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A hybrid denoising and artificial neural network approach for diesel fuel price prediction

P Boye [1,*], YY Ziggah [2] and S Asante-Okyere [3]

[1] *Department of Mathematical Sciences, Faculty of Computing and Mathematical Sciences, University of Mines and Technology, Tarkwa, Ghana.*
[2] *Department of Geomatic Engineering, Faculty of Geosciences and Environmental Studies, University of Mines and Technology, Tarkwa, Ghana.*
[3] *Department of Petroleum and Natural Gas Engineering, School of Petroleum Studies, University of Mines and Technology, Tarkwa, Ghana.*

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Abstract

Diesel fuel price (DFP) modeling and prediction are important to an economy since fuel price has direct consequences on retail commodity prices, transportation, and the successful implementation of government policies. In this study, an attempt has been made to propose a DFP prediction model using the wavelet transform backpropagation neural network (WTBPNN) approach. The proposed WTBPNN approach was compared with the following benchmark methods: BPNN, radial basis function neural network (RBFNN), and wavelet transform radial basis function neural network (WTRBFNN). The developed prediction models used interest and inflation rates as the input parameters and DFP as the output parameter. A total of 95 data points obtained from the Ghana National Petroleum Authority and the Bank of Ghana were considered. Thus, 67 served as the training set and 28 were used as the testing set. Model validation was performed using dimensioned error statistic indicators of mean absolute deviation (MAD), mean absolute percentage error (MAPE), coefficient of determination (R2), and Pearson's product-moment correlation coefficient (R). Overall, the statistical results revealed that the proposed WTBPNN approach gave the best performance and thus could be used to predict DFP.

Keywords: Diesel Fuel Price; Prediction; Artificial Intelligence; Hybrid Denoising

1. Introduction

With the technological progression and expansion of global economic integration, the demand and supply of crude oil are being influenced by many complex events and various market participants worldwide. These, together with many influential factors like weather conditions, political stability, economic prospects, consumer expectations, and business indicators, to mention a few, have led to the enormous fluctuating price movement in the crude oil market. In recent years, these problems have aggravated in addition to the wave of liberalisation and globalisation, which are beyond the exploratory abilities of the traditional model-based methods (Zhu et al., 2014; Lescaroux and Mignon, 2008; Stevens, 1995; Hagen, 1994, and references therein).

As a distinctive nonlinear and dynamic system, crude oil price fluctuations are difficult to predict and its challenging accurate prediction remains a well-researched topic for its supposed increasingly significant role in the macroeconomic performance of the world economy (Malik, 2016; Wang and Wang, 2016; Zhu et al., 2014; Shaari et al., 2013). Statistical and econometric models have traditionally been the normal approach to forecasting crude oil prices. The autoregressive

* Corresponding author: P Boye

moving average (ARMA) represents the distinctive time series approach, while the regression and vector autoregressive (VAR) models represent the distinctive multivariate approaches. In general, these methods face several limitations, particularly in handling the complexities in the crude oil market, and offer satisfactory performance over the medium to long time horizons, but fail over the short time horizons and cannot meet practical needs in predicting crude oil prices since they often assume linear relationship and satisfactory data. This indication reveals that the characteristics of prices in the crude oil market comprise unknown nonlinear interrelationships with other macroeconomic factors in the case of multivariate models. These current approaches alone can only offer insufficient clarification and predictive power for the crude oil price movement (Chiroma, 2016; Morana, 2001; Abramson and Finizza, 1995; Huntington, 1994 and references therein).

Usually, the traditional model-based methods can provide good prediction results when the price series under study is linear or near linear (Shi and Zhuang, 2019). However, in real-world crude oil price series, a great deal of unpredictable nonlinearity and irregularity exists. According to Weigend and Gershenfeld (1994), crude oil price prediction performance might remain very poor if one continues to use these traditional models, since they are built on linear assumptions and cannot capture the nonlinear patterns in the crude oil price series (Shi and Zhuang, 2019).

Due to the numerous limitations of the traditional model-based methods, nonlinear and artificial intelligence (AI) models are the alternative methods available for researchers and crude oil industry practitioners because the methods provide powerful solutions to the nonlinear crude oil price prediction (Shambora and Rossiter, 2007; Mirmirani and Li, 2004; Tang and Hammoudeh 2002 and references therein). From the existing literature, many AI-based models often had some advantages over the traditional model-based methods (Chiroma, 2016; Kulkarni and Haidar, 2009, and references therein). However, these AI models also have their shortcomings and disadvantages. For example, artificial neural networks (ANN) often suffer from local minima and overfitting, while some AI models, including ANN, are sensitive to parameter selection (Shi and Zhuang, 2019; Sheela and Deepa, 2013; Bashiri and Geranmayeh, 2011; Liu et al., 2019, and references therein).

