JENRM, Vol. 4, No. 7, 48-55, 2017
Research Article

Predicting Stock Trends Using Tsk-fuzzy Rule Based System

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Abstract
Stock investment is often regarded by investors as a green opportunity that is characterized by high rewards and its attendant risk. Consequently, investors are preoccupied with analysis and prediction of the future performance of stocks, and the direction and magnitude of future changes in the stock value. In this study, the Takagi-Sugueno-Kang - Fuzzy Rule Based System (TSK-FRBS) was used to analyzed the trend of stocks using historical data gathered over a period of five months between January and May 2015. The TSK-FRBS was implemented in R. The input data is split into training and testing data for experimentation, testing and further analysis. Predictive accuracy was evaluated using the root mean squared error (RMSE) and symmetric mean absolute percentage error (SMAPE). Final results showed consistency obtained from feeding the model with the data and hence proved that patterns that allow for prediction can be deduced from the chaotic nature of the stock exchange market.

Keywords
adaptive-network-based inference system (ANFIS). Fuzzy, Fuzzy rule based system (FRBS), stock market, stock prediction.

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1. Introduction

Trends analytic from the financial markets, fiscal and monetary policies, managerial practices and the general economy ecosystems are primary focus of investors as they monitor their stock investments in order to predict their future investment choices or decisions. It is a known and generally acceptable fact that the stock exchange market index acts as a major indicator for gauging the healthiness of a particular nation's economy[1]. Investment in stocks is therefore predicated on the financial health status of companies and their stocks listed on a nation stock exchange. The preoccupation of investors is concerned on investing in stocks that would yield total utilitarian value and ultimate maximum profit should in case the investor decides to sell, hold, buy or acquire additional stocks. The decision reached is based more often than not on the present or future state of a company's financial health status arising from its profitability and performance of its stock in the market. It is however pertinent to note that predicting stock performance is often arduous on a perfect scale due to the uncertainties and high fluctuations in the financial markets, economic environment and the unstable integrity (sharp practices) of some management boards with collaborations of some stock brokers, and the avalanche of predictive models and methods being used [2]. Ugwu and OnwuachuUzochukwu [3] postulated that the stock value cannot be predicted because it follows a random walk pattern. Consequently, forecasting stock indices is very difficult because of the market volatility that needs an accurate forecast model. Several computing paradigms and methods such as Artificial Neural Network (ANN), Genetic Algorithm, Neuro-Fuzzy and regression based models, have been used to improve the precision of stock prices predictions [4] Succinctly, this study focused the application of fuzzy rule based system in predicting future values of stocks. A Takagi-Sugueno-Kang fuzzy rule based system (TSK-FRBS) was implemented using R.

