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Prediction of Stock Market Price using Hybrid of Wavelet Transform and Artificial Neural Network

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Abstract

Background/Objectives: Accurate prediction of stock market is highly challenging. This paper presents a forecasting model based on Discrete Wavelet Transform (DWT) and Artificial Neural Network (ANN) for predicting financial time series. **Methods/Statistical analysis:** The idea of forecasting stock market prices with discrete wavelet transform is the central element of this paper. The proposed forecasting model uses the Discrete Wavelet Transform to decompose the financial time series data. The obtained approximation and detail coefficients after decomposition of the original time series data are used as input variables of back propagation neural network to forecast future stock prices. Approximation coefficients can characterize the coarse structure of the data and detail coefficients capture ruptures, discontinuities and singularities in the original data, to recognize the long-term trends in the original data. **Findings:** The proposed model was applied to five datasets. For all of the datasets, accuracy measures showed that the presented model outperforms a conventional model. It also proved that the hybrid forecasting technique has achieved better results compared with the approach which is not using the wavelet transform. **Applications/Improvements:** The accuracy of the proposed hybrid method can also be improved by developing a model using artificial neural network with Adaptive Neuro Fuzzy Interference System.

Keywords: Artificial Neural Network, Discrete Wavelet Transform (DWT), Time Series and Stock Market Prediction

1. Introduction

Stock market is a public market for security where organized issuance and trading of company stocks take place either through exchange or over the counter in physical or electronic form. It is nowadays a common notion that huge amounts of capital are traded through stock market all around the world[1]. So, accurate prediction of stock market is highly challenging and important issue for investors and it has received much attention in financial time series, financial researchers and experts. However, due to non-linear, non-stationary, highly noisy and chaotic characteristics of stock market, the forecasting of stock market is always considered to be very difficult and challenging process[2].

Different kinds of technical, fundamental and statistical measures have been proposed and used in forecasting financial forecasting such as simple moving average, linear regression, Support Vector Machine (SVM) and Back Propagation Neural Network (BPNN). Recently, Wavelet transform have been successfully applied to many fields such as engineering, physics, signal processing and financial time series because of its powerful feature extraction capability[3]. Wavelet transform is a promising signal processing technique that simultaneously analyzes the time domain and frequency domain. It decomposes the given input data into Approximation (low frequency) Coefficients (AC) and Detail (high frequency) Coefficients (DC). Approximation coefficients used to characterize the coarse structure of data to identify long term trends and detail coefficients used to capture rupture, singularities and discontinuities. Wavelet analysis allows us to extract the important hidden information and significant temporal features of the original time series data.

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The fundamental and novel contribution of the paper is to use Discrete Wavelet Transform (DWT) to decompose the historical data series into a set of well-behaved coefficients (AC and DC). Then, both low and high frequency coefficients are used as input variables to forecast closing price using back propagation neural network, The proposed hybrid model will be compared to the standard model, in which original data series are used as predictive input to be fed into the BPNN. Comparing proposed hybrid technique with the standard model allows us to check whether hybrid approach can be effective in stock market prediction.

The rest of the paper is organized as follows: The next section briefly discusses the some related work. In section 3, the design of the proposed prediction model is provided. Section 4 presents the data collection and performance measured criteria. The empirical results are presented in section 5.Section 6 concludes the paper followed by references.