To improve on the shortcomings to overcome the drawbacks of single ANN models and to generate a synergetic effect in prediction, hybrid models have been proposed recently to predict crude oil and its constituents' prices. Such an innovative and advanced approach of blending the robustness of traditional statistical methods with the sophistication of modern computational techniques is designed to leverage the strengths of both paradigms to produce more accurate, reliable, and adaptable predictions. Results from existing empirical literature showed that the hybrid models performed better than the single ANN models and are also suitable for accurate crude oil and its constituents' price prediction (Mahdiani, 2017; Zhang, 2003; Zhang et al., 2014, and references therein). In this regard, it is imperative to know the long-term trend in crude oil prices because it is essential for ensuring global future economic stability. Consequently, the modeling and prediction of crude oil useful information will assist government agencies and policymakers in planning and managing their economic resources more efficiently (Lee and Huh, 2017; Ahmad, 2012). As a result, this study will employ the hybrid technique to develop an effective hybrid denoising ANN reliable model for accurate diesel fuel price (DFP) prediction, and its prediction performance will be compared with some existing single ANN models as well as some hybrid ANN models.

2. Generation of the data

In developing the various models, the monthly data set of seven years and eleven months was obtained from the Ghana National Petroleum Authority (GNPA) and the Bank of Ghana (BoG). Table 1 shows the specific parameters, their units of measurement, and the respective statistical measures of the data set.

Table 1 Statistical Description of the Data Set

Parameters	Minimum	Maximum	Average	Standard Deviation
Inflation Rate (%)	8.3900	20.7400	13.1651	3.9271
Exchange Rate (₵)	8.8000	435.5750	173.2754	79.6525
Diesel Fuel Price (₵) Per Litre	85.0100	330.4999	170.7023	71.2596

3. Overview of methods applied

3.1. The Wavelet Transform

The wavelet transform (WT) is one of the methods used to catch smooth functions by decomposing the time series into detail and approximation parts through multi-level multi-resolution analysis (Moosavi and Riazi, 2018; Yousefi et al., 2005); and it has broad applications for stationary and nonstationary signals. These applications include the removal of electrical noise from signals, the detection of abrupt discontinuities, and the compression of large amounts of data. The use of WT in crude oil price prediction is no exception (Zou et al., 2015; Jin and Kim, 2015; Shabri and Samsudin, 2014; He et al., 2012).

With the WT, signal decomposition into a group of constituent signals called wavelets is possible; each with a well-defined dominant frequency analogous to the Fourier transform (FT). Here, the representation of a signal is by sine and cosine functions of unlimited duration. In WT, signals consist of different features in time and frequency, but their high-frequency components would have a shorter time duration than the low-frequency components. To attain good time resolution for high-frequency transients and good frequency resolution for low-frequency components, the idea of wavelets as short-duration transient functions of a single function called a mother wavelet was presented, and it is defined as Equation (1) (Qunli et al., 2009):

$$\varphi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\varphi\left(\frac{t-b}{a}\right), \quad a,b \in \square,\ a \neq 0 \qquad \text{..... (1)}$$

where a is the scaling parameter that measures the degree of compression or scale, b is the translation parameter that determines the time location of the wavelet.

The problem with FT is that when passing from the time domain to the frequency domain, the information about what happens in time is lost. Thus, observing the frequency spectrum obtained using the FT reveals the frequency content of the signal being analysed, but it is not possible to deduce at what time the components of the signal of the frequency spectrum appear or disappear. Unlike the FT, the WT allows an analysis in both time and frequency domains, giving information on the evaluation of the frequency content of a signal over time (Ramos, 2017).

As in the case of FT, the WT is discretised and it is called discrete wavelet transform (DWT); and it presents an important advantage over the traditional FT methods. The WT decomposes a data set into several scales representing different frequency bands, and at each scale, the position of the WT can be determined at the important time characteristic at which the data set noise can be known and efficiently removed. Short-time wavelets allow information to be extracted from high-frequency components. Consequently, this information helps to eliminate the noise in the dataset since it exhibits high-frequency fluctuations (Lahmiri, 2014). On the other hand, long-term wavelets allow for information extraction from low frequencies. With the information of the high and low frequencies, a threshold is defined and zero the frequencies below the undesired threshold of the data set noise (Cheng et al., 2000).

