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A hybrid evolutionary dynamic neural network for stock market trend analysis and prediction using unscented Kalman filter

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ABSTRACT

Stock market prediction is of great interest to stock traders and investors due to high profit in trading the stocks. A successful stock buying/selling generally occurs near price trend turning point. Thus the prediction of stock market indices and its analysis are important to ascertain whether the next day's closing price would increase or decrease. This paper, therefore, presents a simple IIR filter based dynamic neural network (DNN) and an innovative optimized adaptive unscented Kalman filter for forecasting stock price indices of four different Indian stocks, namely the Bombay stock exchange (BSE), the IBM stock market, RIL stock market, and Oracle stock market. The weights of the dynamic neural information system are adjusted by four different learning strategies that include gradient calculation, unscented Kalman filter (UKF), differential evolution (DE), and a hybrid technique (DEUKF) by alternately executing the DE and UKF for a few generations. To improve the performance of both the UKF and DE algorithms, adaptation of certain parameters in both these algorithms has been presented in this paper. After predicting the stock price indices one day to one week ahead time horizon, the stock market trend has been analyzed using several important technical indicators like the moving average (MA), stochastic oscillators like K and D parameters, WMS%R (William indicator), etc. Extensive computer simulations are carried out with the four learning strategies for prediction of stock indices and the up or down trends of the indices. From the results it is observed that significant accuracy is achieved using the hybrid DEUKF algorithm in comparison to others that include only DE, UKF, and gradient descent technique in chronological order. Comparisons with some of the widely used neural networks (NNs) are also presented in the paper.

1. Introduction

Price index forecasting is one of the most important problems in financial markets that make the investors worry about their investments. In the past decades, the stock market prediction has played a vital role for the investment brokers and individual investors and researchers are on the constant lookout for a reliable method for predicting stock market trends. The nonlinear and nonstationary characteristics of the stock market make it difficult and challenging for forecasting stock indices in a reliable manner. Traditionally the basic methodology for financial time series has been a series of statistical methods like ARMA, ARIMA, GARCH, etc., which have been used over the years but suffer from the assumption of linear variation of the stock prices during a certain period of time. In general, the statistical models do not yield a process that can be easily automated, as it requires adaptation and changes at every stage requiring certain regularities and stationary nature in the target data. Accordingly, traditional statistical methods cannot be used to track the complexity and nonstationary nature of the stock markets.

In their search for methods for addressing these shortcomings, many market analysts, traders, and researchers have investigated the various intelligent system techniques for analyzing the stock markets and making trading decisions. The various tools of computational intelligence include artificial NN (ANN) [1–4], fuzzy logic systems [5–8], support vector machines (SVM) [9,10]. The different types of ANNs used for stock market analysis include radial basis function NN (RBFNN) [11], recurrent NN (RNN) [12,13], multilayer perceptron (MLP) [14–16], generalized regression NN (GRNN) [17], random vector functional link net (FLANN) [18,19], local linear wavelet NN (LLWNN) [20,21], wavelet NN (WNN) [22], etc. These neural models, however, do not perform so successfully due to the dimensionality, volatility, and noise of the stock price data. Fuzzy logic theory is preferred by several investigators due to its superior capabilities to handle uncertainties in the data and a synergic combination of fuzzy logic systems and NN have evolved for stock market prediction. These models include fuzzy NN (FNN) [23], adaptive network fuzzy information system (ANFIS) [24], wavelet fuzzy NN (WLFNN) [25], etc. To improve the accuracy of prediction and automate stock market forecasting and trend analysis other

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inputs like the technical indicators and qualitative factors due to political effects, etc. are used along with the price data. Even with these indicators, the NN models suffer from computational complexity because they need as many as 800 neurons in the input layer and 600 neurons in the hidden layers for predicting reasonably well stock price indices over a certain time frame. Further search techniques like the genetic algorithm (GA), particle swarm optimization (PSO) [26], bacterial foraging optimization (BFO), DE [27], etc. are used to obtain optimal parameters of the network that includes the network weights, the number of neurons in the hidden layer, etc. to improve the accuracy of the prediction.

DNN models provide an excellent means for forecasting and prediction of nonstationary time series. In particular, a neural architecture, known as locally recurrent NN (LRNN) [28], is preferred to the traditional MLP because the time varying nature of a stock time series can be better represented using LRNN. The use of LRNN has demonstrated superioriority in comparison to other NN approaches for temporal sequence processing and a number of successful applications exists in the areas of electrical load forecasting, non linear system prediction, and economic time series prediction.

