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ORIGINAL RESEARCH

Fusion model of wavelet transform and adaptive neuro fuzzy inference system for stock market prediction

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Abstract

Stock market prediction is one of the most important financial subjects that have drawn researchers' attention for many years. Several factors affecting the stock market make stock market forecasting highly complicated and a difficult task. The successful prediction of a stock market may promise attractive benefits. Various data mining methods such as artificial neural network (ANN), fuzzy system (FS), and adaptive neuro-fuzzy inference system (ANFIS) etc are being widely used for predicting stock prices. The goal of this paper is to find out an efficient soft computing technique for stock prediction. In this paper, time series prediction model of closing price via fusion of wavelet-adaptive network-based fuzzy inference system (WANFIS) is formulated, which is capable of predicting stock market. The data used in this study were collected from the internet sources. The fusion forecasting model uses the discrete wavelet transform (DWT) to decompose the financial time series data. The obtained approximation and detailed coefficients after decomposition of the original time series data are used as input variables of ANFIS to forecast the closing stock prices. The proposed model is applied on four different companies' previous data such as opening price, lowest price, highest price and total volume share traded. The day end closing price of stock is the outcome of WANFIS model. Numerical illustration is provided to demonstrate the efficiency of the proposed model and is compared with the existing techniques namely ANN and hybrid of ANN and wavelet to prove its effectiveness. The experimental results reveal that the proposed fusion model achieves better forecasting accuracy than either of the models used separately. From the results, it is suggested that the fusion model WANFIS provides a promising alternative for stock market prediction and can be a useful tool for practitioners and economists dealing with the prediction of stock market.

Keywords Adaptive neuro fuzzy inference system · Average absolute error · Discrete wavelet transform · Stock price prediction · Fuzzy rules · Fusion model

1 Introduction

Financial time series forecasting, especially stock market forecasting is one of the hottest fields of research and has attracted a lot of interest from many scientists and experts. Prediction of price movements in stock markets has been a major challenge for common investors, brokers and businesses. The accurate forecasting of financial prices is an important issue in investment decision making. Forecasting involves an assumption that past publicly available information has some predictive relationship to future stock values. Prediction of stock market is very tricky and highly complicated task because there are too many factors that may influence stock prices such as political events, economic conditions, traders' expectations and other environmental factors. Moreover, stock price series are generally quite noisy, dynamic, non-linear, complicated, non-parametric, and chaotic by nature (Boyacioglu and Avci 2010; Zhang and Wu 2009).

Several techniques have been developed to predict nonlinearity of time series and improve the accuracy of stock market prediction such as linear regression (LR), autoregressive random variance (ARV) model, autoregressive conditional heteroskedasticity (ARCH), general autoregressive conditional heteroskedasticity (GARCH) and chaos theory (Abiyev and Abiyev 2012; Box and Jenkins 1970; Yu et al. 2007; John et al. 2012; Vellido et al. 1999). But for the uncertainty in stock market, these techniques may be good candidate for a particular situation; they do not provide satisfactory

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results for the nonlinear time-series. Soft computing techniques, such as neural networks (NNs), fuzzy systems (FSs), genetic algorithms (GAs), support vector machines (SVMs) has become important for time series prediction (Billah et al. 2015; Jang 1993; Kaur et al. 2014a, b). Neural network has the ability to adjust itself according to the given information. On the other hand, fuzzy can handle uncertainty well. ANFIS has covered both merits of neural network and fuzzy. So, ANFIS have been used for prediction purposes in many areas (Kaur et al. 2014a, b; Nikam et al. 2013; Thuillard 2001; Nguyen and Le 2014; Devadoss and Ligori 2013).