The pioneering work of removing noise from crude oil price data set using the WT has its origin in the works of Donoho and Johnson (1994), which proposed the use of a threshold for the removal of Gaussian white crude oil price data set noise. In this study, we employed DWT, a method for analysing irregularities in data sets to decompose the inflation and foreign exchange rate data sets into four Daubechies levels comprising low and high frequencies. Figure 1 shows the DWT modeling procedure flowchart.

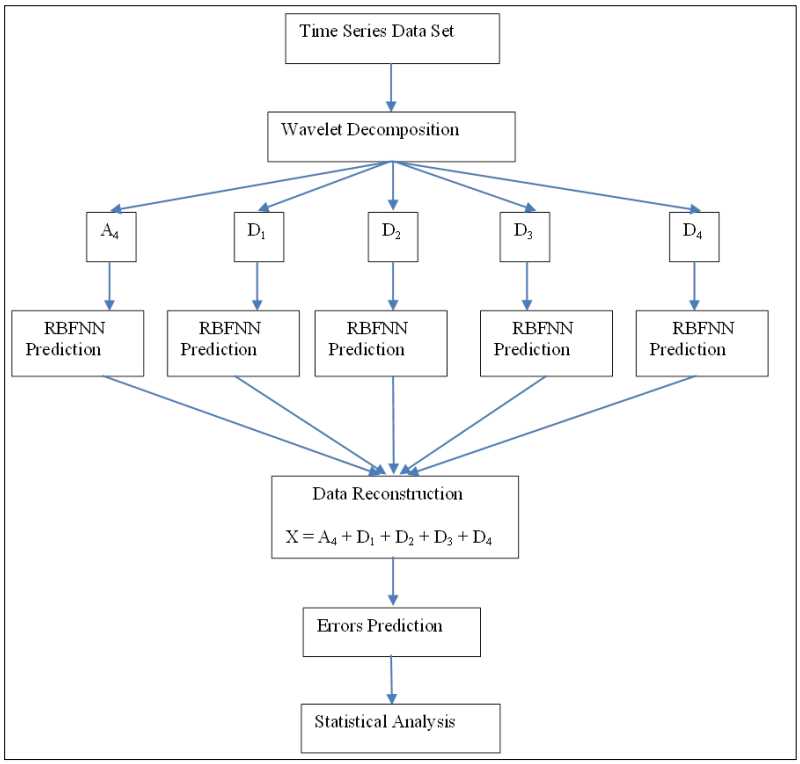

Figure 1 DWT Model Flowchart

3.2. The Backpropagation Neural Network

The backpropagation neural network (BPNN) is a multi-layered, feed-forward neural network that was first proposed by Paul Werbos in the 1970s. However, it was rediscovered by Rumelhart and McClelland in 1986, and it is the most extensively used neural network for forecasting purposes (Suliman and Zhang, 2015). BPNN is also considered one of the simplest and most universal approaches used for supervised training for multi-layered neural networks (Rene et al., 2013). Neural networks obtained their name from the simple processing units in the brain called neurons, which are interconnected by a network that transmits signals between them. These can be thought of as a black box device that receives inputs and produces a desired output (Zihni et al., 2020; Benitez et al., 1997).

The multilayer perceptron is the most common neural network model, and it is known as a supervised network since it requires a desired output to learn. In general, they are characterized by a network topology comprising the following: input, hidden, and output layers, as shown in Figure 2. The basic principle of this type of network is to create a model that maps the input perfectly to the output using a historical data set so that the model can then be used *t* produce the output when the desired output is unknown (Zahraa, 2019; Sheela and Deepa, 2013; Chukwu and Nwachukwu, 2012).

In the backpropagation algorithm, a series of input and output data sets is fed to the network. Each hidden layer neuron and output layer neuron process the input data set by multiplying it with its corresponding interconnection weights and then applying a transfer function to process it one last time in the output layer to generate the neural network output (Chukwu and Nwachukwu, 2012; Haider et al., 2008). The work of the backpropagation approximates the nonlinear relationship between the input and the output data set by adjusting the weights of the connections in the network repeatedly. minimise the measure of the difference between the actual output vector of the network and the desired output vector. Due to the weight adjustments, internal hidden units, which are not part of the input or output, come to represent important features of the task domain, and the regularities in the task are captured by the interactions of these units (Rumelhart et al., 1986).