2. Review of Related Work

Huang et al.[4] have presented a model for financial time series analysis using discrete wavelet transform. The proposed model uses Recurrent Self-Organizing Map (RSOM) neural network for partitioning and storing the temporal context of the feature vector space. It uses multiple kernel partial least squares regression for forecasting purposes. The authors concluded that the proposed system achieves the lowest root-mean-squared forecasting errors in comparison with the other traditional model. Hsieh et al. have applied the wavelet decomposition to analyze the stock price. They have used Recurrent Neural Network (RNN) was to do the forecasting task. The Artificial Bee Colonyalgorithm (ABC) was employed to optimize the RNN weights and biases. The simulation results indicated that the proposedmodel is highly promising than other techniques. A hybrid method by combining wavelet analysis with kernel Partial Least Square (PLS) regression for stock index forecasting is developed by Huang[5]. The author used Discrete Wavelet Transform (DWT) to identify financial time series characteristics and PLS to generate the most efficient subspace that maintains maximum covariance between inputs and outputs. The experimental results showed thatthe hybrid DWT-PLS model outperformed traditional neural networks, support vector machines and GARCH models. Wang et al.[6] has introduced a method to forecast Shanghai Stock Exchange (SSE) prices. Wavelet transform are used to decompose the original price into many levels. For each level of decomposition, the Backpropagation neural network (BPNN) was applied to predict SSE prices while using low-frequency coefficients. BPNN with fourth level low-frequency coefficients outperforms than BPNN that uses past values of the original data. Lahmiri[7] have applied discrete wavelets todecompose the S & P 500 price index. The author uses low-frequency coefficient, support vector machines with different kernels were used as the base line forecasting model. The simulation results shows that the SVM with the wavelet analysis can predict accurately than SVM with macroeconomic variables as predictive variables. Stock market forecasting that integrates both the DWT and BPNN is introduced by salimlahmiri[8]. The designed model uses the DWT to decompose the financial time series data. Then, the approximation and detail components the original time series are used as input variables to forecast future stock prices. Accuracy measures showed that the presented model outperforms a conventional model that uses only low-frequency components.

3. Design of the Proposed Forecasting Technique

The proposed prediction system consists of three steps: (1) The historical stock price time series o(t) are processed with a discrete wavelet transform; (2) Both approximation A(t) and detail D(t) coefficients are extracted to form the main feature vector and (3) The formed feature vector feeds the input of a back-propagation neural network.

4. The Wavelet Transform

In this section, a brief description of the wavelet transform is given. The wavelet analysis is a mathematical model that allows decomposing a given signal o(t) into many frequency bands[9]. In particular, the signal o(t) is decomposed into smooth coefficients a and detail coefficients d, which are represented by,

$$A_{i,j} = \int o(t)\Phi_{i,j}(t)dt \quad (1)$$

$$D_{i,j} = \int o(t)\Psi_{i,j}(t)dt \quad (2)$$

where Φ and Ψ represents the father and mother wavelets, and j and k denotes the scaling and translation parameters. The father wavelet approximates the approximation coefficients and the mother wavelet approximates the detailed coefficients. The father wavelet Φ and Ψ are defined as follows:

$$\Phi_{i,j}(t) = 2^{-i/2}\Phi(2^{-i}j - j) \tag{3}$$

$$\Psi_{i,j}(t) = 2^{-i/2}\Psi(2^{-i}j - j) \tag{4}$$

The two wavelets Φ and Ψ satisfy the condition given in Eq.5 and 6:

$$\int \Phi(t)dt = 1 \tag{5}$$

$$\int \Psi(t)dt = 0 \tag{6}$$

As a result, the orthogonal wavelet representation of the original signal o(t) is defined by,

$$o(t) = \sum_j a_{i,j}\Phi_{i,j}(t) + \sum_j d_{i,j}\Psi_{i,j}(t) + \sum_j d_{i-1,j}\Psi_{i-1,j}(t) + \ldots + \sum_j d_{1,j}\Psi_{1,j}(t) \tag{7}$$

The decomposition process of the DWT is shown in Figure 1.The original signal O(t) is divided into approximation coefficients A(t) and detail coefficients D(t).The low-pass filtered signal is the input for the next level decomposition and so on. A(t) contains the low-frequency components of the signal O (t) and D(t) contains the high-frequency components. In financial time series forecasting, different types of wavelets can be used, such as the Daubechies, Haar, Morlet and MexicanHat and wavelets. In this paper, Haar wavelet is applied to decompose the original signal O(t). The decomposition level is set to two. Finally, the Matlab Wavelet Toolbox is employed to perform the DWT on the data.

