Developing Machine Learning Prediction Models for Construction Material Prices in Nigeria

Ahmadu, H. A., Ibrahim, Y. M., Abdulrahman, R. S., Jibril, U. S. and Yamusa, M. A.

Department of Quantity Surveying, Ahmadu Bello University Zaria Nigeria

Ahmaduhassan@rocketmail.com, makarfi@gmail.com, ridwanshuayb2@gmail.com, jibrilusman21@gmail.com, yamusajf@yahoo.com

Abstract

This study aims to develop machine learning prediction models for construction materials susceptible to price fluctuations in Nigeria. Data relating to construction material price influencing factors and construction material prices were obtained from Nigerian Bureau of Statistics (NBS), Central Bank of Nigeria (CBN), and vendors. Making use of Python programming language on Spyder version 3.6 software, a combination of Back Propagation Neural Network (BPNN) and Autoencoder was utilised for data training/model development. The developed models' predictive performance was validated by comparing predicted and actual prices of building material prices using mean-square error (MSE). Results revealed that the developed Autoencoder-BPNN model had an accuracy ranging from 82.04% to 96.92% and was found to be the best for reinforcement. While the BPNN only model, on the other hand, had accuracy ranging from 92.87% to 98.69% and was found to be the best for steel and cement. The models are expected to assist both client quantity surveyors and contractors in coming up with more accurate estimates of construction material prices for efficient cash flow management of construction projects in Nigeria. The developed models put forward a new course for predicting future prices of construction materials most susceptible to price fluctuations in Nigeria.

Keywords: *construction materials, price, cost overrun, prediction, machine learning*

Introduction

Nigeria's infrastructure deficit has been and remains a major impediment to her economic growth. A leading rating agency reported that Nigeria's infrastructure gap is estimated at $3trn, six times its annual GDP (Moody's Investors Service, 2020). The World Bank (2021) reported that the construction industry accounts for between 3 to 8 per cent of the Gross Domestic Product (GDP) in developing countries.

Accordingly, the Nigerian Economic Sustainability Plan (2020) contain a programme expected to deliver up to 300,000 homes annually, with an average growth of 5.36% between 2017 and 2020 using both private and public investment. However, the increased inflation rate as well as the COVID-19 pandemic, severely affected the prices of construction materials, resulting in a very high cost of building materials and, consequently, poor actualisation of the plan.

Construction cost has always been a primary concern to project managers due to the fickle nature of building materials' prices (Mir, Kabir, Nasirzadeh & Khosravi, 2021). Fluctuations in prices of building materials are one of the major factors causing deviations from the initial estimated cost. Furthermore, these fluctuations are influenced by several factors, including market conditions, energy prices and macroeconomic variables. As a result, it becomes more difficult to predict the fluctuations in material prices owing to the uncertain nature of these influencing factors.

Several studies revealed that construction practitioners are incapable of predicting the future prices of building materials, particularly during economic instability (Shiha, Dorra & Nassar, 2020; Mir et al., 2021). This inability of practitioners to predict accurately the prices of building materials can more often than not lead to overestimation or underestimation of building material prices, which eventually may lead to cost and time overrun project abandonment, amongst other forms of project failure (Shiha, Dorra & Nassar, 2020). This clearly sign post a major concern that needs to be addressed because in a typical construction, materials take up to 50% of the total project cost (Alabi & Fapofunda, 2021).

Efforts towards predicting the fluctuation in building material prices have resulted in modelling using country-specific factors and, more importantly, using a variety of methodologies such as regression analysis, Holt-winters exponential smoothing, Vector error correction and Univariate ARIMA. More recently, in order to boost accuracy with increased forecasting period, efforts have gravitated towards using artificial neural networks to predict the fluctuations in building material prices (Wong & Ng, 2010; Shahandashti & Ashuri, 2016; Faghih & Kashani, 2018; Hwang, 2011; Shiha, Dorra & Nassar, 2020; Mir et al., 2021). Amongst these efforts include neural network models for the prediction of construction material prices using macroeconomic indicators (Shiha et al., 2020) and Mir et al., 2021).

In Nigeria, following the dire influence of inflation on construction material prices, Olatunji (2010) and Oba (2019) have assessed the impact of macro-economic factors on construction material prices and developed a model for predicting the future price of cement. However, these efforts result in suboptimal models, as several other construction materials susceptible to price fluctuations in Nigeria are yet to be modelled.

As the impact of macroeconomic indicators and other price fluctuation influencing factors on the economies of various countries differ, it is evident that existing building material price prediction models for materials susceptible to fluctuations are context and country-specific and cannot be used to predict construction material prices in Nigeria accurately. This study thus addressed how machine learning prediction models can be used to accurately predict the future prices of construction materials susceptible to price fluctuations in Nigeria.

Literature Review

Construction Materials

Construction materials or building materials can be used to develop any given construction project (Alabi and Fapohunda, 2021). Such materials include cement, sand, gravel, iron, bricks, and blocks. Akanni et al. (2014) opined that construction materials play an important role in building construction as they serve as the major input in developing construction projects. It has been reported that building materials take up to 50% of the total project cost (Alabi and Fapofunda, 2021).

As a result, fluctuation in the prices of building materials influences the rate of project execution as well as the ability to complete the project (Hasware et al., 2020; Windapo and Cattell, 2012). These fluctuations have become exacerbated by the fact that a contractor cannot meet the requirements of various aspects of construction work despite presenting the right offer before project execution.

Consequently, it has become necessary to identify materials whose prices change over the course of a project so as to predict materials' prices accurately. Although only a few literature clearly specify the materials susceptible to fluctuations, Table 1 shows the list of materials that previous studies have reported to be susceptible to price fluctuation. Price prediction models have been developed for these construction materials over the years and across various countries.

Although over twelve different materials have been used in several studies, materials such as cement, reinforcement, sand and gravel were the most reoccurring materials among researchers, as shown in Table 1. This clearly suggests that the prices of concrete materials fluctuate more than all other materials in construction projects. In addition, Shiha et al. (2020) stated that cement and reinforcement are the major construction materials. Similarly, Hassanein and Khalil (2006) reported that cement, reinforcement and bricks are the main material components in Egypt.