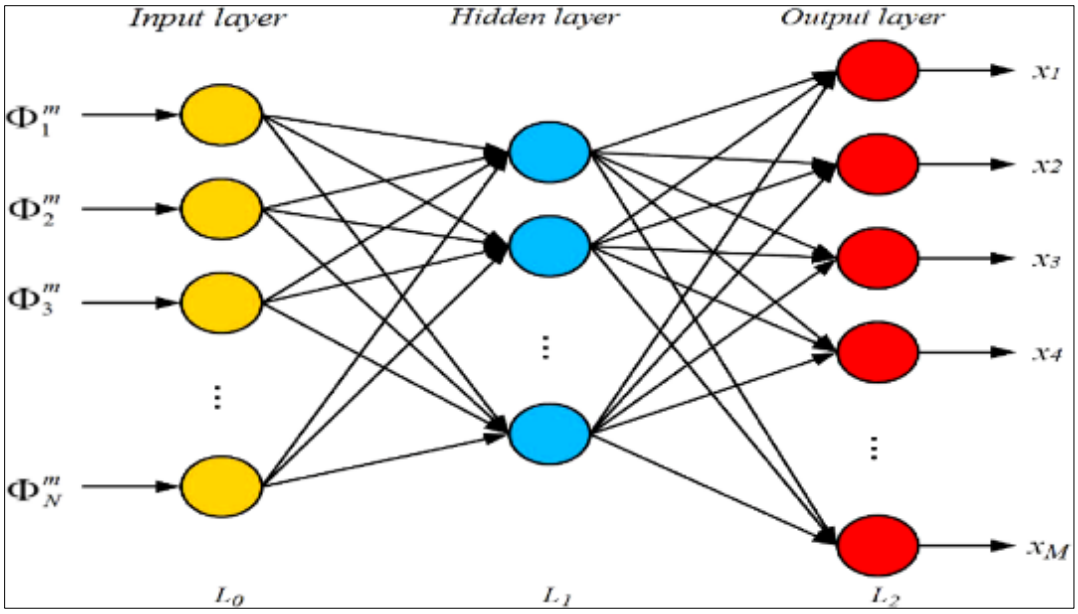

Figure 2 Three-layer BPNN Architecture

In the algorithm phase, a bias term θ_j is provided to introduce a threshold for the activation of neurons. The input data X_i is presented to the network through the input layer, which is then passed to the hidden layer along with the weights. Consequently, the neuron input I_j, a weighted sum in the output layer, which passes through an activation function $f\left(I_j\right)$ to produce the desired output Y_j is given as Equation (2) (Rene et al., 2013)

$$I_j = \sum_{i,j=1}^{i,j=N} W_{ij} X_i + \theta_j \quad \text{.....(2)}$$

The most commonly used activation function is the logistic sigmoid function (Equation (3)), which takes the form (Rene et al., 2013; Rumelhart et al., 1986):

$$f\left(I_j\right) = \frac{1}{1+e^{-I_j}}. \quad \text{.....(3)}$$

In Figure 2, $\Phi^m{}_1, \ldots, \Phi^m{}_N$ is the input parameter and $x_1, \ldots, x_M$ is the output. Figure 3 shows the BP modeling flowchart.

