Journal of Computational Science 12 (2016) 23–27

Contents lists available at ScienceDirect

Journal of Computational Science

journal homepage: www.elsevier.com/locate/jocs

Intraday stock price forecasting based on variational mode decomposition

Salim Lahmiri

ESCA School of Management, 7, Abou Youssef El Kindy Street, BD Moulay Youssef, Casablanca, Morocco

ARTICLE INFO

Article history:
Received 15 August 2015
Received in revised form
18 November 2015
Accepted 27 November 2015
Available online 28 November 2015

Keywords:
Variational mode decomposition
Artificial neural networks
Particle swarm optimization
Intraday stock price
Forecasting

ABSTRACT

This paper presents a hybrid predictive model for forecasting intraday stock prices. The proposed model hybridizes the variational mode decomposition (VMD) which is a new multiresolution technique with backpropagation neural network (BPNN). The VMD is used to decompose price series into a sum of variational modes (VM). The extracted VM are used to train BPNN. Besides, particle swarm optimization (PSO) is employed for BPNN initial weights optimization. Experimental results from a set of six stocks show the superiority of the hybrid VMD–PSO–BPNN predictive model over the baseline predictive model which is a PSO–BPNN model trained with past prices.

1. Introduction

Time series modeling and prediction is receiving a large attention in different applications; including flood monitoring [1], social network modeling [2], fire prediction [3,4], commodity price forecasting [5], stock market modeling [6], and financial risk evaluation [7]. In particular, stock price time series modeling and forecasting is a hot topic in quantitative finance since accurate prediction of stock price is crucial to financial risk evaluation and asset allocation. However, forecasting stock price is difficult because of the complexity and influence of industrial and economic factors; for instance. Therefore, because of the importance of the topic several studies have proposed different models for stock price prediction; including for instance combination of vector error correction model and multi-output support vector regression [8], combination of ant colony optimization and auto-regression [9], evolutionary trend reversion model [10], wavelet components [11,12], and hybrid econometrics and artificial neural networks models [13].

Recently, the variational mode decomposition (VMD) [14] was introduced as an entirely non-recursive decomposition technique based on the concept of searching a specific number of modes and their respective center frequencies used to reproduce the input time series exactly or in least-squares sense [14]. In short, it decomposes a given signal into a set of modes around a central frequency. As a new multiresolution technique, the VMD was recently applied in biomedical image and signal denoising [15,16] and studying long memory of international stock markets during 2008 international financial crisis [17].

The main purpose of this paper is to employ the VMD in forecasting intraday stock price. The advantages of employing the VMD follow. First, it has the ability to separate tones of similar frequencies [14] for better time series characterization. Second, using simulated harmonic functions, it was found that the VMD is effective in denoising time series [14]. In this regard, the VMD would be helpful to better characterize intra-day stock prices as they are known to be very noisy.

For instance, the VMD is applied to the underlying intraday stock price series for decomposition purpose to obtain component series (called variational modes, VM) used to describe original time series characteristics. Then the obtained components are used as predictors for backpropagation neural network (BPNN) [18] to predict next-minute stock price. Besides, a BPNN trained with past prices is adopted as baseline model for comparison purpose. In our work, BPNN is adopted because it is capable to approximate an arbitrary nonlinear function with satisfactory precision [19]. Indeed, it is able to learn from examples to extract patterns with no prior assumptions regarding data generating process. In addition, it is robust to noisy data. In recent years, BPNN was effective in a stock market prediction [11–13]. In this work, particle swarm optimization (PSO) [20] is adopted to optimize

E-mail address: slahmiri@esca.ma

http://dx.doi.org/10.1016/j.jocs.2015.11.011
1877-7503/

BPNN initial weights. As a heuristic optimization technique, it is fast and effective optimizing technique. Finally, the performance of each predictive model will be assessed by four common evaluation metrics: mean absolute deviation (MAD), mean absolute error (MAE), root mean of squared errors (RMSE), and the mean absolute percentage error (MAPE) statistic.

The paper is organized as follows. In Section 2, we briefly introduce the variational mode decomposition, artificial neural network, and PSO. The obtained forecasting results are described in Section 3. Finally, Section 4 concludes.

2. Methodology

2.1. Variational mode decomposition

The purpose of the VMD is to decompose an input time series into k discrete number of modes where each mode has limited bandwidth in spectral domain [14]. Each mode k is required to be mostly compact around a center pulsation ω_k determined along with the decomposition [14]. For instance, the time series f is decomposed into a set of modes u_k around pulsation ω_k according to the following constrained optimization problem [14]:

$$\min_{u_k,\omega_k} = \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2 \qquad (1)$$

Subject to:

$$\sum_k u_k = f \qquad (2)$$

where δ is the Dirac distribution, t is time script, k is number of modes, and * is convolution operator. The mode u with high-order k represents low frequency components. There is no methodology regarding optimal selection of the parameter k. Therefore, its value is arbitrarily set to 10.