In line with the discussion above, Marzouk and Amin (2013) assessed materials that are susceptible to fluctuations. The study found reinforcement bars, steel, blocks, cement and aluminium to be the top five materials susceptible to fluctuations. Marzouk and Amin (2013) study has validated previous studies since at least one material from the top five materials found to be vulnerable to fluctuations in their study was mentioned in all previous studies.

Table 1: Construction Materials Susceptible to Price Fluctuation

S/N	MATERIALS	AUTHORS/YEAR										
		Alabi and Fapohunda, (2021)	Mir, Kabir, Nasirzadeh and Khosravi, (2021)	Musrat, Alaloul, Qureshi and Altaf (2020)	Shiha, Dorr and Nassar (2020)	Hasware, Baviskar, and Narwade, (2019)	Oba, (2019)	Elfahham (2019)	Suveka, and Priya, (2017)	Vinodhini and Velumani, (2015)	Akanni, Oke and Omotilewa (2014)	Marzouk and Amin (2013)
1	**Aggregate**					■		■			■	
2	**Aluminium**	■				■		■	■	■	■	■
3	**Asphalt**											
4	**Brick/Block**		■									
5	**Cement**	■						■			■	■
6	**Crush**				■		■			■		
7	**Sand**			■ ■		■ ■						
8	**Formwork**	■ ■		■ ■		■ ■					■	
9	**Reinforcement**	■	■	■	■	■		■				■ ■
10	**Wood**											

Factors Influencing Construction Material Prices

Determining the factors affecting the price of construction materials will help determine the causes of construction materials price fluctuations. Several studies have explored various factors that influence construction material prices (Kamaruddeen, Noor, & Wahi, 2020; Rajaprabha, Velumani, & Jayanthi, 2016; Akanni, Oke, & Omotilewa, 2014; Huan & Jianhua, 2013; Windapo & Cattell, 2012; Oladipo & Oni, 2012; Braden, 2009). Table 2 summarises these factors influencing construction material prices as identified by authors across a wide range of countries.

Table 2: Factors Influencing Construction Material Prices

S/No	Factors	Authors/Year	Country
1	Interest Rate	Oladipo and Oni (2012); Huan and Jianhua (2013); Kamaruddeen et al. (2020)	Nigeria, China, Malaysia
2	Inflation Rate	Oladipo and Oni (2012); Huan and Jianhua (2013); Danso and Obeng-Ahenkora (2018); Kamaruddeen et al. (2020)	Nigeria, China, Ghana, Malaysia
3	Exchange Rate	Oladipo and Oni (2012); Huan and Jianhua (2013); Akanni, et al. (2014); Kamaruddeen et al. (2020)	Nigeria, China, Malaysia
4	Money Supply	Akintoye et al. (1998); Ng et al. (2004); Ashuri et al. (2012)	United Kingdom, Hong Kong, United States
5	Gross Domestic Product (GDP)	Ng et al. (2004); Olatunji (2010)	Hong Kong, Nigeria
6	Consumer Price Index (CPI)	Ashuri et al. (2012); Cao et al. (2015); Ernest et al. (2019)	United States, Taiwan, Ghana
7	Lending Rate	Ng et al. (2004); Olatunji (2010); Cao et al. (2015)	Hong Kong, Nigeria, Taiwan
8	Producer Price Index (PPI)	Ashuri et al. (2012); Ernest et al. (2019)	United States, Ghana
9	Stock Market Indices	Ashuri et al. (2012); Cao et al. (2015)	United States, Taiwan
10	Monetary Policy	Huan and Jianhua (2013); Kamaruddeen et al. (2020);	China, Malaysia
11	Crude Oil Prices	Windapo and Cattell (2012); Akanni, Oke, and Omotilewa (2014); Danso and Obeng-Ahenkora (2018)	South Africa, Nigeria, Ghana

Existing Predictive Models

Several studies in the past have adopted time series analysis in developing models for forecasting construction costs. The models developed based on time-series analysis have been broadly classified into two. The first set of models is the univariate time series analysis. A popular example is the ARMA model promoted by Box and Jenkins (Box and Jenkins 1976). Other works that have forecasted construction costs using the ARMA or its generalisations, for instance, the ARIMA model, include Ashuri et al. (2012) and Wong et al. (2005).

However, the univariate time series models have been noted to take only the historical values of the variable under investigation into account (Xu and Moon 2013). The models fail to capture the basic change drivers and also fail to appraise the relationships between the dependent and independent variables (Fan et al., 2011). Hence, the time-series models are unsuitable for formulating policies and making decisions.

Moreover, the general applicability of the univariate time series analysis is on short-term forecasting, making it unsuitable for the long-term forecast of construction material prices (Jiang et al., 2013; Xu and Moon, 2013; Wong and Ng, 2010). The multivariate time series analysis is employed for the second model category. This has been applied in forecasting indices of construction costs (Shahandashti and Ashuri, 2015; Ashuri et al., 2012; Wong and Ng, 2010; Ng et al., 2000; Akintoye et al., 1998).

Xu and Moon (2013) developed a bivariate Vector Autoregression (VAR) model for forecasting indices of construction costs (Xu and Moon, 2013). Shahandashti and Ashuri (2016) employed a Vector Error Correction (VEC) model to predict the National Highway construction cost indices in the United States. Faghih and Kashani (2018) also used VEC to forecast the prices of construction materials.

Several authors have used Neural Networks in predicting cost index (Williams, 1994), construction costs (Hegazy and Ayed, 1998), final cost (Pewdum et al., 2009), duration (Pewdum et al., 2009), the impact of economic conditions on the Construction Cost Index (Cao et al., 2015); construction material prices (Issa, 2000; OuYang, Zhang & Hu, 2013; Shiha, Dorra & Nassar, 2020; Mir et al., 2021).