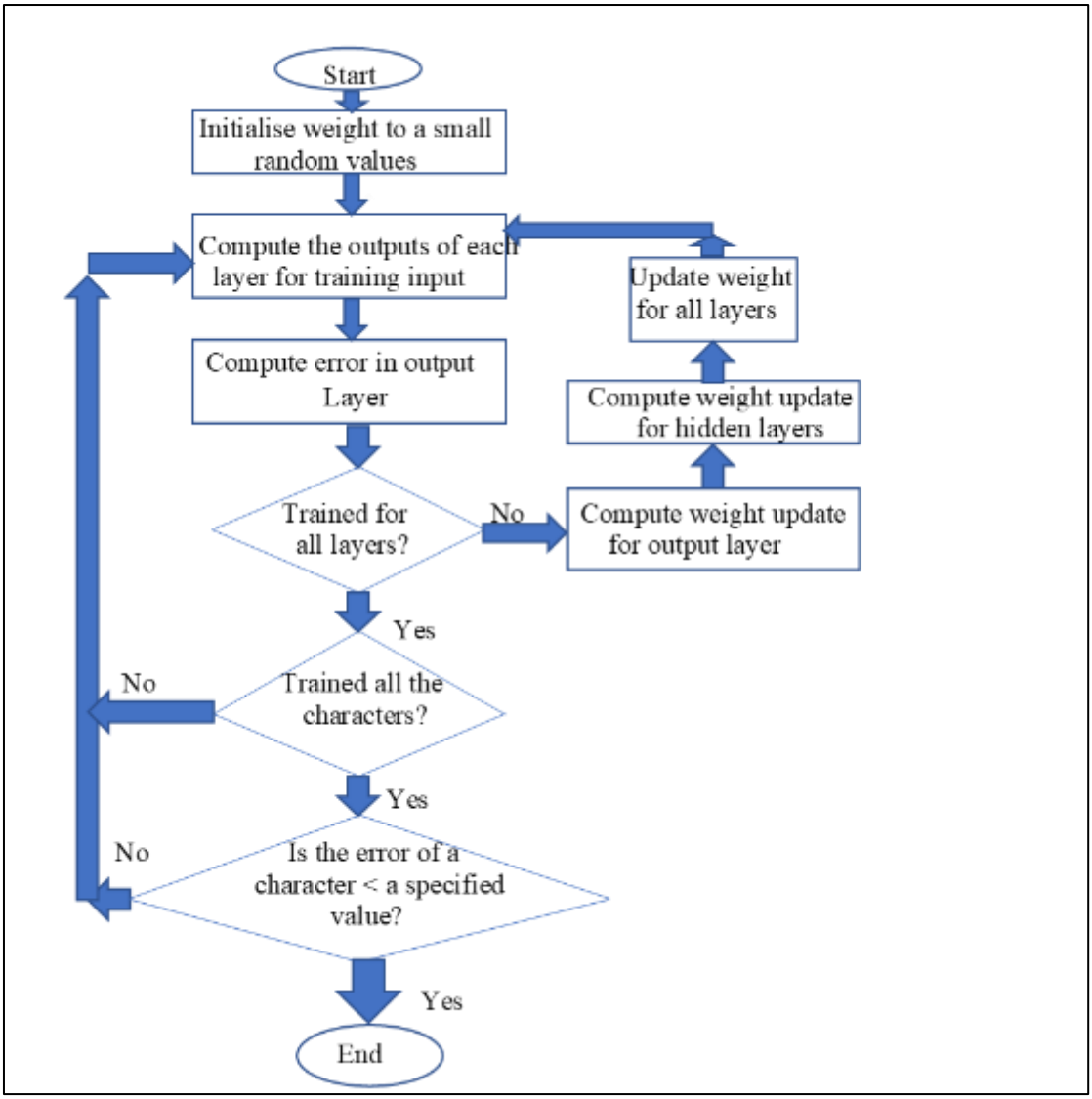

Figure 3 BP Training Algorithm Flowchart

3.3. Radial Basis Function Neural Network

The radial basis function neural networks (RBFNNs) are another class of artificial neural networks (ANN) that uses RBFs as activation functions. It was first proposed by Powell in the 1980s to solve interpolation problems in multi-dimensional space. This method has experienced unprecedented development with continuous updates in computing kits. Compared with other neural networks, it has a simple architecture, less training time, faster learning convergence, is not dependent on initial guesses for the network weights, and always provides global minima when minimisation of error is carried out. RBFNNs offer efficient mechanisms for complex nonlinear function approximation, pattern recognition, modeling, and controlling dynamic systems. Besides its superior worldwide approximation ability, it can approximate any continuous network, and it has a good noise tolerance. Consequently, it is widely used in practice (Mansor et al., 2020; Zhao et al., 2019; Basak et al., 2014; Han et al., 2010).

Similar to ANN architecture, the special three-layer RBFNN consists of a single or more hidden layers, each containing three important parameters: output weights, widths, and centers, as shown in Figure 4. For the RBF network to achieve greater learning rate performance, these parameters must be selected appropriately. The advantage of the RBFNN architecture is, that once the centers are determined, the network estimation reduces to a linear least squares problem. Generally, the parameter values are unknown and may be determined during the network learning process. The number of nodes in the input and output layers is decided by the research objectives. The nodes in the input and output layers represent the vector from an input space and a desired network response, respectively. Through a defined learning algorithm, the error between the actual response is minimised by optimisation criteria (Mansor et al., 2020; Pislaru and Shebani, 2014; Leung et al., 2001).

Input data to the network is done via the input layer and it is locally transferred directly to the hidden layer by a nonlinear activation function and this results in their unsupervised faster training. Finally, with a linear transformation function, the network response is attained in the output layer.