2. An Overview of Related Works

Traditionally, there are two basic techniques employed in the decision making process of buying and selling stocks which are fundamental analysis and technical analysis [5]. However, the introduction of soft computing methods for classification and regression tasks transformed the traditional approaches that were used in discovering of patterns in historical dataset, and in using the data to predict the future values. Soft computing method is a synergistic integration of four computing paradigms: neural networks, fuzzy logic, rough sets and evolutionary algorithms which provide a framework for flexible information processing applications [6]. Specifically, Artificial Neuron Network (ANN) has been used extensively in the area of predicting stock market trends [7] Akinwale Adio, et al. [8] [9]; Bello and Chiroma [10]. Fuzzy set and logic theory [11] has also been applied to several areas such as pattern recognition, air conditioners, washing machines, vacuum cleaners, antiskid braking systems, transmission systems, control of subway systems, transmission systems, malaria diagnosis etc. Fuzzy logic was implemented in a temperature control system by [12] using a fuzzy logic controller. The system adjusted the temperature of a room by obtaining details such as the current temperature of a room value defined by the system from the set fuzzy rules. An, et al. [13] used the fuzzy set theory to predict wind speed using data collated from a Chinese firm with dataset containing 62,466 samples collected within 434 days where each sample was the average wind speed during 10 min. The fuzzy principle used by [13] consisted primarily of three steps of which are fuzzy partition, fuzzy approximation and regression attribute value estimation. Fuzzy logic has also witnessed success in financial management especially in the area of forecasting time series [14-17]. Ijegwa, et al. [18] deployed a fuzzy inference system to study the trends of the stock market using technical indicators, where the fuzzy rules were the combination of the trading rules for each indicator used as input variables of the fuzzy system and for all the four indicators used, the membership functions were also defined. Zarandi, et al. [19] used type-2 fuzzy rule-based expert system model for stock price analysis modeling rule uncertainties and every membership value of an element by the application of technical and fundamental indexes as the input variables. Hegazy, et al. [20] in their paper implemented a neuro-fuzzy system using quantum differential evolution algorithm to predict the gold price in the foreign exchange market which was specified by an optimization technique based on a double chains quantum differential evolution algorithm, their proposed model showed better performance compared with Artificial neural networks and the Adaptive Neuro-fuzzy Inference system (ANFIS). Neenwi, et al. [21] exploited the learning capability of a feed forward neural network with back-propagation for the prediction of daily stock prices of securities quoted on the Nigerian Stock Exchange. Neenwi, et al. [21] in their research also investigated the predictive capability of the fuzzy inference system (FIS) on stocks listed on the Nigerian Stock Exchange using data ranging over a two-month window where the system used at least 30 days (past) stock price data to make forecast. Chang and Liu [22] developed the Takagi-Sugueno-Kang (TSK) - fuzzy rule based system for the prediction of stock price, and applied the technical index as input variables and the consequent part was a linear combination of the input variables. The fuzzy rule based system (FRBS) package developed in R by Riza, et al. [23] which implements the most widely used Mamdami and Takagi-Sugueno-Kang (TSK) models in fuzzy rule based systems, illustrates the their proficiencies in solving problems that are characterized by uncertainty, imprecision, and non-linearity.

2.1 Methodology

The increase in the volume of historical data generated publicly in stock markets across the world has necessitated the need for more efficient processes, methods, algorithms and tools for analyzing the existing datasets. A. Architecture of the fuzzy rule based system model The following steps are followed in the implementation of the fuzzy rule based system (FRBS) model which are based on fuzzy concepts that addresses real world complex problems using the Adaptive-network fuzzy inference system (ANFIS) structure. The ANFIS is the hybridization of neural and fuzzy systems which combines the problem modeling capabilities of fuzzy systems and the learning capability of the neural networks [24]. The general architecture of the ANFIS is given in figure 1, which shows the ANFIS with multiple layers that perform various operations showing the input variables, rules and consequent output. The network consists of nodes with clearly defined functions collected in layers.

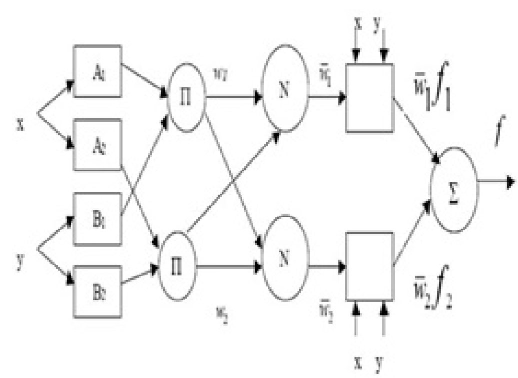

Figure 1. Structure of the ANFIS network.A

The architecture of the fuzzy rule based system is depicted in the figure below.

Generally, an FRBS consists of four functional parts:

- A fuzzification interface which transforms the crisp inputs into degrees of membership functions of the linguistic term of each variable.
- A knowledge base consisting of a database(DB) and a rulebase (RB). While the database includes the fuzzy set definitions, the rulebase contains fuzzy IF-THEN rules. This will represent the knowledge as a set of rules.