Methodology

To achieve the aim of the study, a quantitative approach was adopted where data was sourced and analysed to develop predictive models for construction material prices. The various steps taken to achieve the aim of this study are discussed in this section

Data Collection

The study used factors influencing construction material prices as predictors/explanatory variables for determining variations in construction material prices. Factors influencing construction material prices are statistics or readings that reveal the production or output of an economy, government, or sector. They often fluctuate, resulting in continuous changes in the prices of construction materials. Hence, the decision to be similar to several other previous studies makes use of them as predictors/explanatory variables in this study.

Over the years, several efforts have been made to study how various factors affect the cost of construction and tender price indices in several countries. It was found that every country's economic conditions are peculiar; thus, each country has a set of unique principal economic indicators affecting its construction market. For the purpose of this study, similar to Shiha et al. (2020), an extensive review of extant literature and availability of data formed the basis for the factors influencing construction material prices as well as construction materials considered for the construction material price model development.

Essentially, a total of twelve (12) construction material price influencing factors were considered for this study, namely Interest Rate, Inflation Rate, Exchange Rate, Money Supply, Gross Domestic Product (GDP), Consumer Price Index (CPI), Lending Rate, Producer Price Index (PPI), Stock Market Indices, Monetary Policy, Crude Oil Prices. Also, three (3) construction materials were considered for the study: steel trusses, reinforcement and Portland cement.

The Nigerian Bureau of Statistics (NBS), the Central Bank of Nigeria (CBN) as well as vendors were the main sources where data relating to both sets of variables (construction material price influencing factors and construction material prices) were obtained for this study. Similar to previous studies (Marzouk & Amin, 2013; Shiha et al., 2020), data retrieved from these sources spanned a period of 10 years (2012 to 2021). This period was used as it had numerous economic and political volatilities, which include the 2016 and 2020 economic recessions, the global economic crisis due to COVID-19, capital outflows, intensified risk aversions, low oil prices, and shrinking foreign remittances (World Bank Group, 2021). A total of 120 material price influencing factor data points were obtained within the study period (monthly data for ten years).

Model Development

The construction material price influencing factors and construction material price data were partitioned into training and testing. This is similar to Rafiei and Adeli's (2017) and Rafiei and Adeli (2018b) studies. The data partitioning was done in the ratio of 85:15 for training and testing, respectively. Thereafter, using the Python programming language on Spyder version 3.6 software, a combination of supervised and unsupervised learning tools were utilised for the data training/model development.

The combination of supervised and unsupervised learning tools addresses the requirement for extensive training data, thereby increasing the accuracy and performance of a predictive model (Rafiei & Adeli, 2018a; Shiha et al., 2020). For this study, the supervised learning tool used was a neural network, specifically, the Back Propagation Neural Network (BPNN). At the same time, the unsupervised learning tool used was Autoencoder. Table 4 summarises the network architectures, which capture the input layer, hidden layers, output layer, and the number of iterations for each network architecture.

Table 4: Summary of Network Architectures

Model	Input Layer	Hidden Layer 1	Hidden Layer 2	Hidden Layer 3	Output Layer	Number of Iterations
Autoencoder-BPNN	32	24	8	24	32	500
BPNN-only	64	32	8	NA	1	200

The Autoencoder is an unsupervised learning algorithm capable of discovering structure in a dataset. The Autoencoder constitutes layers of a neural network and learns through an iterative process. The layers function by simulating the learning pattern of the human brain's neural layers. They extract features via received perceptions and reconstruct them numerous times consecutively. The BPNN, on the other hand, fine-tunes the weights of the neural network by feeding a forward propagation error rate backwards through neural network layers. In this study, training the proposed algorithm started by using the Autoencoder to extract patterns from the dependent variables of the training dataset. The features are extracted in the output layer of the Autoencoder network and fed to train in the BPNN network. The output of the BPNN network is the building material prices. The network architecture of the Autoencoder is represented in Figure 1, while that of the BPNN is represented in Figure 2. The Autoencoder-BPNN model starts in Figure 1 and ends in Figure 2, where the output from Figure 1 serves as the input for Figure 2. For the BPNN-only model, it starts directly in Figure 2.

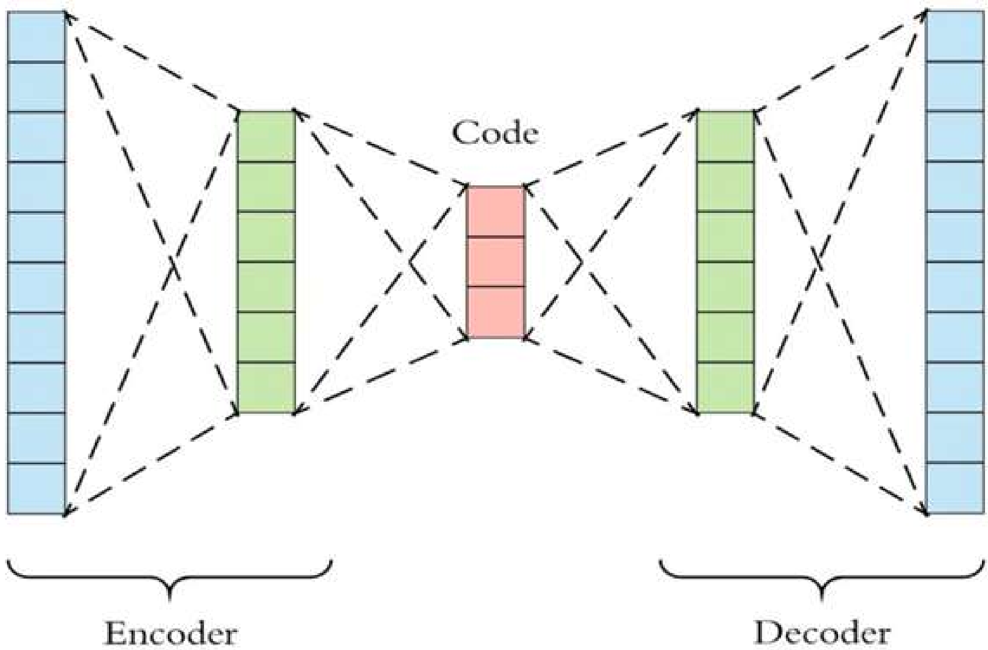

Figure 1: Autoencoder network architecture.