This paper proposes a novel forecasting technique to predict the closing price of stock market by integrating discrete wavelet transform (DWT) with adaptive neuro fuzzy inference system (ANFIS) named as WANFIS (wavelet-adaptive network-based fuzzy inference system). The proposed fusion model is also the extension method of the work presented in Abiyev and Abiyev (2012). In this case, DWT is used to decompose the raw data. Coefficients are used as an input to Back Propagation Neural Network (BPNN) to predict the closing price. Here, the original time series data are normalized. Then Wavelet transform is employed to decompose the normalized data into two components namely approximation and detail components. Both the coefficients are extracted as a feature vector and used as an input for ANFIS to predict the closing price.

The performance of the proposed fusion model is evaluated using five static measures such as Root Mean Squared Error (RMSE), Average Absolute Error (AAE), Coefficient of variation (CoV), Mean Absolute Percentage Error (MAPE) and the coefficient of multiple determinations (R^2). Performance of the proposed fusion model will be compared with Standard Artificial Neural Network (ANN) model and hybrid model of Wavelet with ANN. From the empirical results, it can be seen that the proposed fusion model is able to predict the stock market accurately than existing other models.

The choice of solution in predicting the stock market values is based on the parametric indices. In this case for analysis, the statistical performance measure like root mean square error (RMSE), co-variance, average absolute error (AAE) and few other parameters are considered. The impact of these solutions on the performance of neuro-fuzzy inference system is that, the predicted values should go in convergence with that of the actual values. This possibility is achieved only when the parameter indices like RMSE and AAE all possess a minimal value and the proposed algorithm aims to minimize the error values and it impacts on-par value of predicted values and actual values for the considered system.

The rest of the paper is organized as follows. Section 2 provides a review of prior literature. Section 3 introduces proposed fusion model for stock prediction. Section 4 describes the research data and detailed analysis of the experimental results. Section 5 discusses the major conclusions and findings of this work followed by relevant references.

2 Literature review

There exist enormous literatures which concentrate on the predictability of stock market. In the following section, the paper focuses on the review of the previous studies regarding the prediction of stock market with Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy Interference System (ANFIS).

Boyacioglu and Avci (2010) developed an adaptive neuro fuzzy system to predict stock market return of Istanbul Stock Exchange (ISE).The system uses six macroeconomic variables and three indices as input variables. The author uses two different membership functions gbell and Gaussian to find the best choice for prediction. The experimental results show that the model with two input Gaussian function successfully forecasts monthly return of ISE National 100 Index with an accuracy rate of 98.3%. Time series prediction model is developed by Abiyev and Abiyev (2012), which is the integration of neural networks wavelet and fuzzy logic system. The training was performed using feed forward NN, ANFIS and using fuzzy wavelet neural networks (FWNN). The training of FWNN was performed with traditional genetic algorithm that uses selection, crossover and mutation procedure and using differential evolution (DE) algorithm. From the results, it is observed that the proposed technique outperforms when it is trained using DE algorithm. Stock market closing price prediction using fuzzy logic system is proposed by Billah et al. (2015).

This paper makes a comparison between artificial neural network and adaptive neuro fuzzy inference system for predicting closing price of Dhaka Stock Exchange (DSE) data. Five major companies' historical stock data have been used. Their analysis shows that, ANFIS has minimal error than ANN and higher R^2 value. R^2 indicates strong correlation with output. Nikam et al. (2013) have investigated the performance of ANFIS and Functional Link Neural Network architecture (FLANN) for stock market closing price prediction. The authors have utilized some parameters namely simple moving average, accumulation or distribution line, on balance volume, price rate of change and main important factor is closing price, opening price, lowest value in the day, highest value in the day and the total volume of stocks traded. They have applied three different types of membership function bell, Gaussian and sigmoid to find the good choice for prediction. Simulation results show that the ANFIS model with bell type membership function gives the comparatively minimal errors than that of the other membership functions. Mirzapour et al. (2017) proposed a forecast model that included a feature selection filter and hybrid forecast engine based on neural network (NN) and an intelligent evolutionary algorithm. This method not only could maintain the SOC of batteries in suitable range, but also could decrease the on-or-off switching number of wind turbines and PV modules. Wang (2018) proposed a hybrid method incorporating principal component analysis, categorical regression tree and a back propagation network (PCA–CART–BPN) to engine failure time prediction.