Therefore, in this paper, a simple feed forward DNN comprising one or more layers of dynamic neurons is presented for forecasting stock price indices and profits from one day ahead to 30 days in advance. The DNN includes one or more IIR (infinite impulse filter) filters in the forward path providing feedback connections between outputs and inputs. This allows signal flow in both forward and backward directions, giving the network a dynamic memory useful to mimic dynamic systems. Further for globally recurrent networks, the stability is hard to be proved, but locally recurrent networks allow easy checking of the stability by the examination of poles of their internal filters However, training these networks presents difficulties due to the feedback connections. The possible algorithms that can be used for training RNNs are: (1) the back propagation through time (BPTT) [29] where the recurrent network is unfolded into a multilayer feed forward network that increases by one at each time step; (2) the real time recurrent learning (RTRL) which is based on the supervised learning method where the feedback from the output of a unit is replaced by the output of the true system in subsequent computations. However, the RTRL algorithm suffers from low convergence speed and multiple local minima.

Considering the chaotic nature of the time series prediction and noise problem, extended Kalman filter (EKF) [30] and unscented Kalman filter (UKF) [31,32] have been proposed for fast convergence and good tracking performance. A key property of the EKF is that it is the minimum-variance estimator for the state of a nonlinear dynamical system and when applied to IIR filter NN training, it produces faster convergence than gradient-based algorithms; also, it overcomes the vanishing-gradient problem. The EKF algorithm provides first-order approximations to optimal nonlinear estimation through the linearization of the nonlinear system, which might produce large errors in the true posterior mean and covariance of the transformed (Gaussian) random variable, leading to suboptimal performance, and sometimes, filter divergence. The UKF first proposed by Julier and Uhlmann [31] and further extended by Wan and van der Merwe [32], is an alternative to the EKF algorithm and provides third-order approximation of process and measurement errors for Gaussian distributions. Consequently, the UKF does not require the computation of Jacobeans, needed for linearizing the process and measurement equations and thus produces better estimates of the weights of the recurrent NN.

UKF is based on the unscented transformation (UT) theory, and has a greater ability to cope with non-linearities in one-step ahead prediction. Instead of linearizing a nonlinear system, a statistical distribution of the state is propagated through the non-linear system that provides better estimates of the actual state and the posterior covariance matrices. Thus, instead of using the standard gradient or back propagation algorithm for adjusting the weights and some parameters of the DNN, an UKF is used in this paper to provide fast convergence and better accuracy with respect to chaotic variations in the inputs. However, its accuracy significantly reduces, if Signal-to-Noise Ratio is low and the noise co variances and some of the parameters used in unscented transformation are not chosen correctly. Thus to obtain an optimal forecasting performance, it is proposed in this paper to use DE technique for optimizing the objective function obtained from the UKF algorithm alternately during the beginning of the learning cycle. Once initialized using DE, the optimized UKF algorithm updates the weights of the DNN and exhibits superior convergence in tracking a chaotic time series like the stock market indices. Unlike traditional EAs (Evolutionary algorithms), DE employs the difference of the parameter vectors to explore the objective function landscape. The advantage of DE is that there is a possibility of finding the global minimum of a multimodal function irrespective of the values of its initial parameters. Additionally, DE takes very few control parameters (typically the population size *Np*, the scale factor *F*, and the crossover rate *Cr*), which makes it easy to use.

It is well known that the technical indicators play a great role in predicting the dynamic behavior of the stock market indices, and hence they can be used to predict the next day's trend whether the stock indices are going up or down. Turning point of this trend can be used as a buy or sell decision for the traders and investors in the market. The technical indicators chosen for this purpose are the 25 and 65 days moving average, relative strength index, trading volume, stochastic oscillators, and William indicator, etc. With the help of a few simple rules, the up and down trend of the stock indices can be ascertained, which can be used for automatic buying or selling decision.

This paper is organized as follows: in Section 2, the architecture of the DNN is proposed. The state space model of the UKF is described in Section 3 along with the learning strategy of the DNN and this section also deals with the DE technique and various steps in implementing the algorithm are described. In Section 4 the performance of the prediction algorithms are analyzed using various technical indicators, while the stock market trend analysis is presented in Section 5. Section 6 provides the original datasets and an overview of input selection for the various stock market data and the stock value prediction results and the errors for different data sets with and without the use of DE. Trend prediction using certain technical indicators and a pertinent rule base are also given in this section. Finally, conclusion is given in Section 7. Further some of the well known NNs like the FLANN, LLWNN, and a slightly modified RBFNN are used for comparison.

2. Feed forward DNN architecture

The IIR-MLP NN architecture considered in this paper is similar to the multi-layered feed-forward one comprising locally recurrent dynamic neurons. The proposed model exhibits dynamic properties by introducing an infinite impulse response (IIR) filter into the neuron structure. Fig. 1 shows the structure and the topology of the dynamic neuron and multilayered dynamic neural network (DNN). Consequently incorporating an IIR filter between input weights and the output, the neuron can reproduce its own past inputs using two signals: the lagged input pattern input and filter output. For the *j*th dynamic neuron, the weighted sum of the inputs (lagged stock indices and technical indicators) to it is computed at the *k*th instant as

$$s_{j,k} = \sum_{i=1}^{p} w_{ji} x_i \tag{1}$$