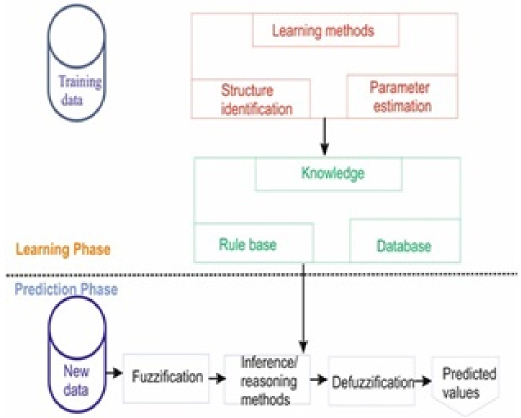

Figure 2. Architecture of a fuzzy rule based system showing its learning and prediction phase.

- An inference engine which performs the inference operations on the fuzzy IF-THEN rules. There are two kinds of inference for fuzzy systems bassed on linguistic rules: The Mamdani and the Takagi-Sugeno-Kang model.

- A defuzzification process to obtain the crisp values from linguistic values. There are several methods for defuzzification such as weighted average, centroid, etc.

The ANFIS architecture consists of two processes, the forward and the backward stages. In the forward stage, the network inputs propagate forward until layer 4, where the consequent parameters are identified by the least-squares method. The overall output for the ANFIS learning algorithm when the premise parameters are fixed is given by:

$$f = (\overline{w}_1 x)c_{11} + (\overline{w}_1 y)c_{12} + \overline{w}_1 c_{10} + (\overline{w}_2 x) + c_{21} + (\overline{w}_2 y)c_{22} + \overline{w}_2 c_{20}$$

The forward stage has five layers and are discussed as follows:

Layer 1: The fuzzification process which transforms crisp values into linguistic terms using the Gaussian function as the shape of the membership function.

Layer 2: The inference stage using the t-norm operator (the AND operator)

Layer 3: Calculating the ratio of the strengths of the rules at the nodes.

Layer 4: Calculating the consequent parameters on the layer 3 output.

Layer 5: Calculating the overall output as the sum of all incoming signals.

The backward stage is a process of parameter learning. In this step, the least squares method is used in order to obtain the parameters, which are coefficient of linear equations on the consequent part, and mean and variance in the antecedent part, [25]. The backward stage is a process to estimate the database which consists of the parameters of the membership functions in the antecedent part and the coefficients of the linear equations in the consequent part. Since this method uses the Gaussian function as membership function, optimizing the two parameters of this function: mean and variance. In this step, the least squares method is used to perform the parameter learning. For the prediction phase, the method performs normal fuzzy reasoning of the Takagi-Sugueno-Kang (TSK) model [26].

B. The Takagi-Sugueno-Kang(TSK) model

The TSK model was developed by Takagi, Sugueno and Kang as a process of algorithmically generating fuzzy rules given an input-output dataset [27] which was based on the fuzzy partition of input space where a linear input-output relation is formed in each subspace. The general algorithm identification format for the TSK model was given as: If X_1 is A_1 and ... X_k is A_k then $y = P_0 + P_1.X_1 + ... + P_k.X_k$

The three items that make up the parameters of the TSK model are determined using the input-data of an objective system:

1. X_1, ..., X_k comprises of variables composing the premises of implications.

2. A_1, ..., A_k are membership functions of the fuzzy sets in the premises, abbreviated as premise parameters.

3. P_0, ..., P_k Parameters in the consequences [27].

However, performance of the model was tested against statistical model with the results obtained being better than those obtained by statistical models [28]. The advantage of the TSK model lays in its representative power i.e. its capability in describing a highly nonlinear system using a small number of generated rules. A Learning algorithms such as fuzzy neuro system ANFIS, is conventionally used identify the parameters of the model given its explicitly represented in a functional form [25].

C. Algorithm for Stock Prediction

Step 1: Load external library frbs

Load frbs

Step 2: The excel file in a .csv format is selected as input data for the fuzzy rule based system. The input data has to be entered in the correct format.

Load stock_data.csv

Step 3: The initial part of the system takes the data entered in step 2, and splits the data into training and test data.

Split stock_data.csv into training_data and test_ data

The independent and dependent variables are also determined. The training data is used to train the frbs model using the TSK model and ANFIS learning method while the test data is used to check the closeness between the desired output ($Output_d$) and the simulated output ($Output_s$) from the system.