Liu et al. (2018) developed an accurate forecast model based on improved wavelet transform, informative feature selection and hybrid forecast engine. The proposed forecasting engine is based on support vector machine which is an appropriate prediction forecast engine due to its ability to discover natural structures of wind speed/power variation. Ye et al. (2017) proposed a new fusion method to make full use of all kinds of forecast information to improve the performance of forecasting and made an application to oil price forecast fusion by it. Yu et al. (2018) reviewed back-propagation neural network algorithm and genetic algorithm and developed an agricultural product price forecasting model.

On performing literature review on the existing methods available to carry out stock market prediction, it is inferred that the possible strengths are, more statistical measures are used and higher datasets are employed for training rather than testing to improve the accuracy of the model. The observed limitations on the existing works include—the developed algorithms getting stuck in local and global minima problem, higher computational time and the error values are reasonably high. Hence, in order to overcome the said limitations of the existing methods, this work contributed to the development of variant of ANFIS model i.e., a hybrid wavelet ANFIS for predicting the stock market values.

2.1 Research issue and problem statement

The major research issue is to predict the stock market values when there is a rapid change in the stock markets which leads to highest non-linearity. Day-by day, minute-by-minute, second-by-second is the variation in the stock market and to avoid the loss of the investors, it is highly essential to predict the stock market values. There exist several indices for the same, and this research work considers few datasets along with the set indices to predict the stock market value.

The need for stock market prediction is to overcome the unavoidable loss in the stock exchange rates and to ensure beneficial for the investors.

The parameters pertaining to the statistical measure are considered to be evaluated employing the proposed hybrid wavelet based ANFIS model. The datasets are scaled and are presented as input to the hybrid WANFIS and the set parameters are evaluated to predict the stock market values and their convergence is tested and validated with that of the actual values.

3 Proposed fusion model: hybrid wavelet–ANFIS model

The prime objective of the research is designing and rendering stock market closing price prediction model with the help of wavelet adaptive neuro fuzzy inference system (WANFIS). The proposed WANFIS fusion model is shown in Fig. 1.It consists of four phases: (1) The original historical stock price time series data are per processed with a normalization; (2) Normalized data is decomposed using Haar wavelet transform (3) Both approximation and detail coefficients are extracted from the decomposed data to form the feature vector and (4) The resulting feature vector feeds the input of a ANFIS.

In this work wavelet transform is employed along with ANFIS module. For ANFIS structure, directly the scaled raw inputs are given as inputs, but in case of WANFIS module, 'Haar' wavelet transform in employed for the analysis for the decomposition of time series. The approximation and detail coefficients are extracted in WANFIS to form the feature

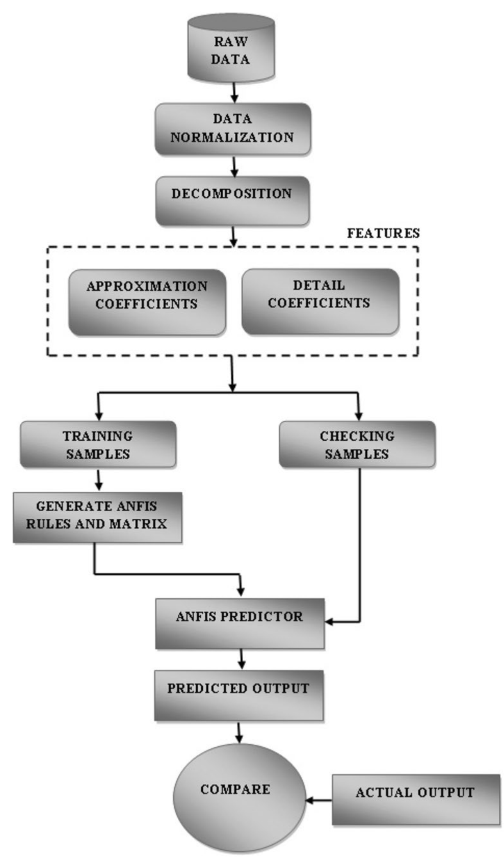

Fig. 1 Work flow of proposed fusion model

vectors and these extracted feature vectors are fed as input to the ANFIS module. In hybrid wavelet–ANFIS model, the features are extracted considering the prominent approximation and detail coefficients. When these most prominent extracted features are given as input to the ANFIS model, the convergence rate is faster, and results in increased accuracy. Hence, this paper focused on hybrid fusion model of the wavelet transform into the ANFIS module and resulted in developing a WANFIS model.