2.2. Neural network and particle swarm optimization

The backpropagation neural network (BPNN) [18] is a neural network with one input layer, one or more hidden layers, and an output layer. The output equation of the network is expressed as follows:

$$\text{Output}_j = S\left(\sum_{i=1}^{q} w_{ij} x_i + \theta_j \right) \qquad (3)$$

where w_{ij} is the weight connecting input i to neuron j, θ is the bias, q is sample size, and S is a non-linear transfer function. The goal is to find the error E between the obtained output and the desired one given by

$$E = \frac{1}{2} \sum_{j=1}^{k_j} \left(d_j - y_j \right)^2 \qquad (4)$$

where y_j and d_j are the actual and the desired output in each node j, respectively. In this paper, we adopted the sigmoid function as non-linear transfer function. The Levenberg–Marquardt algorithm [18] is used to train the BPNN because of fast convergence, whilst PSO is employed to find a combination of weights and biases which provide the minimum error E for each BPNN.

There is no formal theory on methodology to design architecture of an ANN. Therefore, the architecture of the BPNN adopted in our study is arbitrarily determined and is described as follows. For the VMD-based approach, the number of nodes in the input layer is set to the number of extracted variational modes; for instance, ten nodes. The number of nodes in the hidden layer is set to be the double of nodes in the input layer. The output layer has only one node corresponding to the predicted stock price. For the single BPNN predictive model used as main benchmark one, the input layer has one node corresponding to the actual stock price, the hidden layer has two nodes, and the output layer has only one node corresponding to the predicted stock price. Finally, all input data are normalized within [−1,1] for better convergence of the BPNN.

2.3. Particle swarm optimization

Particle swarm optimization [18] is a heuristic optimization technique based on a population of particles. For instance, in order to discover the optimal solution, particles are used to move through a multidimensional search space where each one changes its position in direction of its previously best position (*pbest*) and best position of all other particles (*gbest*). At time t, the velocity (v) and the position (p) of the each particle (i) are updated as follows:

$$v_i(t+1) = wv_i(t) + c_1 r_1 (pbest_i - p_i(t)) + c_2 r_2 (gbest - p_i(t)) \qquad (5)$$

$$p_i(t+1) = p_i(t) + v_i r(t+1) \qquad (6)$$

where r_1 and r_2 are uniform random variables in the range [0,1], c_1 and c_2 are positive acceleration coefficients related respectively to personal and social learning factors, and w is the inertia weight. For a given particle, initial position and velocity are generated randomly. In our work, BPNN weights and biases are optimized by PSO. This is achieved by minimizing the fitness function of the ith training sample:

$$\text{fitness}(X_i) = E(X_i) \qquad (7)$$

In our study, c_1 and c_2 are set to 2, r_1 and r_2 are two random numbers generated in the interval [0,1], w decreases linearly from 0.9 to 0.4, and the initial velocities of particles are randomly generated in the interval [0,1]. Finally, the population size is set to 50.

3. Data and experimental results

We used four weeks intra-day stock prices of six American stocks; namely, Apple, Dell, Hewlett-Packard, IBM, Microsoft, and Oracle. The time period spans from 2011 February 28th to 2011 March 3th where the time interval between samples is one minute. Thus, the total number of samples is 3910. The first 80% of the samples are used for training the predictive models and the remaining 20% are used for testing. Fig. 1 shows the evolution of each stock price. The obtained performance statistics are all presented in Fig. 2 for each stock and for each prediction approach. The lower are the statistical performance metrics (MAE, MAD, RMSE, MAPE), the better is the accuracy. Based on all four performance metrics, it is clearly shown that for all stocks the values of performance measures of the VMD-based approach are the smallest (Fig. 2). Therefore, the deviation between actual and predicted values of the VMD–PSO–BPNN prediction model is the smallest in comparison to the standard Single-PSO–BPNN. In sum, according to all performance metrics, the PSO–BPNN system trained with VMD-based components provides better prediction results than that trained with historical prices. In other words, the experimental results suggest that variational modes extracted by VMD allow significantly improving the forecasting accuracy of the PSO–BPNN. Thus, VMD based components were able to characterize intraday stock price generating process better than historical price.

One can notice that differences in performance measures can be due to differences in distributions of testing samples shown in Fig. 3. In particular, it is observed that higher standard deviation in price levels yields to higher RMSE achieved by the reference model; namely, the Single-BPNN–PSO. In other words,