981; Do and Grudnitski, 1992). The present study therefore is focused on the comparative performance of neural network and the multiple regression analysis methods of valuing housing units in Nigeria.

RESULTS AND DISCUSSION

There are standard statistical methods of estimating forecast errors and accuracy. The most common measures are: Mean Absolute Percentage Error (MAPE), Adjusted Mean Absolute Percentage Error (AMAPE), Root Mean Squared Percentage Error (RMSPE) and Theil's Inequality Coefficient (U) (Ferries, 1998). The summary of the results of these four measurements of forecast accuracy were used to compare the predictive performances of BMNN and MRM with the actual as shown in the Table 1.

Table 1: Predictive Model of BMNN versus MRM

Measurement of forecast accuracy	BMNN (%)	MRM (%)	Actual
MAPE	2137.399	49959.52	2.94
AMAPE	2269.804	53054.35	1.07
RMSPE	3354.935	78418.14	1.71
THEL'S U	0.914435	0.996013	5.45

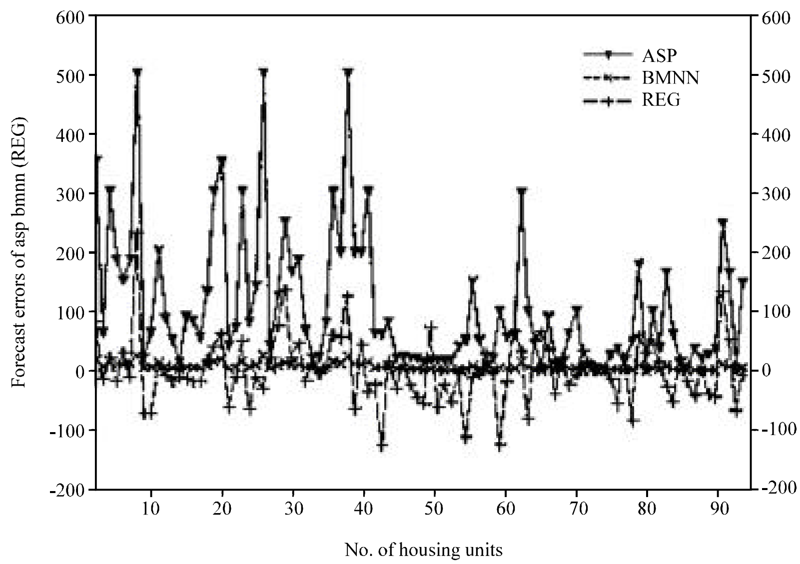

Fig. 1: Graph of ASP, BMNN and REG and their forecast errors

Using MAPE as an evaluation criterion to compare BMNN and MRM, the MRM value of 49959.52 is much higher than that of BMNN's value of 2137.399. The deficiency in using MAPE solely is its biased treatment. To correct for this deficiency, we employed the Adjusted Mean Absolute Percentage Error (AMAPE). MRM again has a value of 53054.35 as against a lower value of 2269.804 of BMNN.

The most common measure of forecast accuracy is the Root Mean Squared Percentage Error (RMSPE). The RMSPE value using BMNN is 3354.935 while that of the MRM is 78418.14%. This clearly shows that BMNN performs better than MRM using RMSPE.

The fourth procedure is the Theil's Inequality Coefficient (U). The comparisons are strictly between forecasts and values for a given time period, t. a perfect t fit would generate a U of zero and a poor fit, if U is approaching a value of 1. Using this criterion, BMNN performs better with a lesser value of 0.914435 as against the MRM value of 0.996013%. In addition, the results of the three methods are in Fig. 1.

Figure 1 shows the graph of the forecast errors of the actual, the regression and the neural network models, respectively.

From Fig. 1, the BMNN depicts an averagely stable trend. Both the actual sales price errors and the regression model show great disparity or fluctuations. The implication of this is that there is an unstable price pattern in the prices of housing units in Nigeria which needs to be addressed by the use of the neural network.

CONCLUSION

We have made a preliminary attempt to compare the predictive performance of BMNN and MRM models using 1,316 observations. Four forecast accuracy criteria were used in this study to evaluate the two models. These are MAPE, AMAPE, RMSPE and Theil's Inequality Coefficient (U). These large sample observations were used to clearly determine the predictive performance of the two models. The BMNN performs better than the MRM in all the four criteria. The BMNN model's performance can be attributed to the model being one of the latest nets that has overcome the limitations of other nets in use. For example, the problem of parameter setting; absence of methodological approach to choosing the best setting, the fact that many experiments must be conducted to determine the best data representation, model specification, the determination of number of hidden layers, number of neurons on each hidden layers, learning rate and number of training cycles have been overcome by BMNN. This has made it easy for fewer input variables outside the standard variables used by other nets and have produced good results in previous studies. The net has provision for expanded data usage. Given the level of growth and nature of housing industry in Nigeria, where most people strive to build their houses with little success, there is need to introduce a measure that would enhance proper valuation of housing units. However, the result could be different in developed markets where the housing industry has become a major sector of their capital markets and economies. And the fact that the sector has become a major sector these economies calls for tools that can enhance fair valuation in such economies.