3.1 Data preprocessing

For the purpose of WANFIS forecasting model, all data were normalized to the [0, 1] interval using the following equation:

$$y_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}(h_i - l_i) \tag{1}$$

where, y_i normalized value of the input or the output value, x_i original input or output value, x_{min} minimum original input or output value, X_{max} maximum original input or output value, h_i upper bound of the normalizing interval (in this case 1), l_i lower bound of the normalizing interval (in this case 0)

3.2 Wavelet decomposition

Wavelets are promising mathematical tool used to decompose a given continuous-time signal or functions into components of different scales. A Wavelet Transform (WT) is the representation of a function by wavelets. The wavelets are scaled and translated copies of a finite-length or fast-decaying oscillating waveform (Devadoss and Ligori 2013). WT have the advantages over traditional Fourier Transforms (FT) for representing functions that have discontinuities and sharp peaks, and for accurately reconstructing finite, non-periodic and/or non-stationary signals. WT can be categorized into two types i.e., Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). In CWT, during computation, the analyzing wavelet is shifted smoothly over the full domain of the analyzed function. Calculating wavelet coefficients at every possible scale can be very tedious task and data generated can be difficult to analyzed (Atsalakis and Valavanis 2009; Wang and Choi 2013; Masoud 2014; Lai and Liu 2014; Chong et al. 2017; Gu 2017). By choosing the scales by the power of two, the analysis can become more accurate and faster. Hence, the proposed fusion model WANFIS employ the DWT for prediction.

There are different types of DWT available for different types of series being analyzed. This paper uses "Haar" wavelet in the analysis for the decomposition of time series. The level of decomposition is set to three. Then, approximation and detail coefficients are extracted to form the feature vectors, which are later fed as an input to the ANFIS for training. There have been lots of research efforts on wavelet fuzzy systems, in which wavelets are used for denoising purpose only. But, the proposed fusion model will restrict to studying the effect of de-noising by wavelets and then feeding the reconstructed de-noised signal into the ANFIS, instead of training the ANFIS with wavelet high and low frequency components (Rout et al. 2017; Gu and Shao 2016; Caraiani 2017; Yoshihara et al. 2014; Zhong and Enke 2017).

3.3 Prediction

Soft computing techniques have been widely applied in most of the fields of computation studies. They present useful tools in forecasting noisy environments like stock markets, capturing their non-linear behavior. Utilizing intelligent systems such as artificial neural networks, fuzzy systems and genetic algorithms for the purpose of prediction in the field of finance has extensive applications. Recently, artificial neural networks (ANNs) have been successfully applied to solve the problems of predicting financial time series (Xu 2013; Yang et al. 2018; Yang et al. 2017; Fischer and Krauss 2018; Malagrino et al. 2018). Main feature of this ANN is the ability of self learning and self-predicting some desired outputs. The learning may be done with a supervised or an unsupervised method. Neural Network and Fuzzy Logic are the basic areas of artificial intelligence concept. ANFIS combines these two methods and uses the merits of both methods (Kia et al. 2018; Cheng and Yang 2018; Kim and Won 2018).

