Journal of King Saud University – Computer and Information Sciences (2017) 29, 536–552

King Saud University

Journal of King Saud University – Computer and Information Sciences

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Forecasting financial time series using a low complexity recurrent neural network and evolutionary learning approach

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Received 14 March 2015; revised 24 May 2015; accepted 3 June 2015
Available online 2 November 2015

KEYWORDS

Low complexity FLANN models;
Recurrent computationally efficient FLANN;
Differential Evolution;
Hybrid Moderate Random Search PSO

Abstract The paper presents a low complexity recurrent Functional Link Artificial Neural Network for predicting the financial time series data like the stock market indices over a time frame varying from 1 day ahead to 1 month ahead. Although different types of basis functions have been used for low complexity neural networks earlier for stock market prediction, a comparative study is needed to choose the optimal combinations of these for a reasonably accurate forecast. Further several evolutionary learning methods like the Particle Swarm Optimization (PSO) and modified version of its new variant (HMRPSO), and the Differential Evolution (DE) are adopted here to find the optimal weights for the recurrent computationally efficient functional link neural network (RCEFLANN) using a combination of linear and hyperbolic tangent basis functions. The performance of the recurrent computationally efficient FLANN model is compared with that of low complexity neural networks using the Trigonometric, Chebyshev, Laguerre, Legendre, and tangent hyperbolic basis functions in predicting stock prices of Bombay Stock Exchange data and Standard & Poor's 500 data sets using different evolutionary methods and has been presented in this paper and the results clearly reveal that the recurrent FLANN model trained with the DE outperforms all other FLANN models similarly trained.

1. Introduction

Financial time series data are more complicated than other statistical data due to the long term trends, cyclical variations, seasonal variations and irregular movements. Predicting such highly fluctuating and irregular data is usually subject to large errors. So developing more realistic models for predicting financial time series data to extract meaningful statistics from it, more effectively and accurately is a great interest of research

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Peer review under responsibility of King Saud University.

Production and hosting by Elsevier

http://dx.doi.org/10.1016/j.jksuci.2015.06.002
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in financial data mining. The traditional statistical models used for financial forecasting were simple, but suffered from several shortcomings due to the nonlinearity of data. Hence researchers have developed more efficient and accurate soft computing methods like Artificial Neural Network (ANN); Fuzzy Information Systems (FIS), Support Vector Machine (SVM), Rough Set theory etc. for financial forecasting. Various ANN based methods like Multi Layer Perception (MLP) Network, Radial Basis Function Neural Network (RBFNN), Wavelet Neural Network (WNN), Local Linear Wavelet Neural Network (LLWNN), Recurrent Neural Network (RNN) and Functional Link Artificial Neural Network (FLANN) are extensively used for stock market prediction due to their inherent capabilities to identify complex nonlinear relationship present in the time series data based on historical data and to approximate any nonlinear function to a high degree of accuracy. The use of ANN to predict the behavior and tendencies of stocks has demonstrated itself to be a viable alternative to existing conventional techniques (Andrade de Oliveira and Nobre, 2011; Naeini et al., 2010; Song et al., 2007; Lee and Chen, 2007; Ma et al., 2010).

A system of time series data analysis has been proposed in Kozarzewski (2010) for predicting the future values, based on wavelets preprocessing and neural networks clustering that has been tested as a tool for supporting stock market investment decisions and shows good prediction accuracy of the method. MLP neural networks are mostly used by the researchers for its inherent capabilities to approximate any non-linear function to a high degree of accuracy (Lin and Feng, 2010; Tahersima et al., 2011). But these models suffer from slow convergence, local minimum, over fitting, have high computational cost and need large number of iterations for its training due to the availability of hidden layer. To overcome these limitations, a different kind of ANN i.e. Functional Link ANN (Proposed by Pao (1989)) having a single layer architecture with no hidden layers has been developed. The mathematical expression and computational calculation of a FLANN structure is evaluated as per MLP. But it possesses a higher rate of convergence and lesser computational load than those of a MLP structure (Majhi et al., 2005; Chakravarty and Dash, 2009). A wide variety of FLANNs with functional expansion using orthogonal trigonometric functions (Dehuri et al., 2012; Mili and Hamdi, 2012; Patra et al., 2009), using Chebyshev polynomial (Mishra et al., 2009; Jiang et al., 2012; Li et al., 2012), using Laguerre polynomial (Chandra et al., 2009) and using Legendre orthogonal polynomial (Nanda et al., 2011; George and Panda, 2012; Rodriguez, 2009; Das and Satapathy, 2011; Patra and Bornand, 2010) has been discussed in the literature. The well known Back Propagation algorithm is commonly used to update the weights of FLANN. In Yogi et al. (2010), a novel method using PSO for training trigonometric FLANN has been discussed for equalization of digital communication channels.