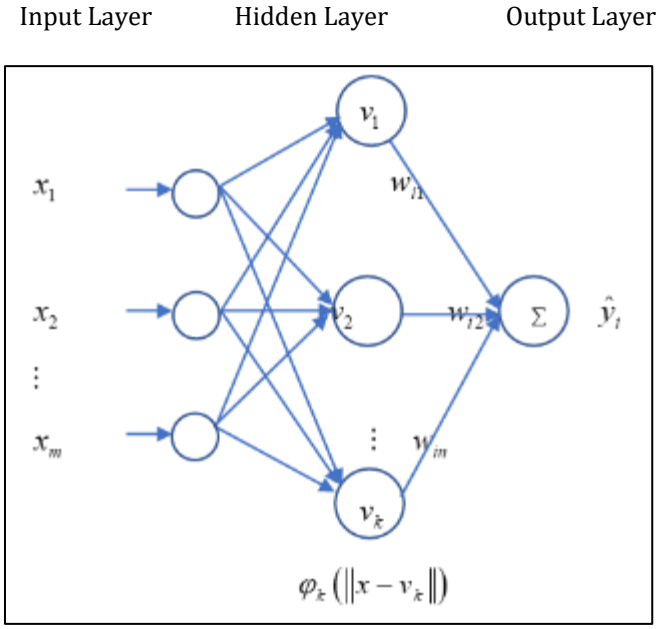

Figure 4 RBFNN Architecture

Several nonlinear activation functions can be used to transfer the input data to the hidden layer. For the RBF network, activation of the hidden units is controlled by the distance between the input vector and the center. That is, by computing the Euclidean distance between them using the Gaussian function. The training process of the network parameters between the hidden layers and the output layer is supervised with learning algorithms. Besides the adjustment of the weights, modifying the center of the activation function is needed in training the network (Mansourkhaki et al., 2018; Markopoulos et al., 2016). The weights and the center of activation functions are adjusted by using the gradient descent method to minimise the sum of squared errors.

In this study, the Gaussian function as defined in Equation (4) was used (Mansourkhaki et al., 2018; Ji et al., 2016; Gullu, 2010). The i^{th} output $\hat{y}_i$ is a linear combination of neurons in the hidden layer and it is computed in Equation (1) as (Basak et al., 2014; Han et al., 2010):

$$\hat{y}_i = \sum_{k=1}^{N} w_{ik} \varphi_k \left(\|x - v_k\| \right), \quad i = 1, 2, \ldots, m \quad \text{.....(4)}$$

where $x = \left[x_1, x_2, \ldots, x_n \right]^T$ is an input value; n is the number of input nodes; v_k is the position of the center vector for neuron k and N is the number of neurons in the hidden layer. $\|x - v_k\|$ denotes the Euclidean distance between v_k and x, $\varphi_k(\bullet)$ is the nonlinear transfer function of the k^{th} RBF node, w_{ik} is the weighting value between the k^{th} RBF node and the i^{th} output node, and m is the number of output nodes.

This study employed a supervised learning algorithm to train the RBFNN. A written MatLab code was used to carry out the RBFNN training. The Gaussian activation function as shown in Equation (5) was also applied (Basak et al., 2014; Han et al., 2010):

$$\varphi(x) = \exp\left(-\frac{\|x-v\|^2}{2\delta^2}\right) \quad \text{.....(5)}$$

where v and δ are the parameters of the center values of the basis function and width of the RBF nodes respectively. The most commonly used activation function for classification and regression problems is the Gaussian function because it is continuous and differentiable. Besides it provides a softer output and improves the interpolation capabilities (Han et al., 2010). The final output classification of the RBFNN $f\left(\|x-v_k\|\right)$ is expressed as Equation (6) (Mansor et al., 2020):

$$f\left(\|x-v_k\|\right) = \begin{cases} 1, & \sum_{k=1}^{N} w_{ik}\varphi_k\left(\|x-v_k\|\right) \geq 0 \\ 0, & \sum_{k=1}^{N} w_{ik}\varphi_k\left(\|x-v_k\|\right) < 0 \end{cases} \quad \text{.....(6)}$$

Figure 5 shows the RBFNN modeling flowchart.