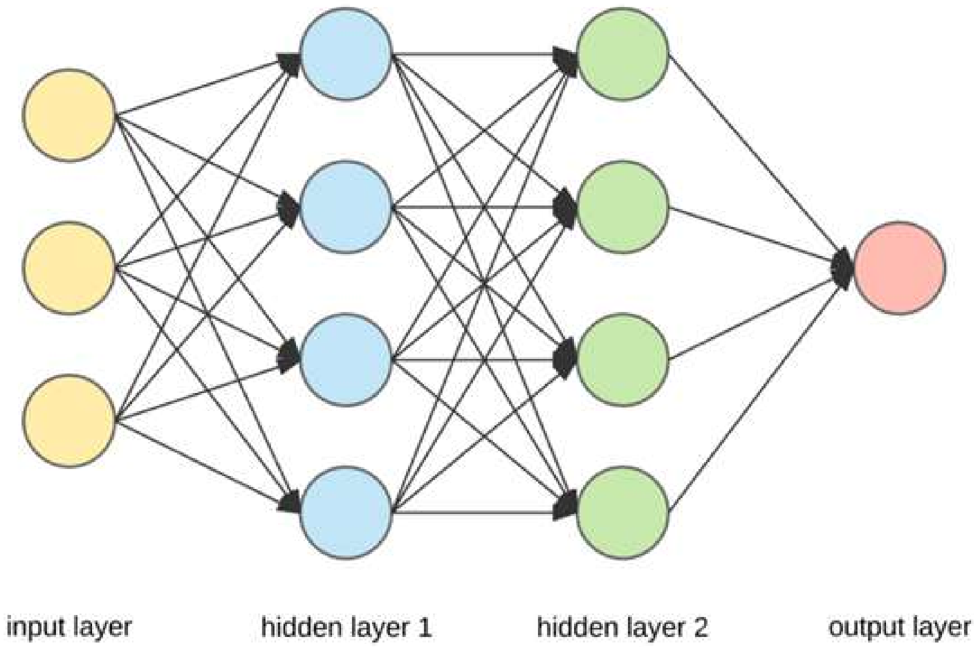

Figure 2: BPNN network architecture.

Testing the Model/Algorithm

After the training, the model was introduced to the testing dataset, constituting 15% of the entire dataset. The model is seeing the testing dataset for the first time. Hence, its predictive performance was validated by comparing the predicted and actual prices of the building material prices using the mean-square error (MSE).

Implementation

The developed model was implemented in Python using a Laptop (Intel(R) Core (TM) i5-8250U CPU @ 1.60GHz 1.80 GHz).

The steps for the Autoencoder-BPNN models development are summarised in Figure 3.

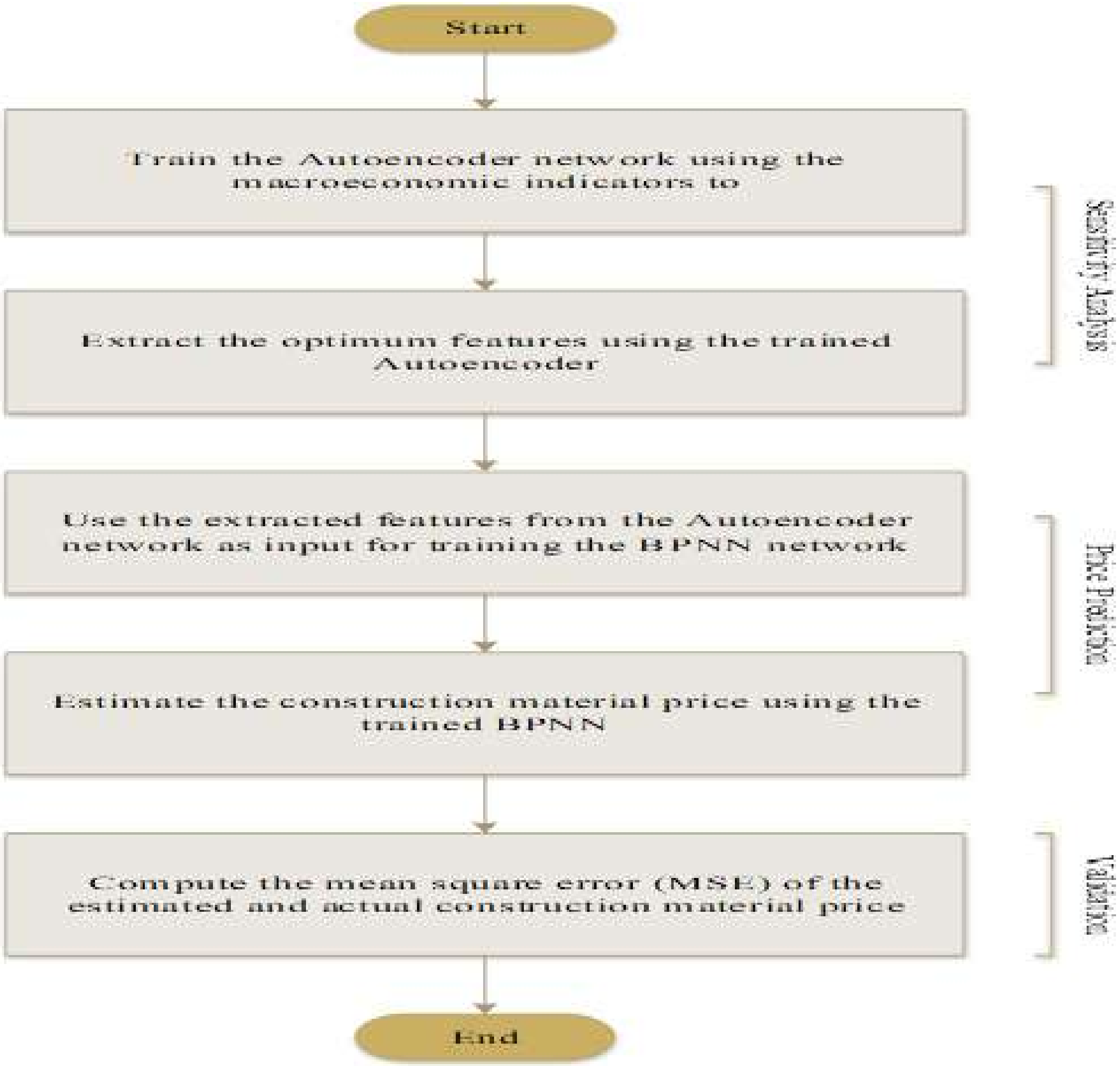

Figure 3: Steps for developing the proposed model.