Train frbs with training_data.csv using TSK and ANFIS

Compare $Output_d$ *with* $Output_s$ *with test_data.csv*

Step 4: The minimum and maximum data range for each columns of the data is determined.

Set $Min_{(i,j)}$ and $Max_{(i,j)}$ **Step 5:** The training method for the developed system is set to the ANFIS method.

Set Training_Method $\rightarrow$ *ANFIS*

Step 6: The control parameters set includes: number of linguistic labels, maximum iterations, step size, t-norm type, s-norm type, implication function.

Step 7: The fuzzy model is then generated following the control parameters that were entered into the system in the previous step.

Step 8: Calculating prediction error (MSE, RMSE)

Step 9: Print error measurement

Step 10: Plot comparison between simulation and real data

3. Data Analysis and Model Building

Transnational Corporation of Nigeria plc., a leading diversified conglomerate in the conglomerate sector of the Nigerian Stock Exchange Market with focus on acquiring and managing strategic businesses that create long-term shareholder returns and socio-economic impact and Access Bank, a financial institution is listed in the financial sector of the NSE were chosen at random from the listed stocks in the Nigerian Stock Exchange Market. The data collected over the period of five months from the Nigerian Stock exchange market had ninety-one observations where the data was randomly divided into forty-five observations for training the model and forty-six for testing the predictive capability of the system. The technical indicators used for the independent variables include number of deals, closing price and value traded while quantity traded was used as the dependent variable for prediction purposes.

A. Fuzzy Rules Generated for Access Bank and Transcorp Prediction Model

The fuzzy rules generated by the using the Takagi-Sugeno-Kang Fuzzy Rule Based System (TSK-FRBS) training method. The fuzzy rule based generated by the fuzzy rule based system would look incomplete at a first glance, the takagi-sugueno-kang examined in section 3.2 shows that the consequent part of the if-then fuzzy rule generated from the model is a multiple regression equation.

The linear equations on the consequent part as stated in the summary of the model generated from the fuzzy rule based system (FRBS) shows the β_0, β_1, β_2 and constant which are linear parameters of the generated multiple regression equation. The general form of the consequent part of the generated fuzzy if-then rules is:

Y=β_0+$\beta_1 x1$+$\beta_2 x2$+$\beta_3 x3$.......(2)

Where the dependent variable Y is Quantity Traded, the intercept β_0 is represented by the Const Value of the generated fuzzy IF-THEN rules described below The value β_1 is Var.1 β_2 is Var.2 and β_3 is Var.3 respectively. The fuzzy IF-THEN rules and linear equations for the consequent parts of the IF-THEN rules for access and transcorp data are enumerated below: Fuzzy IF-THEN rules for Access bank using the TSK linear model for the consequent parts

1 IF Current.Price is medium and No.of.Deals is small and Value.Traded is small THEN Current.price (0.65008649) No.of.Deals (-0.10720679) Value.Traded (0.1643677) Constant (-0.1021505)

2 IF Current.Price is medium and No.of.Deals is small and Value.Traded is medium THEN Current.price (0.35521840) No.of.Deals (0.36879305) Value.Traded (0.2609426) Constant (0.5629472)

3 IF Current.Price is small and No.of.Deals is small and Value.Traded is small THEN Current.price (0.52777443) No.of.Deals (-0.07142768) Value.Traded (0.4775339) Constant (0.1001339)

4 IF Current.Price is small and No.of.Deals is medium and Value.Traded is small THEN Current.price (-0.46892492) No.of.Deals (0.04856254) Value.Traded (-0.1864747) Constant (-0.3917333)

5 IF Current.Price is large and No.of.Deals is medium and Value.Traded is medium THEN Current.price (0.02756924) No.of.Deals (0.07099705) Value.Traded (0.4805997) Constant (-0.1020416)

6 IF Current.Price is medium and No.of.Deals is medium and Value.Traded is medium THEN Current.price (-0.04887714) No.of.Deals (-0.27619178) Value.Traded (-0.5888071) Constant (-0.5388088)