A large part of the Nigerian population have no houses of their own and workers are forced to look towards prohibitive owner- occupier housing estates built by realtors in most of the urban cities in Nigeria. The present Government is gearing the economy towards private-driven economy. Against that background, the neural network as a means of evaluating houses would assist in ensuring a standardized, fair and just valuation of the housing units across the country.

The use of BMNN and other nets in evaluating housing units in Nigeria should be encouraged if the present civilian administration is to succeed in its housing agenda. In addition, the use of nets would attract both local and foreign investors to the fast growing and emerging housing sector of the Nigeria capital market.

APPENDIX

S. No.	MRM errors	BMNN errors	Actual	S. No.	MRM errors	BMNN errors	Actual
1	78.7856	83	350	21	-12.4132	-15.608	70
2	-17.7835	-23.305	60	22	48.5189	85.91	300
3	19.7662	88.94	300	23	-66.1384	5.665	80
4	-21.1063	-14.3	185	24	-14.6383	-51.43	140
5	27.5008	59.18	150	25	-32.5859	89.17	500
6	-13.9498	18.19	185	26	18.2772	-101.24	40
7	229.9584	107.6	500	27	71.3379	3.64	125
8	-74.5454	-58.517	18	28	133.9386	98.94	250
9	-73.9262	-64.76	60	29	19.5051	46.43	165
10	5.2039	11.48	200	30	42.8928	39.64	185
11	-8.9905	-6.911	85	31	-19.8	-37.57	65
12	-19.3634	-28.699	50	32	11.1107	-19.925	19.5
13	-13.5231	-49.289	10.5	33	-4.2252	-33.304	22
14	-15.5941	6.968	87	34	4.5464	-4.517	80
15	-21.1448	-29.67	82	35	56.8533	83.36	300
16	-21.0849	-50.09	52	36	51.8705	68.7	200
17	16.0305	5.12	130	37	122.6581	146.51	500
18	35.9611	38.75	300	38	-65.8774	-55.18	200
19	57.5885	68.03	350	39	41.7954	90.15	200
20	-63.1847	-40.881	40	40	-37.434	-72.4	300

Appendix: Continued

S. No.	MRM errors	BMNN errors	Actual	S. No.	MRM errors	BMNN errors	Actual
41	-24.2175	-29.123	60	68	23.0443	-42.82	12
42	-127.593	-52.03	60	69	-23.3211	19.24	60
43	15.1309	-92.48	80	70	-6.6283	-44.637	100
44	-30.0447	-66.161	21	71	33.9128	-44.168	8
45	8.7636	-73.699	23.5	72	11.3354	-59.971	7.5
46	-25.6996	-92.48	21	73	2.7484	-62.371	6
47	-45.4921	-67.608	21	74	3.8712	-32.61	3.6
48	-56.7536	-44.82	14	75	-12.0063	-83.42	27.3
49	72.2855	-24.592	18	76	-56.0462	-14.516	36
50	-62.7546	-14.591	17.5	77	23.4564	-55.85	18
51	-23.8055	-26.895	15.5	78	-82.4241	87.24	50
52	-54.054	-54.214	17.5	79	56.9292	-15.439	180
53	-7.1145	-92.33	40	80	32.067	6.634	3.5
54	-113.472	-93.79	50	81	51.3307	-46.457	100
55	-13.4845	-57.18	150	82	15.095	51.76	40
56	-5.9801	-14.091	50	83	-25.7768	1.423	165
57	28.4274	-14.304	8	84	-50.8371	-14.091	60
58	-2.1497	-94.82	21	85	20.9481	-24.412	12
59	-125.188	-28.305	100	86	-16.8989	-50.396	5.8
60	-19.858	-30.214	55	87	-39.6444	-87.883	38
61	65.4684	110.51	60	88	5.4594	-98.33	20
62	32.408	-5.97	300	89	-37.5012	-81.06	28
63	-81.3021	-32.735	100	90	-43.6354	83.56	38
64	48.7418	-88.214	45.6	91	133.9274	91.513	250
65	63.3601	29.505	6	92	52.9803	-25.243	165
66	35.0973	-66.85	90	93	-65.0641	-72.46	7
67	-39.1767	-45.244	11	94	-4.3447	-1289.71	150

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