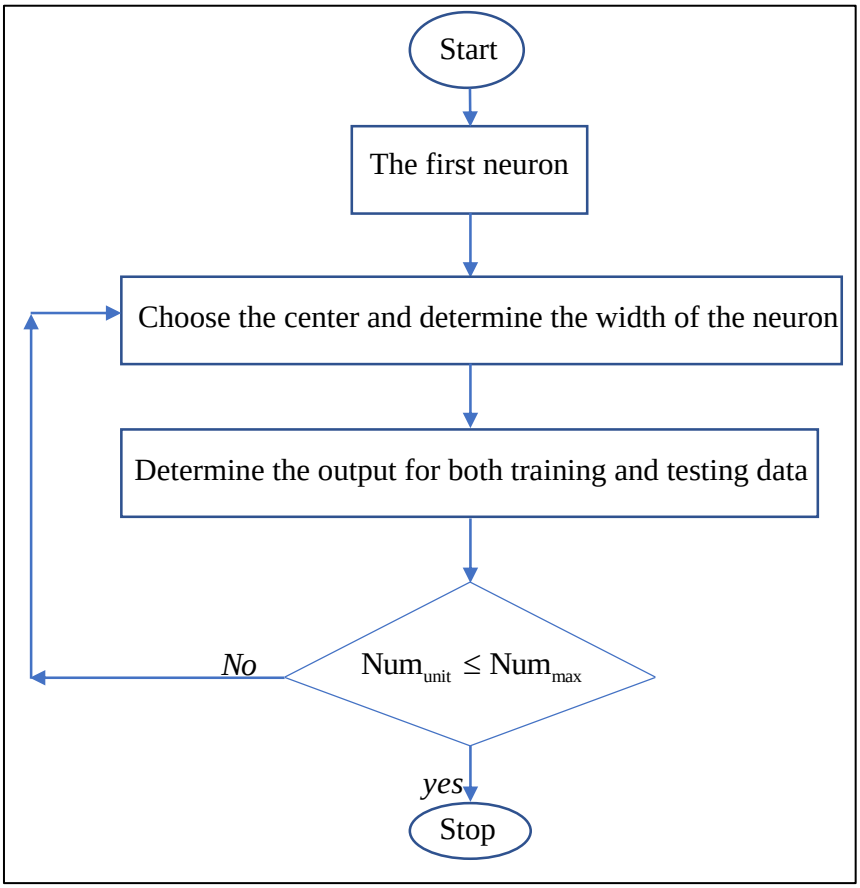

Figure 5 RBFNN Using Supervised Learning Flowchart

4. Model performance assessment

The evaluation of model suitability is an indispensable step of the modeling process because it indicates the level of precision and accuracy of the model predictions. Thus, the developed model's usefulness depends on how near its predictions fit well with the observed dataset. In that regard, the following statistical performance indicators were used to assess the rightness and promote the acceptance and usability of the AI prediction models: mean absolute deviation (MAD), *Mean absolute* percentage *error (MAPE),* coefficient of determination (R^2) and Pearson's product moment correlation coefficient (R) (Obilor and Amadi, 2018; Kim and Kim, 2016; Ren and Ren, 2016; Montgomery et al., 2006). Equations (7) – (10) show their mathematical notations respectively.

$$MAD = \sum_{i=1}^{n}\left(\frac{|e_i|}{n}\right) \quad \text{.....} \quad (7)$$

$$MAPE = \left(\frac{100}{n}\sum_{i=1}^{n}\left|\frac{e_i}{y_i}\right|\right)\% \quad \text{.....(8)}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}|e_i|^2}{\sum_{i=1}^{n}(\hat{y}_i)^2} \quad \text{.....(9)}$$

$$R = \frac{n\sum_{i=1}^{n}(x_i y_i) - \left(\sum_{i=1}^{n}x_i\right)\left(\sum_{i=1}^{n}y_i\right)}{\sqrt{\left[n\sum_{i=1}^{n}x_i^2 - \left(\sum_{i=1}^{n}x_i\right)^2\right]\left[n\sum_{i=1}^{n}y_i^2 - \left(\sum_{i=1}^{n}y_i\right)^2\right]}} \quad \text{.....(10)}$$

where for Equations (7) - (10), e is the modeling error and it is the difference between the actual and the predicted variable, n is the number of sample data and it assumes values from i to n, x and y are the input variables, and $\hat{y}$ is the predicted variable.

5. Results

5.1. Pre-Processing of Data

During the DFP model development, the 95-sample data set was partitioned into 67 (approximately 70%) training set and the remaining 28 (approximately 30%) testing set was used as unseen data to check the reliability of the trained models. The most extensively used hold-out cross-validation method was applied in the data partitioning process, and ensured that the percentage division conformed to practices in literature (Swingler, 1996; Taheri et al., 2017; Awwalu and Nonyelum, 2019; Sayevand et al., 2019, and references therein). To circumvent under- and overfitting situations, which prevent models from generalising well on the testing data set, the mean square error (MSE) criterion was utilised. Thus, a trained model whose errors are minimised for the testing data set with a marginal error difference between the training and testing sets, was classified as an efficient model.

In the model formulation, inflation and exchange rates served as input variables, and the DFP was used as an output variable. Normalisation of the data set was performed by using Equation (11) to find new data ranges from the existing one, and this technique minimised the impact of bigger input values on the smaller ones. As a result, the method improves the convergence speed of the developed AI models (Patro et al., 2015).

$$X = Lowest + \frac{(Highest - Lowest)(Y - Min)}{(Max - Min)} \quad \text{.....(11)}$$

where,

Y is the current position;

Max is the maximum value of a column;

Min is the minimum value of a column;

$Highest$ is the higher value of a chosen range; and

$Lowest$ is the lower value of a chosen range.