7 IF Current.Price is large and No.of.Deals is medium and Value.Traded is small THEN Current.price (-0.22175255) No.of.Deals (-0.12436815) Value.Traded (0.5778096) Constant (0.5078264)

8 IF Current.Price is small and No.of.Deals is large and Value.Traded is medium THEN Current.price (0.47340660) No.of.Deals (0.01988052) Value.Traded (0.3435916) Constant (-0.4347904)

9 IF Current.Price is small and No.of.Deals is medium and Value.Traded is medium THEN Current.price (0.14083031) No.of.Deals (0.27377505) Value.Traded (0.1590357) Constant (-0.5098178)

10 IF Current.Price is large and No.of.Deals is small and Value.Traded is small THEN Current.price (-0.11717149) No.of.Deals (0.06176325) Value.Traded (0.4400688) Constant (-0.3394827)

11 IF Current.Price is large and No.of.Deals is large and Value.Traded is large THEN Current.price (0.62156551) No.of.Deals (0.59569247) Value.Traded (0.1462705) Constant (-0.2748185)

12 IF Current.Price is medium and No.of.Deals is medium and Value.Traded is large THEN Current.price (0.21511829) No.of.Deals (0.03919762) Value.Traded (-0.3773942) Constant (0.1869818)

13 IF Current.Price is medium and No.of.Deals is small and Value.Traded is large THEN Current.price (0.11921673) No.of.Deals (0.52022089) Value.Traded (0.3002 Constant (-0.4855795)

14 IF Current.Price is large and No.of.Deals is large and Value.Traded is medium THEN Current.price (-0.10580230) No.of.Deals (0.01629439) Value.Traded (0.61630 Constant (-0.3944314) Also, the Fuzzy IF-THEN rules for Transcorp using the TSK linear model for the consequent parts

1. IF Current.Price is medium and No.of.Deals is small and Value.Traded is small THEN Current.price (0.95573818) No.of.Deals (0.7001870) Value.Traded (0.5199293) Constant (-0.21948214)

2 IF Current.Price is medium and No.of.Deals is medium and Value.Traded is small THEN Current.price (0.06486300) No.of.Deals (0.2460213) Value.Traded (0.3736135) Constant (0.44137781)

3 IF Current.Price is small and No.of.Deals is medium and Value.Traded is small THEN Current.price (-0.04515961) No.of.Deals (-0.1174111) Value.Traded (0.4557433) Constant (-0.09231713)

4 IF Current.Price is medium and No.of.Deals is medium and Value.Traded is medium THEN Current.price (0.42685942) No.of.Deals (0.1080503) Value.Traded (0.2271270) Constant (-0.22783399)

5 IF Current.Price is small and No.of.Deals is small and Value.Traded is small THEN Current.price (-0.04582968) No.of.Deals (0.3114044) Value.Traded (0.7888288) Constant (0.12119097)

6 IF Current.Price is small and No.of.Deals is medium and Value.Traded is medium THEN Current.price (0.11797642) No.of.Deals (-0.1348099) Value.Traded (0.4567781) Constant (-0.05214856)

The relationship that exists between the variables in the access and transcorp data were described using a correlation scatter-diagram in the Fig 2 and Fig 3, thereby validating the usage of the data for further analysis and prediction purposes. The scatter plot diagrams show that a relationship exit between the variables with Table 1 and Table 2, showing the detailed information between the dependent variable which is the quantity traded and the independent variables which are current price, value traded, and number of deals respectively.