Results and Discussions

This section presents the results of the models developed. The results of the Autoencoder-BPNN models as compared to the BPNN-only model for each material, are captured in Table 5. However, Figures 4-9 capture the actual and validation loss of the materials' Autoencoder-BPNN model and BPNN-only models. The MSE and Accuracy for only Reinforcement show a better accuracy for the Autoencoder -BPNN over the BPNN-only model.

For all other situations, i.e., Cement and Steel, the BPNN model has a better performance than the Autoencoder-BPNN. This is as opposed to the study of Rafiei and Adeli (2018b), whose encoder-BPNN model performs better than the BPNN-only model. The training was done using 500 iterations each for the Autoencoder-BPNN, and 200 iterations for the BPNN-only model. The Autoencoder-BPNN has accuracy ranging from 82.04% to 96.92%. The BPNN-only model, on the other hand, has accuracy ranging from 92.87% to 98.69%. From the results, the Reinforcement price prediction performs better with the Autoencoder-BPNN. For the Cement and Steel price prediction, the BPNN-only models have better performance.

Table 5: Top five combinations of the predicted values, MES and accuracy for the Autoencoder-BPNN are compared to the BPNN-only models

		BPNN only		Autoencoder-BPNN	
Material	Actual	Predicted	MSE (Accuracy %)	Predicted	MSE (Accuracy %)
Cement	2,550.00	2,554.58	0.0155 (98.45)	1,831.44	0.0811 (91.89)
	2,550.00	2,757.81	0.014 (98.60)	1,780.00	0.1024 (89.76)
	1,400.00	1,490.47	0.0187 (98.13)	2,002.24	0.1237 (87.63)
	2,600.00	2,605.77	0.0211 (97.89)	2,060.49	0.107 (89.30)
	2,550.00	2,439.17	0.0207 (97.93)	2,012.89	0.0839 (91.61)
Steel	10,500.00	10,537.83	0.0166 (98.34)	9,564.02	0.1079 (89.21)
	13,800.00	13,717.43	0.0159 (98.41)	10,278.84	0.1592 (84.08)
	8,500.00	8,428.53	0.0131 (98.69)	10,395.05	0.1562 (84.38)
	10,100.00	10,046.13	0.0142 (98.58)	9,648.86	0.1294 (87.06)
	10,900.00	10,643.94	0.0191 (98.09)	9,962.91	0.1796 (82.04)
Reinforcement	147,500.00	160,544.89	0.0513 (94.87)	204,531.33	0.0308 (96.92)
	234,000.00	234,882.19	0.0519 (94.81)	203,006.44	0.0391 (96.09)
	98,000.00	103,272.13	0.0605 (93.95)	180,447.33	0.0494 (95.06)
	155,000.00	182,632.47	0.0713 (92.87)	204,638.70	0.0689 (93.11)
	180,000.00	179,967.64	0.0696 (93.04)	202,709.17	0.0494 (95.06)

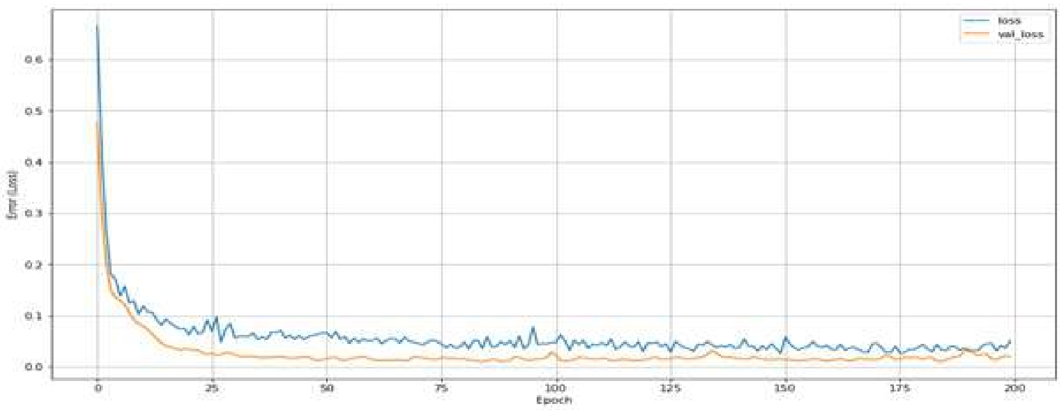

Figure 4: Cement actual loss vs. validation loss (BPNN only)

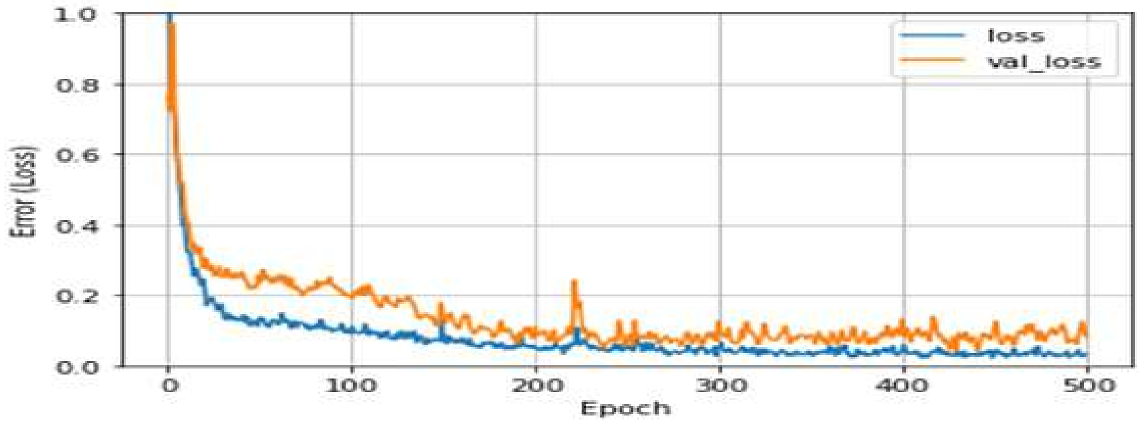

Figure 5: Cement actual loss vs. validation loss (Autoencoder-BPNN)