Adaptive neuro fuzzy interference system not only includes the characteristics of both methods, but also eliminates some demerits of their lonely-used case. Operation of ANFIS looks like feed-forward back propagation network. Consequent parameters are calculated forward while premise parameters are calculated in backward (Nguyen and Le 2014). There are two learning methods in neural section of the system: Hybrid learning method and back-propagation learning method. In fuzzy section, only zero or first order. Since ANFIS combines both neural network and fuzzy logic, it is capable of handling nonlinear and complex problems. Even if the targets are not given, ANFIS may reach the optimum result rapidly. In this paper, extracted feature vectors from the decompose data are given to the input of ANFIS to make rule and predict the stock market closing price. The hybrid learning algorithm for ANFIS has been used in this study. Algorithm for stock market closing price prediction is given in Table 1.

Table 1 Algorithm of predictive fusion model

```
Step 1: Import the historical data.

        [~,~,raw,dateNums]= xlsread (filename,'table','','',@ convert Spreadsheet Dates);

Step 2:Assign the opening price, lowest price, highest price and volume as an input and closing

    price as the output variable.

     In=[open low high volume],tar=closing price

Step 3: Normalize the variables.

Step 5: Decompose the variables using Haar wavelet transform upto three levels.

     In=A3+ D3+ D 2+ D1

Step 6: Extract the approximation and detailed coefficients to form the feature vectors.

     X=[ A3  D3  D 2  D1 tar]

Step 7: Select the samples for training and for checking data

     traindata(:, n) = X(a:b);

    checkdata(:, m) = X(i:j);

Step 8: Generate the fuzzy rule using the training data

    Infismat = genfis1(traindata,2,'gbell');

Step 9: Generate the ANFIS matrix using fuzzy rule.

[trainfismat,trainerror,[],ckeckfismat,checkerror] = anfis(traindata, Infismat,[],[],checkdata);

Step 10: Predict the closing price using ANFIS rule and measure the performance.

   output = evalfis( In, trainfismat);
```

4 Research data sets and experiments

This section consists of two subsections. First section presents the data set used for forecasting and second section will present the criteria which have been used to make fair comparison of the proposed fusions model with the other models.

4.1 Data set

The research data used in this study are the stock prices of four different companies. The stocks are Tata steel, Wipro, SBI and TCS. The historical data of four largest companies have been collected from Yahoo finance website (Wang and Choi 2013). The data set contains daily opening price, lowest price, highest price, closing price and total number of share traded. The whole data set covers the period from January 2010 to June 2015, a total of 1414 observations. The whole data set is divided into two groups. The first group of the data (1314 observations) is utilized for training the model. The second group of the data (100 observations) is utilized for testing the model. Table 2 contains the list of selected companies, variables and number of observations.

4.2 Statistical performance measures

Numerous statistical measures are used for measuring the accuracy and performance of prediction models. This paper uses Root Mean Squared Error (RMSE), Average Absolute Error (AAE), Coefficient of variation (CoV), Mean Absolute

Table 2 Data source information

Selected variables	Name of company	Total data points	No. of training DATA	No. of test data	Stock period
Opening price Lowest price	TATASTEEL	1414	1314	100	1/1/2010 to10/6/2015
Highest price	WIPRO	1414	1314	100	1/1/2010 to10/6/2015
Closing price	SBI	1414	1314	100	1/1/2010 to10/6/2015
Total share traded	TCS	1414	1314	100	1/1/2010 to10/6/2015

Percentage Error (MAPE) and the coefficient of multiple determinations (R^2) to compare predicted and actual values. The smaller values of error, the closer are the predicted values to the actual values and R^2 value nearer to 1 indicates higher correlation. They statistical measures are defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(\left|A_k - P_k\right|\right)^2} \tag{2}$$

$$MAE = \frac{1}{N}\sum_{k=1}^{N}\left|A_k - P_k\right| \tag{3}$$

$$CoV = \frac{\sqrt{N^{-1}\sum_{K=1}^{N}\left(A_K - P_K\right)^2}}{\left|\overline{P}\right|} \tag{4}$$

$$MAPE = \frac{1}{N}\sum_{k=1}^{N}\left|\frac{A_k - P_k}{A_k}\right| \times 100 \tag{5}$$

$$R^2 = 1 - \frac{\sum_{k=1}^{N}\left(P_k - A_k\right)^2}{\sum_{k=1}^{N}\left(A_k - \overline{A}\right)} \tag{6}$$

Where, N is the total data sample, A_k is the actual value, P_k denotes the predicted value, $\overline{A}$ is the mean of the actual value and $\overline{P}$ represents the mean of predicted value.