5. Back Propagation Neural Networks

The multilayer neural networks that are trained by using the Back Propagation (BP) algorithm are the most popular choice in neural network applications in finance forecasting. The BP neural network is the multilayer feed-forward neural networks, which are capable of approximating any continuous function with desired accuracy[10]. The BPNN consists of three layers. The first layer is an input layer and corresponds to the problem's input variables. The second layer is the hidden layer is used to capture the non-linear relationships among the variables. The third layer is the output layer used to provide the forecasted values[11]. The backpropagation neural network used in this model is trained with Levenberg-Marquardt to forecast the closing price of stock market. The detailed steps for stock prediction using hybrid technique are given as follows:

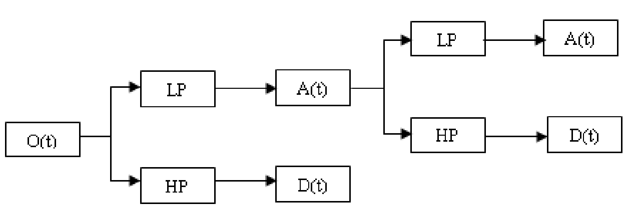

Figure 1. A two-level decomposition of a signal o(t)

Step 1: Data collection: Historical data of stock market are collected from authorized source.

Step 2: Decomposition: The original data series is decomposed using Haar wavelet transform up to 2 levels.

Step 3: Developing prediction system using BPNN to predict the closing price.

Step 4: Measure the performance of the proposed method

6. Data Description and Methodologies

This section consists of three subsections. First section presents the data set used for forecasting, second section will present the criteria which have been used to make fair comparison and then the framework comparison will be presented with more details.

7. Dataset Description

In order to demonstrate the effectiveness of hybrid technique, the data sets of five stock prices are used. The stocks are Tata steel, Wipro, SBI, TCS and Infosys. The historical data were downloaded from the Yahoo finance website[12]. The proposed technique considers the data for the time period from January 1, 2010 to June, 2015 with a total of 1414 observations. The first 80% of the total data points are used as the training sample, while the remaining 20% of the total sample data points are used as the testing sample.

8. Performance Measure Employed

The forecasting performance of the proposed technique is evaluated using the following common statistics: Coefficient of Variation (CoV), Mean Absolute Deviation (MAD) Root Mean Square Error(RMSE), and Mean Absolute Error(MAE). They are given as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(\left|A_k - P_k\right|\right)^2} \tag{8}$$

$$MAE = \frac{1}{N}\sum_{k=1}^{N}\left|A_k - P_k\right| \tag{9}$$

$$CoV = \frac{\sqrt{N^{-1}\sum_{K=1}^{N}\left(A_K - P_K\right)^2}}{\left|\overline{P}\right|} \tag{10}$$

$$MAD = \frac{1}{N}\sum_{K=1}^{N}\left|P_K - \overline{P}\right| \tag{11}$$

9. Comparison Framework

The Discrete wavelet transform divides the input data series into two sets: Approximation coefficients and details coefficients. These two coefficients present a better behavior than original data. In this paper the approximation and detail coefficients have been used since approximation coefficients can capture ruptures, singularities and discontinuities and detail coefficients characterize the coarse structure of the input data. The comparison procedure explained in this paper is given in below:

(i) Historical data is decomposed using Haar wavelet transform. (ii) Both coefficients obtained after decomposition of original data is used as input variable of the neural network to make forecasting.(iii)Performance of the proposed technique is compared with the standard neural network technique used directly to forecast closing price by using above criteria.