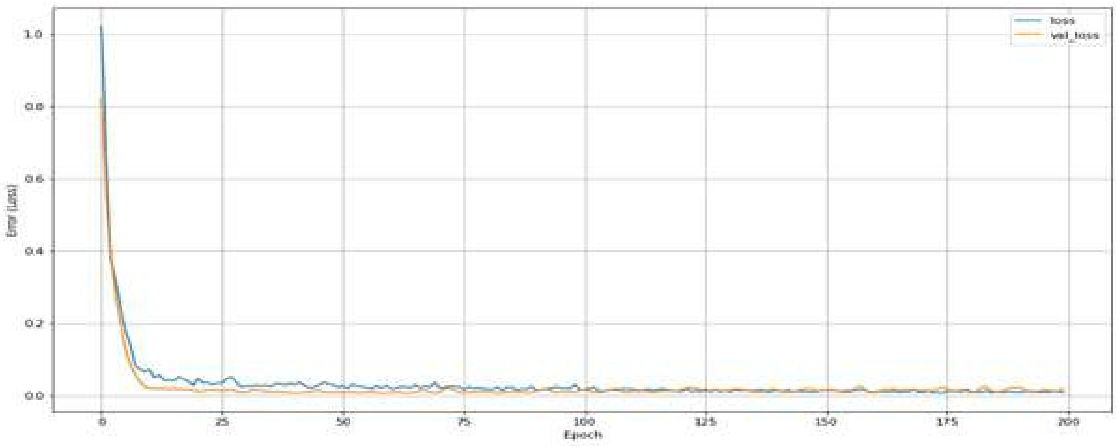

Figure 6: Steel actual loss vs. validation loss (BPNN only)

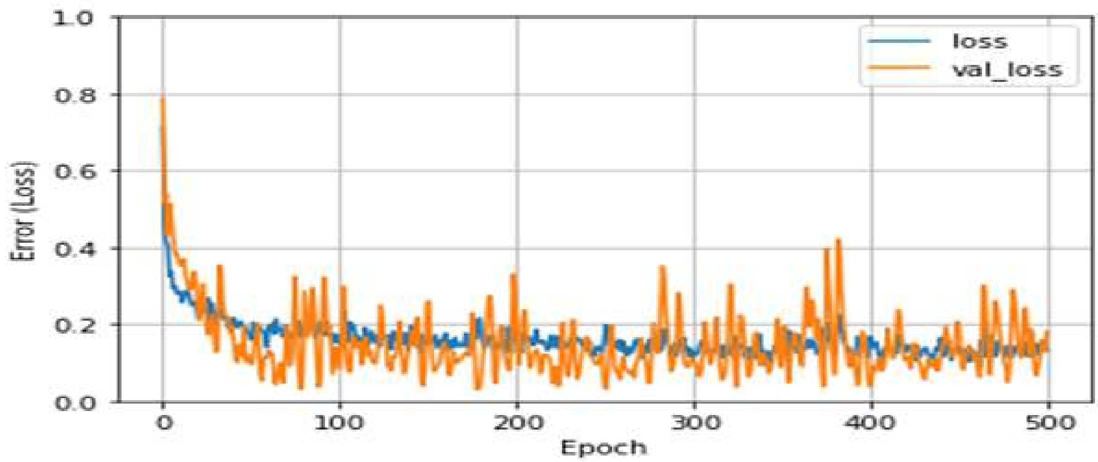

Figure 7: Steel actual loss vs. validation loss (Autoencoder-BPNN)

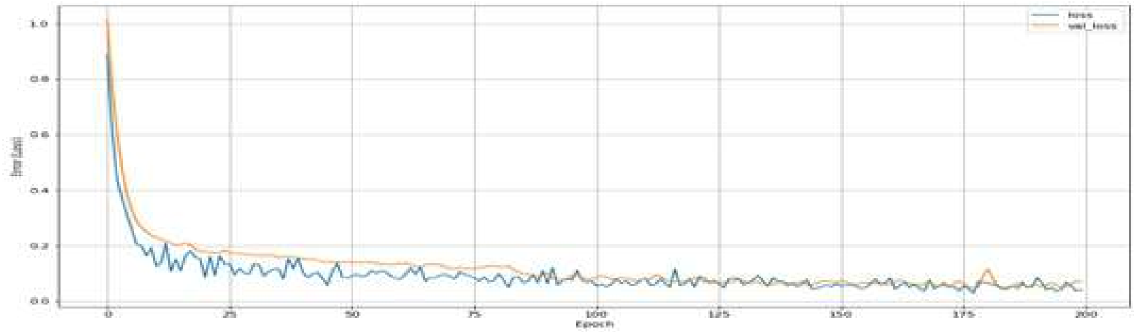

Figure 8: Reinforcement actual loss vs. validation loss (BPNN only)