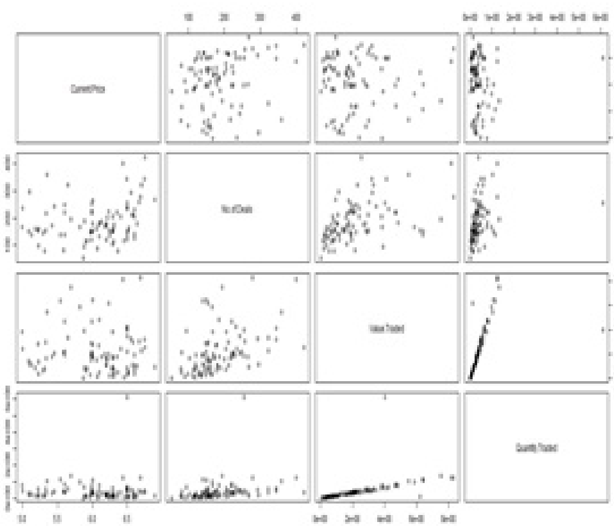

Figure 3. Scatter plot diagram showing the relationship between variables of the ACCESS BANK.

Table 1. Regression output showing the relationship for the test data which contains data from fortyfive trading days for Access Bank.

Regression Statistics	
Multiple R	0.966442
R Square	0.934011
Adjusted R Square	0.907059
Standard Error	14643717
Observations	45

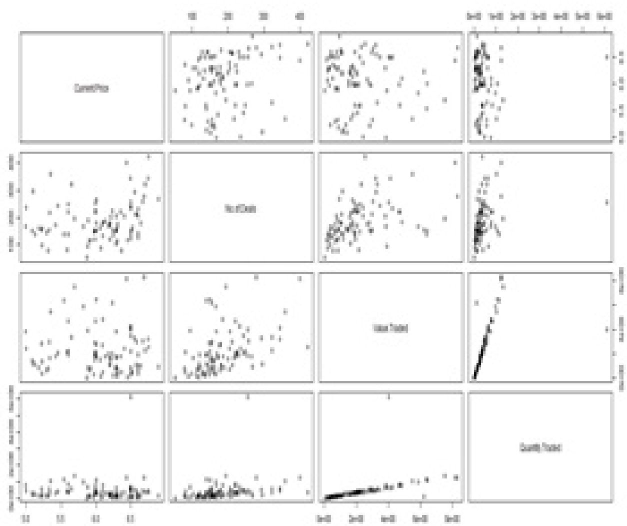

Figure 4. Scatter plot diagram showing the relationship between variables of the TRANSNATIONAL CORPORATION OF NIGERIA PLC.

Table 2. Regression output showing the relationship for the test data which contains data from forty-five trading days for Transcorp.

Regression Statistics	
Multiple R	0.995883
R Square	0.991782
Adjusted R Square	0.967582
Standard Error	2176212
Observations	45

Multiple regression and correlation were used to disentangle and examine the separate effects of the independent variables. The multiple correlation coefficient (R2) shows the combined effects of all independent variables on the dependent variable, R-square can take on any value between 0 and 1, with a value closer to 1 indicating that a greater proportion of variance is accounted for by the model. As shown in Table 1, the R squared valued is usually considered when the number of independent variables are more than one, the R squared value shows that the independent variables explains the dependent variable by 96%. Also, Table 2 above shows that the dependent variable is explained 99% by the independent variables.

Since it may be difficult to obtain information from human experts in the form required, an alternative and effective way to acquire the knowledge is to generate the fuzzy IF-THEN rules automatically from the numerical training data using the ANFIS learning method. The accuracy of prediction can only be determined by considering how well a model performs on new data that were not used when fitting the model.

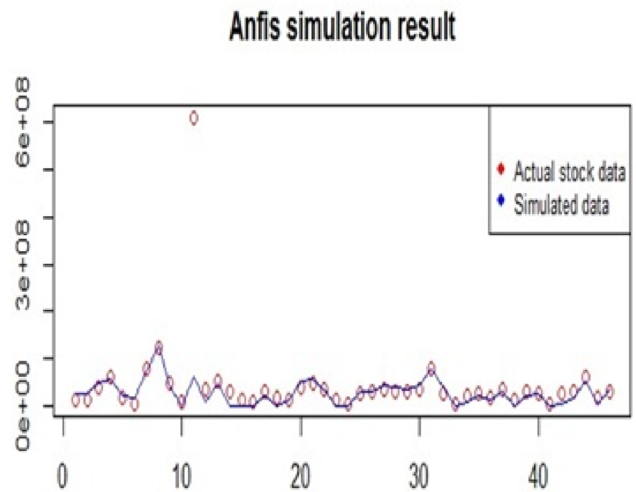

Figure 5. Comparing the prediction output from the FRBS system with the real data for Access Bank of Nigeria over period of 46 trading days