4.3 Simulation results

To show the performance of the proposed fusion model the computer program was performed on MATLAB 7.10 environment by using Wavelet and fuzzy toolbox. We also conduct an experiment to compare the results between the proposed fusion model which predicts stock market based on approximation and detail coefficient features and other models such as the ANN model and the hybrid model of DWT and ANN in Wang and Choi (2013) with the same testing data (100 observations). ANN model was built on a Back Propagation Neural Network (BPNN) which is a type of feed forward network. The BPNN is often used for prediction problems in Atsalakis and Valavanis (2009) and Masoud (2014). The hybrid of DWT and ANN was proposed to improve the effectiveness of time series prediction, especially in stock market forecasting reported in Atsalakis and Valavanis (2009). Furthermore, the paper compared the simulation result of WANFIS model with that of the other models from the literature. Wavelet transform is used to decompose the original time series. Then, low and high frequency components are extracted and have been applied on ANFIS. ANFIS is a fuzzy neural network model which was standardized in MATLAB. It has been applied in several studies in prediction problems. Variation in membership function of fuzzy system brings variation in result. So, to model a system with less error it is necessary to select the right membership function and their number (Kim and Won 2018; Shi et al. 2018; Chou and Nguyen 2018; Hong et al. 2018). For this purpose, the fusion model uses two bell memberships for four input variable and constant membership function for output variable. The prediction performance of fusion model is evaluated using some commonly used statistical metrics such as RMSE, AAE, CoV, MAPE, and R^2. The result of the proposed fusion model is show in Fig. 2 and Table 3. The above comparison clearly shows that the fusion model of wavelet and ANFIS in RMSE, AAE and CoV measures outperforms the other model which uses BPNN in prediction. In MAPE and R^2 measures using WANFIS alone, outperforms all others. Figure 3 illustrates the testing of the proposed fusion model in blue line compared with the original data in red line for two bell membership functions on each of the four inputs. The generated FIS structure contains 16 fuzzy rules. It has been observed that the proposed fusion model able to predict the stock market with high accuracy than the compared models and matching between original data and predicted data is obviously shown.

In Fig. 2, with respect to the derived values of AAE, it is noted that the conventional ANN model possess value of 0.339 and the proposed WANFIS model resulted in achieving a value of 0.002 proving its effectiveness. This