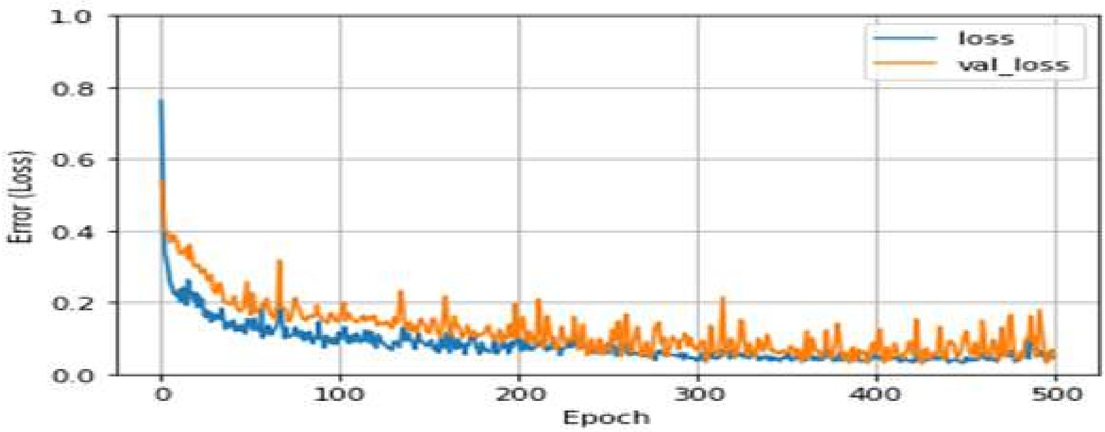

Figure 9: Reinforcement actual loss vs. validation loss (Autoencoder-BPNN)

Conclusion

Incessant fluctuations in prices of construction materials often lead to cost overruns and project abandonment. Nonetheless, accurately predicting the future price of construction materials susceptible to changes facilitates efficient cash flow management of a construction project, reducing the risk of cost overrun and project abandonment.

This study developed machine learning prediction models for construction materials susceptible to price fluctuations in Nigeria, using a combination of supervised and unsupervised learning approaches. The models were developed using a dataset consisting of twelve construction material price influencing factors as independent variables and construction material prices for reinforcement, steel and cement as the dependent variables.

The dataset was collected for a period of 10 years every month. An Autoencoder-BPNN model and a BPNN-only model were developed for each construction material. Validation of the models revealed that the Autoencoder-BPNN model performs better than the conventional BPNN-only model for the Reinforcement price prediction, while the BPNN-only model performs better for Cement and Steel price prediction.

As previous attempts to predict the future price of construction materials susceptible to price fluctuations in Nigeria focused only on cement, the developed models for reinforcement and steel using a novel approach represent the new knowledge this study contributes to the existing literature.

The models are prediction tools that depend on artificial neural networks' predictive supremacy via historical trends learning. They put forward a new course for the prediction of construction materials susceptible to price fluctuations in Nigeria. They are expected to assist both client quantity surveyors and contractors in coming up with more accurate estimates of future construction material prices that are to be relied upon for efficient cash flow management of construction projects in Nigeria.

As the models were developed using price influencing factors whose impact on the economies of various countries differ, the applicability of models is limited to only the region where data for the study was collected.

Acknowledgement

These Authors would like to acknowledge the Tertiary Education Trust Fund of Nigeria for providing the fund under which this study was carried out (TETF/DR&D/UNI/ZARIA/IBR/2020/VOL.1/22).

References

Adeli, H., and Wu, M. (1998). "Regularisation neural network for construction cost estimation." *Journal of Construction Engineering and Management.* 124 (1): 18–24. Https://doi.org/10.1061/(ASCE)0733-9364(1998)124:1(18)

Akanni, P. O., Oke, A. E., and Omotilewa, O. J. (2014). Implications of rising cost of building materials in Lagos State Nigeria. *SAGE Open*.

Akintoye, S. A., Bowen, P., Hardcastle, C. (1998). Macro-economic leading indicators of construction contract prices. *Construction management and economics*. 16:159175.

Alabi, B. and Fapohunda, J. (2021). Effects of increase in the cost of building materials on the delivery of affordable housing in South Africa. *Sustainability*. Https://doi.org/10.3390/su13041772

Ashuri, B., Shahandashti, S. M., and Lu, J. (2012). "Empirical tests for identifying leading indicators of ENR construction cost index."

Construction management and economics. 30 (11): 917–927. Https://doi.org/10.1080/01446193.2012.728709.

Box, G. E., and G. M. Jenkins. (1976). Time series analysis forecasting and control. San Francisco, CA: Holden-Day.

Braden, C. (2009). Construction material cost: Recent years and beyond. *Cost engineering*. 5(1), 17-21.

Cao, M. T., Cheng, M. Y., and Wu, Y. W. (2015). "Hybrid computational model for forecasting Taiwan construction cost index." *Journal of Construction Engineering and Management*. 141 (4): 04014089. https://doi.org/10.1061/(ASCE)CO.1943- 7862.0000948

Ernest, K., Theophilus, A. K., Amoah, P., and Emmanuel, B. B. (2019). "Identifying key economic indicators influencing tender price index prediction in the building industry: A case study of Ghana." *International. Journal of Construction management*. 19 (2): 106–112. Https://doi.org/10.1080/15623599.2017.1389641.

Faghih, S. A. M., and Kashani, H. (2018). "Forecasting construction material prices using vector error correction model." *Journal of Construction Engineering and Management*. 144 (8): 04018075. Https://doi.org/10.1061/(ASCE)CO.1943-7862.0001528.

Fan, R. Y., Ng, S. T., and Wong, J. M. (2011). "Predicting construction market growth for urban metropolis: An econometric analysis." *Habitat International. 35 (2)*: 167–174. Https://doi.org/10.1016/j.habitatint.2010.08.002.

Hassanein, A. A. G., and Khalil, B. N. L. (2006). Developing general indicator cost indices for the Egyptian construction industry. *Journal of financial management of property and construction*, 11(3), 181–194. Https://doi.org/10.1108/13664380680001088.

Hasware, M., Baviskar, S. and Narwade, R. (2020). Prediction of construction materials cost using artificial intelligence tools. *International journal of engineering research & technology (IJERT)*, 8(8), 276-279.

Hegazy, T., and Ayed, A. (1998). "Neural network model for parametric cost estimation of highway projects." *Journal of Construction Engineering and Management*. 124 (3): 210–218. Https://doi.org/10.1061/(ASCE)0733-9364(1998)

Hinton, G. E., and Salakhutdinov, R. R. (2006). "Reducing the dimensionality of data with neural networks." Science 313 (5786): 504–507. Https://doi.org/10.1126/science.1127647.