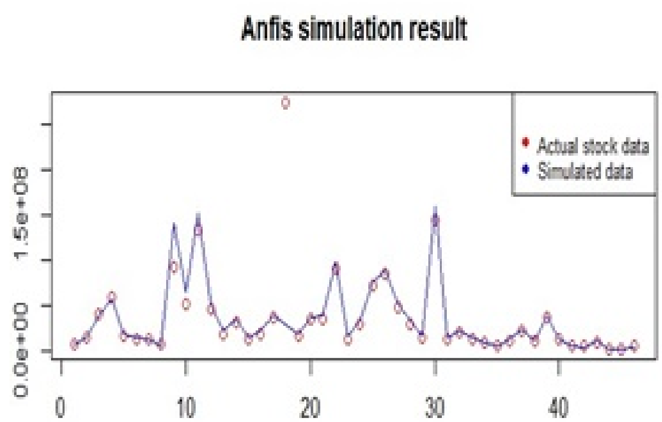

Figure 6. Comparing the prediction output from the FRBS system with the real data for Transcorp over period of 46 trading days

The Fig. 5 and Fig. 6 show the comparison of the predicted values for the period of forty-six trading days. The unison in patterns observed in Fig 4 & 5 shows that the fuzzy rule based system is a valuable tool for investors who intend having an upper hand in the Nigerian stock market, results obtained from the model relatively makes the decision of when to buy, sell or hold a particular stock easier thereby making the investment profitable. It can be seen that the fuzzy rule based system has the best result, as the actual and forecasted trend are in alignment with each other showing a consistent pattern. The trend observed in the figure 4 and figure 5 depicts the movement of the stock, and offers the investor the platform to make decision as to know when to buy, hold or sell the stock over a period of time specified as input to the system.

B. Statistical Measures to Determine the Accuracy of the Forecast In order to evaluate the accuracy of the forecast, the MSE and RMSE are used to evaluate the forecast result as they are both scale dependent errors making their outputs on the same scale as the data. The mean absolute error (MSE) is a quantity used to measure how close the predictions are to the actual values. The mean absolute error where fi is the outcome of the forecast and yi is the real value is given by

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2$$

The Root Mean Square Error **(RMSE)** (also called the root mean square deviation, RMSD) is a frequently used measure of the difference between values predicted by a model and the values actually observed from the environment that is being modelled. These individual differences are also called residuals, and the RMSE serves to aggregate them into a single measure of predictive power. The RMSE of a model prediction with respect to the estimated variable X_{model} is defined as the square root of the mean squared error:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obsi} - X_{model.i})^2}{n}}$$

where X_{obsi} is observed values and X_{model} is modelled values at time/place i.

Table 3. Error analysis

	MSE	RMSE
ACCESS	6.998378*1015	8.365631 *107
TRANSCORP	1.493182*1015	3.864172 *107

The figure 4 and figure 5 shows that there is a correspondence between the predicted values and that of the test data. The fuzzy rule based system using ANFIS leaning method was successful in predicting the future trends of Access Bank and Transcorp stocks quoted on the Nigerian stock exchange market. The RMSE and MSE was carried out on the actual and predicted values having $8.365631*10^7$ as RMSE and $6.998378*10^15$ as MSE for ACCESS bank, $3.864172*10^7$ and as MSE $1.493182*10^15$ for Transcorp. The testing results were very close to actual demonstrating that the fuzzy rule based system was successful in training the relationship between the input and output data with a well scaled acceptable error.

4. Conclusion

Precision and accuracy are essential ingredients in predictive analysis. In this study, we have been able to show that given a set of historical stock data, it is feasible to predict future stock value with precision, using the TSK-FRBS. The TSK-FRBS could therefore be a veritable tool for making decision on whether to buy, sell, or hold a particular stock for a given period of time.

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