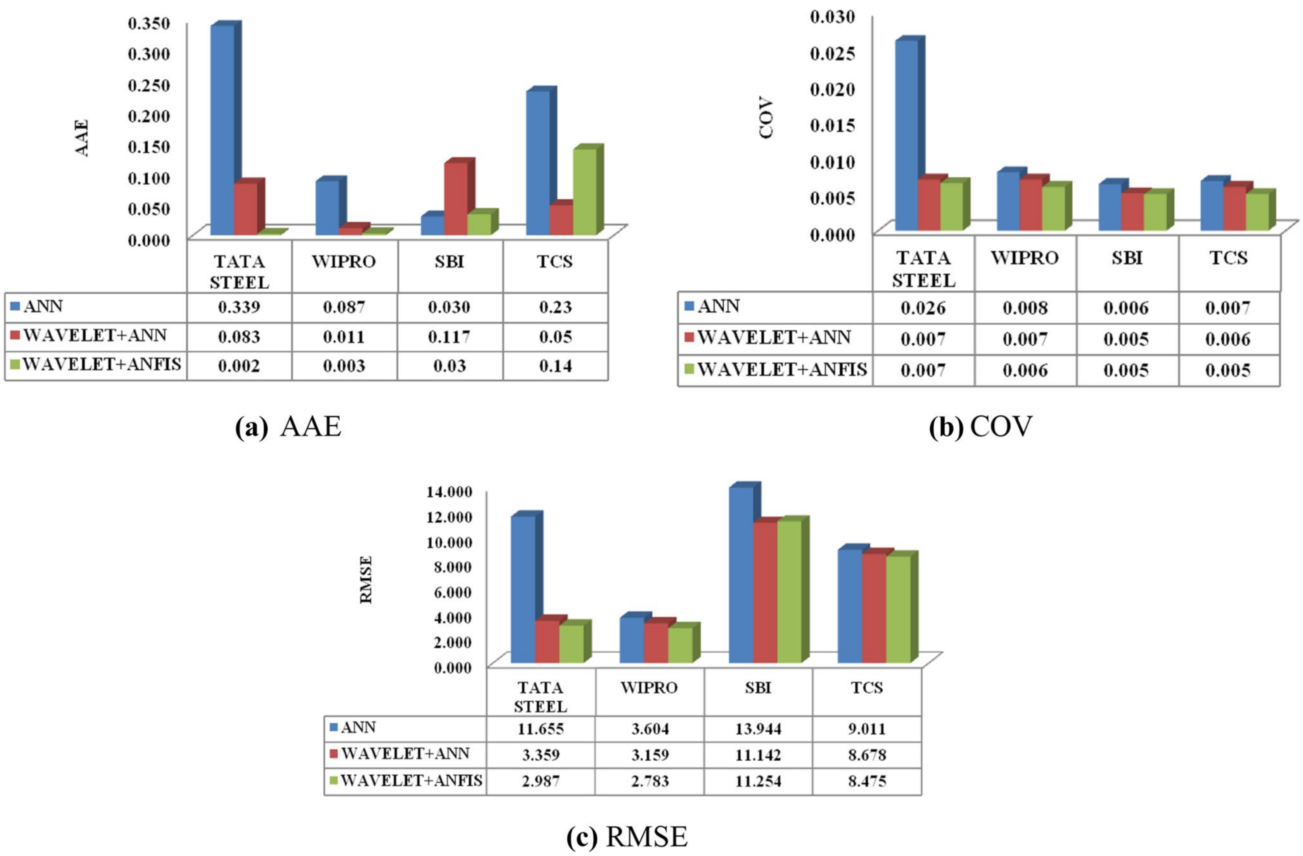

Fig. 2 Performance in terms of statistical measures

Table 3 Result of WANFIS fusion model

Metrics	TATASTEEL	WIPRO	SBI	TCS
MAPE	0.4757	0.4477	0.4386	0.4003
R^2	1	0.882	1	0.9943
Prediction accuracy	97.56%	98.33%	98.17%	96.25%

is observed for all the other datasets also. On the other hand observing the co-variance value for TataSteel and SBI with ANFIS and WANFIS the results computed are the same, but are better than the regular ANN model. In case of co-variance value for WIPRO and TCS, the proposed WANFIS evolved results better than the other two methods considered for comparison. RMSE values show significant variations employing the proposed WANFIS model. The RMSE value has reduced and is minimal with the proposed WANFIS than that of the regular ANN and ANFIS model.

Further, from Fig. 3, for all the four datasets, wherein the proposed approach is tested and validated, it is noted that the predicted values employing developed WANFIS model is converging and is in accordance with that of the actual values, proving their effectiveness.

5 Conclusion

This paper presented a fusion model for prediction by combining wavelet and adaptive neuro fuzzy interference system. Fusion model uses Haar wavelet transform to decompose the original time series data. Then, the obtained low and high frequency components after decomposition of the original time series data are used as an input variable to forecast stock price. The forecasting ability of models accessed on the basis of RMSE, AAE and CoV. It also makes a comparison between ANN, WANN and proposes a WANFIS system for predicting closing price stock market. Four major companies of historical stock data have been used. Based on the experimental results, WANFIS has less error than ANN and WANN. The simulation results show that this fusion model achieves better forecasting accuracy than either of the models used separately. So it is suggested that, WANFIS can be used to predict the closing price of stock market providing previous historical data. The logical next step for the research is to improve the accuracy of prediction using some optimization algorithms such as genetic algorithm, PSO, ACO.