The Min and Max values ranged from -1 to 1.

5.2. Models Formed

5.2.1. BPNN Model

The optimal generalisation BPNN model that predicted the best DFP was [2-30-1]. That is two inputs, thirty-six hidden neurons, and one output. The choice of the model was based on the statistical performance indicators applied in Equations (7) - (10). In the BPNN model formulation, one hidden layer that has been proven by scholars (Hornik et al., 1989; Park and Sandberg, 1991) to approximate very well on any data was used. The scaled conjugate backpropagation (Møller, 1993) was also used as the training algorithm. The hyperbolic tangent and linear transfer functions were respectively utilised in the hidden and output layers.

5.2.2. RBFNN Model

The optimal generalisation RBFNN model that produced the best performance was [2-50-1] with a width parameter of 0.21. The optimal structure is two inputs, fifty neurons, and one output. It must be noted that the width parameter and the maximum number of neurons were the only adjustable parameters that needed to be set to monitor the model's performance.

5.2.3. WT-BPNN Model

The optimal generalisation WT-BPNN model that predicted the best DFP was [2-11-1]. That is two inputs, eleven hidden neurons, and one output. The choice of the model was based on the statistical performance indicators applied in Equations (7) - (10). In the BPNN model formulation, one hidden layer that has been proven by scholars (Hornik et al., 1989; Park and Sandberg, 1991) to approximate very well any data was used. The scaled conjugate backpropagation (Møller, 1993) was also used as the training algorithm. The hyperbolic tangent and linear transfer functions were respectively utilised in the hidden and output layers.

5.2.4. WT-RBFNN Model

The optimal generalisation WT-RBFNN model that produced the best performance was [2-10-1] with a width parameter of 0.21. The optimal structure is two inputs, ten neurons, and one output. It must be noted that the width parameter and the maximum number of neurons were the only adjustable parameters that needed to be set to monitor the model's performance.

5.3. Model Comparison

Table 2 Summary of Test Results

Model	MAD	MAPE (%)	*R*	R^2
BPNN	25.5664	9.3097	0.9707	0.9423
RBFNN	30.3956	11.1967	0.6575	0.4323
WT-BPNN	25.3746	8.4709	0.9849	0.9700
WT-RBFNN	27.1116	10.9729	0.9201	0.8466

Table 2 shows the proposed model's statistical performance indicators and test results. WT-BPNN had the least MAPE and MAD values of 8.4709 and 25.3746, and higher *r* and R^2 values of 0.9849 and 0.9700, respectively, than the other models. This implies that lower values of MAPE and MAD are an indication that the proposed model prediction errors are reduced to a very minimal. Due to this, the proposed model is considered to have good prediction power. An $r > 0.6$ is an indication of a strong positive relationship between the two input macroeconomic variables, exchange and inflation rates. Thus, a positive change in one variable strongly influences the other variable positively and vice versa. Finally, an R^2 value of 0.9700 means that exchange and inflation rates simultaneously explained 97% of the DFP prediction. Consequently, this is a clear indication that WT-BPNN is a very good and efficient model.

6. Conclusion

As DFP prediction requires precision and frequent checks for varying parameters, researchers have worked on numerous AI models to enhance the performance of the existing forecasting approaches. This research has presented a comprehensive study of notable single methods and delineated the state-of-the-art for constructing hybrid models. The

combination of two or more predictive models has been shown in the literature to construct hybrid models for demanding accuracy. BPNN and RBNN and their relevant models have proven fruitful, as these schemes have showcased excellent opportunities in achieving a well-organised model where the DFP can be predicted with minimum error.

In this study, an attempt has been made to apply the hybrid WT-BPNN as a novel technique to predict DFP, and it has been compared with two standard single AI methods (BPNN and RBFNN) and a hybrid WT-RBFNN method. The hybrid WT-BPNN approach gave superior results as compared to the BPNN, RBFNN, and WT-RBFNN approaches applied. This was evident from the statistical analysis performed, where WT-BPNN had low values of MAPE (8.4709 %) and MAD (25.3746) as well as high R (0.9849) and R^2 (97%) values. These results showed that the hybrid WT-BPNN can be used to predict DFP with some reliable level of accuracy. This paper may prove quite useful for researchers who need to model and predict DFP through the use of AI technology.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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