In this paper, the detailed architecture and mathematical modeling of various polynomial and trigonometric FLANNs have been described along with a new computationally efficient and robust FLANN, and its recurrent version. It is well known that the recurrent neural networks (RNNs) usually provide a smaller architecture than most of the nonrecursive neural networks like MLP, RBFNN, etc. Also their feedback properties make them dynamic and more efficient to model nonlinear systems accurately which are imperative for nonlinear prediction and time series forecasting. Many of the Autoregressive Moving Average (ARMA) processes have been accurately modeled by RNNs for nonlinear dynamic system identification. One of the familiar approaches of training the RNNs is the Real-Time Recurrent Learning (RTRL) (Ampolucci et al., 1999), which has problems of stability and slow convergence. In nonlinear time series forecasting problems it gets trapped in local minima and cannot guarantee to find global minima. On the other hand, evolutionary learning techniques such as Differential Evolution, particle swarm optimization, genetic algorithm, bacteria foraging, etc. have been applied to time series forecasting successively. DE is found to be efficient among them and outperforms other evolutionary algorithms since it is simpler to apply and involves less computation with less function parameters to be optimized as compared to other algorithms. DE is chosen because it is a simple but powerful global optimization method and converges faster than PSO. A comparative study between Differential Evolution (DE) and Particle Swarm Optimization (PSO) in the training and testing of feed-forward neural network for the prediction of daily stock market prices has shown that DE provides a faster convergence speed and better accuracy than PSO algorithm in the prediction of fluctuated time series (Abdual-Salam et al., 2010). Differential Evolution based FLANN has also shown its superiority over Back Propagation based Trigonometric FLANN in Indian Stock Market prediction (Hatem and Mustafa, 2012). The convergence speed is also faster to find a best global solution by escaping from local minima even for multiple optimal solutions.

Thus, in this paper various evolutionary learning methods like PSO, HMRPSO, DE for improving the performance of different types of FLANN models have been discussed. Comparing the performance of various FLANN models for predicting stock prices of Bombay Stock Exchange data and Standard & Poor's 500 data set, it has been tried to find out the best FLANN among them. The rest of the paper is organized as follows. In Sections 2 and 3, the detailed architecture of various FLANNS and various evolutionary learning algorithms for training has been described. The simulation study for demonstrating the prediction performance of different FLANNS has been carried out in Section 4. This section also provides a comparative result of training and testing of different FLANNS using PSO, HMRPSO, and DE (Mohapatra et al., 2012; Qin et al., 2008; Wang et al., 2011) based learning for predicting financial time series data. Finally conclusions are drawn in Section 5.

2. Architecture of low complexity neural network models

The FLANN originally proposed by Pao in 1992 is a single layer single neuron architecture, having two components: Functional expansion component and Learning component. The functional block helps to introduce nonlinearity by expanding the input space to a higher dimensional space through a basis function without using any hidden layers like MLP structure. The mathematical expression and computational calculation of a FLANN structure is same as MLP. But it possesses a higher rate of convergence and lesser computational cost than those of a MLP structure. A wider application of FLANN models for solving non linear problems like channel equalization, non linear dynamic system identification, electric load forecasting, prediction of earthquake, and financial forecasting has demonstrated its viability, robustness and ease of computation. The functional expansion block comprises either a trigonometric block or a polynomial