Huan, Z. and Jianhua, Z. (2013). Analysis of Factors that Cause Price Change of Building Materials. *Advanced Material Research*. 683, 668-671. Https://doi.org/10.4028/www.scientific.net/AMR.683.668

Issa, R. R. (2000). "Application of artificial neural networks to predicting construction material prices". *Computing in Civil and Building Engineering, pp. 1129–1132*.

Jiang, H., Y. Xu, and Liu, C. (2013). "Construction price prediction using vector error correction models." *Journal of Construction Engineering and Management*. 139 (11): 04013022. Https://doi.org/10.1061/(ASCE)CO.1943-7862.0000729.

Kamaruddeen, A. M., Noor, N. M. and Wahi, W. (2020). Factors influencing the price of selected building materials in northern Malaysia. *Borneo journal of sciences and technology, 2(1), 7-12*. DOI: https://doi.org/10.35370/bjost.2020.2.1-03

Marzouk, M. and Amin, A. (2013). Predicting construction materials prices using fuzzy logic and neural networks. *Journal of construction engineering and management*, 1190- 1198.

Mir, M., Kabir, H. M. D., Nasirzadeh, F., and Khosravi, A. (2021). Neural network-based interval forecasting of construction material prices. *Journal of building engineering, 39*, https://doi.org/10.1016/j.jobe.2021.102288

Moody's investors service (2020). Significant financing from private sector and multilaterals needed to address Nigeria's infrastructural deficit. Retrieved from https://www.moodys.com/research.moodys-significant-financing-from-private-sector- and-multilaterals-needed-to-PBC_1253651.

Musarat, M. A., Alaloul, W. S., Qureshi, A. H., and Altaf, M. (2020). Inflation rate and construction materials prices: Relationship investigation. *In; 2020 international conference on decision aid sciences and application (DASA), 387-390*

Ng, S. T., Cheung, S. O., Skitmore, M., Lam, K. C., and Wong, L. Y. (2000). Prediction of tender price indices directional changes. *Construction Management and Economics*. 18(7):843–852.

Ng, S. T., Cheung, S. O., Skitmore, M., and Wong, T. C. (2004). An integrated regression analysis and time series model for construction tender price indices forecasting. *Construction Management and Economics*. 22(5), 483–493.

Oba, K. M. (2019). A multiple linear regression model to predict the price of cement in Nigeria. *International journal of economics and management engineering*, 13(12), 1482-1487

Oladipo, F.O. and Oni, O. J. (2012). A Review of Selected Macroeconomic Factors Impacting Building Material Prices in Developing Countries: A Case of Nigeria, *Ethiopian Journal of Environmental Studies and Management EJESM* Vol. 5 No. 2, 131-137.

Olatunji, O. A. (2010). "The impact of oil price regimes on construction cost in Nigeria." *Construction management and economics*. 28 (7): 747–759. Https://doi.org/10.1080/01446191003725162.

OuYang, H., Zhang, X. and Hu, C. (2013). "Application research on the artificial neural network in the building materials price prediction", in: *The 19th International Conference on Industrial Engineering and Engineering Management, Springer*.

Pewdum, W., Rujirayanyong, T., and

Sooksatra, V. (2009). "Forecasting final budget and duration of highway construction projects." *Engineering. construction and architectural management*. 16 (6): 544. Https://doi.org/10.1108/09699980911002566.

Rafiei, M. H. and Adeli, H. (2018a). "Novel machine-learning model for estimating construction costs considering economic variables and indexes," *Journal of Construction Engineering and Management*, 144(12). Available at: https://doi.org/10.1061/(asce)co.1943-7862.0001570.

Rafiei, M. H., and Adeli, H. (2017). "NEEWS: A novel earthquake early warning model using neural dynamic classification and neural dynamic optimisation." *Soil Dynamics and Earthquake Engineering. 100* 417–427. Https://doi.org/10.1016/j.soildyn.2017.05.013.

Rafiei, M. H., and Adeli, H. (2018b). "A novel unsupervised deep learning model for global and local health condition assessment of structures." *Engineering structure*. 156, 598–607. Https://doi.org/10.1016/j.engstruct.2017.10.070.

Rajaprabha, R., Velumani, P., and Jayanthi, B. (2016). Factors Affecting the Cost of Building Material in Construction Projects. *International Journal of Science and Engineering Research,* 4, 1-6.

Shahandashti, S. M., and Ashuri, B. (2016). "Highway construction cost forecasting using vector error correction models." *Journal of management in engineering. 32 (2)*: 04015040. Https://doi.org/10.1061/(ASCE)ME.1943-5479.0000404.

Shiha, A., Dorra, E. M., and Nassar, K. (2020). Neural networks model for prediction of construction material prices in Egypt using macroeconomic indicators. *Journal of construction engineering management,* 146(3).

Williams, T. P. (1994). "Predicting changes in construction cost indexes using neural networks." *Journal of construction engineering and management.* 120 (2): 306–320. Https://doi.org/10.1061/(ASCE)0733-9364(1994)120:2(306).

Windapo, A., and Cattell, K. (2012). Examine the trends in building material prices: Building environment stakeholders' perspectives. In proceedings of the joint CIB international symposium of W055, W605 and W089, W118, TCG46 and TG84. *International conference on construction management research: management of construction research to practice,* Montreal, QC, Canada, 26-29 June 2012; ISBN 978-2- 98133550-0-0.

Wong, J. M., and Ng, S. T. (2010). Forecasting construction tender price indices in Hong Kong using vector error correction model. *Construction management and economics.* 28(12):1255–1268.

World Bank Group (2021). Nigeria economic update: Resilience through reforms, World Bank. World Bank Group. Available at: https://www.worldbank.org/en/country/nigeria/publication/nigeria-economic-update-resilience-through-reforms (Accessed: June 14, 2022).

Xu, J.-w, and Moon, S. (2013). "Stochastic forecast of construction cost index using a cointegrated vector autoregression model". *Journal of management in engineering. 29 (1)*: 10–18.