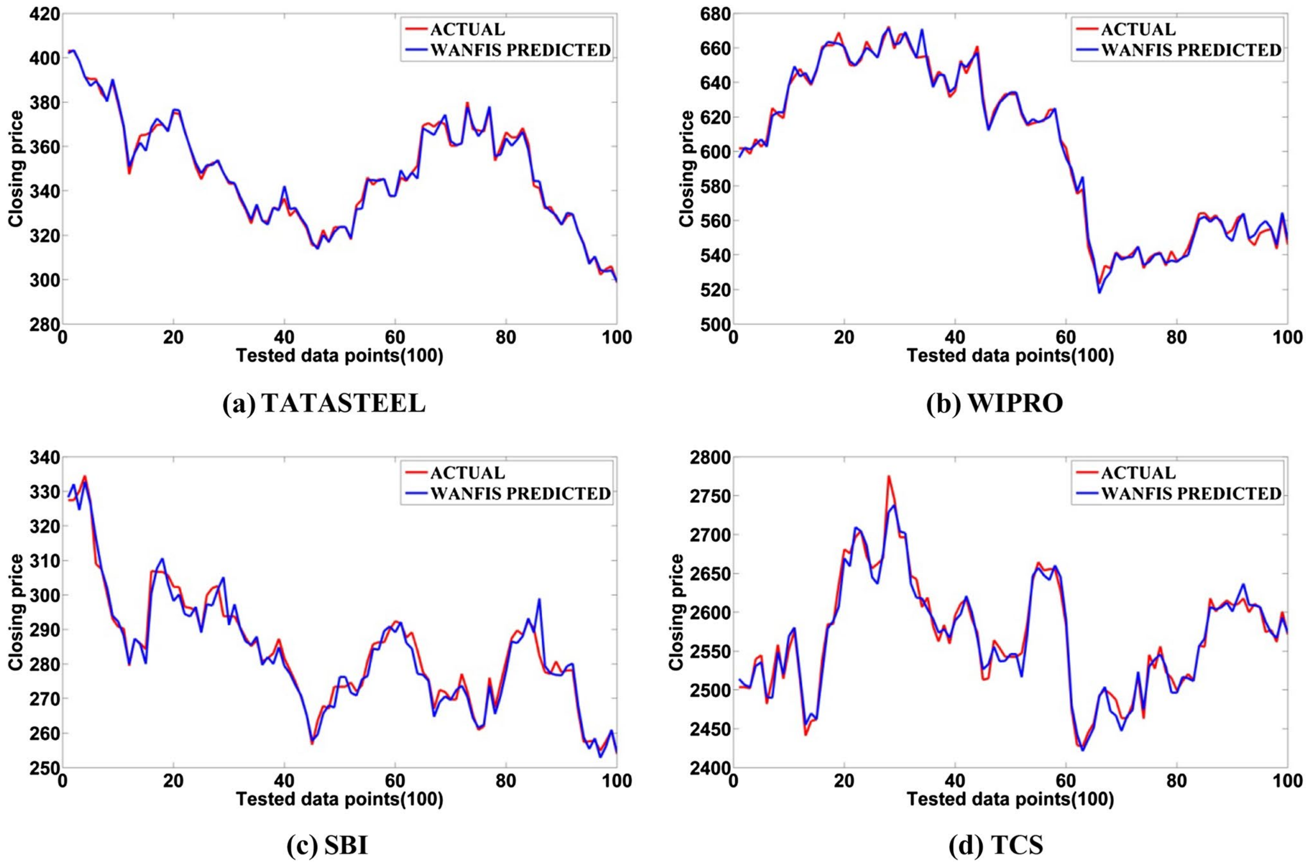

Fig. 3 Comparison of actual and WANFIS predicted values

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