10. Experimental Results and Discussion

The forecasting results of the proposed technique (BPNN+DWT) are shown in Table 1. The performance measures obtained with Back Propagation Neural network (BPNN) using both the coefficients are smaller than those obtained with the standard back propagation approach, which is based on original data. This effect is very pronounced on Tata steel and Wipro[13]. For example, using Tata steel dataset, the RMSE, MAE, CoV and MAD obtained with the standard approach, which is based on original data set, 11.655, 0.34, 0.026 and 2.36 respectively. In contrast, the values obtained with the proposed technique (BPNN+DWT) are 3.359, 0.08, 0.007 and 2.32 respectively. Hence, proposed technique able to predict the future closing price with small errors. For Wipro, the obtained RMSE, MAE, CoV and MAD with the standard approach (versus proposed technique) are 3.604 (3.159), 0.09 (0.01), 0.008 (0.007) and 2.23 (2.19) respectively. Similar results are obtained with the other companies.The performance of proposed technique and standard approach in terms of

Table 1. Summary of simulation results

Input Variable	Company Name	Method	Forecasting Performance			
			RMSE	MAE	COV	MAD
	TATASTEEL	BPNN	11.655	0.34	0.026	2.36
		BPNN+DWT	3.359	0.08	0.007	2.32
	WIPRO	BPNN	3.604	0.09	0.008	2.23
OPENING PRICE		BPNN+DWT	3.159	0.01	0.007	2.19
LOW	SBI	BPNN	13.944	0.03	0.006	8.92
HIGH		BPNN+DWT	11.142	0.01	0.005	7.67
VOLUME	TCS	BPNN	9.011	0.23	0.007	6.02
		BPNN+DWT	8.678	0.05	0.006	5.87
	INFOSYS	BPNN	15.912	0.08	0.006	10.57
		BPNN+DWT	14.763	0.03	0.005	9.71

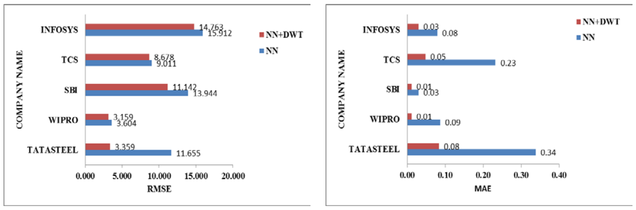

Figure 2. Performance in terms of RMSE and MAE

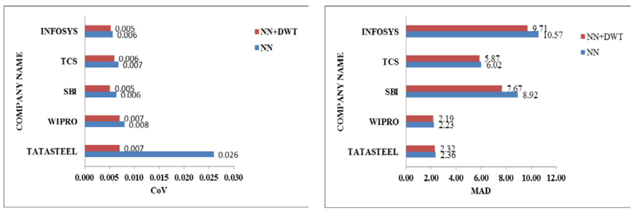

Figure 3. Performance in terms of CoV and MAD

RMSE and MSE is shown in Figure 2 and in terms of CoV and MAD is graphically illustrated in Figure 3.

In summary, for all of the input data sets, the deviations between the forecasted and actual values are smaller when the proposed technique (BPNN+DWT) is employed to predict the closing price 1. Thus, combing the two frequency components (AC+DC) could provide better accuracy. From the empirical results, it is suggested that the proposed technique outperforms the standard technique, which uses original historical data as predictive inputs to be given to BPNN.

11. Conclusion and Future Research

This paper presented a hybrid forecasting technique that integrates discrete wavelet transform and back propagation neural network to forecast closing price of stock market. The presented technique first uses discrete wavelet transform to decompose the historical data. Then, the obtained approximation and detail coefficients after decomposition of the original data are used as an input variable to forecast future stock price. Simulation results showed that the approximation coefficients coupled with detail coefficients resulted in higher accuracy compared to conventional model that uses original data series. Furthermore, empirical finding suggests that the proposed technique to be an effective tool for financial forecasting and gives more accurate results. For future work, the proposed method can be combined with other machine learning algorithms, such as recurrent neural network, Support vector machines and ANFIS to improve the prediction accuracy.

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