Neurocomputing 188 (2016) 23–30

Contents lists available at ScienceDirect

Neurocomputing

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

Regularized dynamic self-organized neural network inspired by the immune algorithm for financial time series prediction

Abir Jaafar Hussain [a,*], Dhiya Al-Jumeily [a], Haya Al-Askar [a], Naeem Radi [b]

[a] Faculty of Engineering and Technology Liverpool John Moores University, Liverpool L3 3AF, UK
[b] Al Khawarizmi International College, Abu Dhabi, United Arab Emirates

ARTICLE INFO

Article history:
Received 13 September 2014
Received in revised form
18 December 2014
Accepted 29 January 2015
Available online 17 December 2015

Keywords:
Dynamic neural network
Exchange rate time series
Financial time series prediction

ABSTRACT

This paper presents a novel type of recurrent neural network, the regularized dynamic self-organized neural network inspired by the immune algorithm. The regularization technique is used with the dynamic self-organized multilayer perceptrons network that is inspired by the immune algorithm. The regularization has been addressed to improve the generalization and to solve the over-fitting problem. In this work, the average values of 30 simulations generated from 10 financial time series are examined. The results of the proposed network were compared with the standard dynamic self-organized multilayer perceptrons network inspired by the immune algorithm, the regularized multilayer neural networks and the regularized self-organized neural network inspired by the immune algorithm. The simulation results indicated that the proposed network showed average improvement using the annualized return for all signals of 0.491, 8.1899 and 1.0072 in comparison to the benchmarked networks, respectively.

1. Introduction

Financial time series analysis is a fundamental subject that has been addressed widely in economic fields. A time series is a collection of observations of well-defined data items obtained through repeated measurements during a period of time. The analyses of financial time series have economic importance. It is a promising and crucial task for any future investment used to make decisions in different areas, such as businesses and financial institutions. Financial time series involve different time scales such as intraday (high frequency), hourly, daily, weekly, monthly, or tick-by-tick stock prices of exchange rates [1]. The distance between variables in financial time series is influenced by real economic activities [2]. The effect of these activities have been represented by a mixture of hills and bumps in financial time series charts [3]. Thus, the prediction aims to forecast these activities. Financial data analysis usually provides the fundamental basis for decision models to achieve good returns [4], which is the first and the most important factor for any investor. This can help to improve companies' strategies and decrease the risk of potentially high losses [5]. Furthermore, it can help investors to cover the potential market risk to establish some techniques to progress the quality of financial decisions. Financial data are naturally dynamic, nonlinear, nonparametric, complex, and chaotic [6]. This type of time series is non-stationary, has a high level of uncertainty, is highly noisy and has an unstructured nature which includes regular structural breaks. In addition, the financial time series holds several types of data, which are incomplete, unclear and unlimited [7]. Financial time series such as the stock market are facing dramatic changes, as well as rapid information exchange all the time. Hence, the prediction of its economic activity in the future is extremely challenging [7,8,9]. Furthermore, Yao et al. [10] identified that there are a number of interrelated factors influencing the direction of the price movement on the stock market, besides the economic factors, which are political factors and psychological factors affecting both powerful decision makers and individuals or consumers. Even traditional economics studies indicated that even microeconomic drivers can affect demand consumption patterns and vice versa, thus forming a very complicated, highly interrelated system to model [10,11]. Therefore, researchers can face many challenges when handling time series forecasting [12]. The selection of an appropriate model for solving time series prediction problem has been considered by many scholars and public investors [13].

Neural networks have been widely applied to the domain of financial time series prediction. During the last decades, a number of neural network architectures have been proposed and investigated in this regard. According to Zekic [14], neural networks have different applications to financial time series analysis, which include classification of stock, recommendation of trading, predicting price changes of stock indexes, stock price forecasting and modeling the time series of stock markets. A number of studies,

* Corresponding author. Tel.: +44 1512312458.
E-mail address: a.hussain@ljmu.ac.uk (A.J. Hussain).

http://dx.doi.org/10.1016/j.neucom.2015.01.109
0925-2312/

including Bansal et al. [15], Yao et al. [10], Vojinovic et al. [16] Dunis and William [17,18], Pissarenko [19], Aryal and Yao-wu [20], Kamruzzaman [1,4], Bagherifard et al. [21] have confirmed that neural networks perform better than traditional prediction models such as the ARIMA model in financial time series prediction in terms of statistical and financial matrices. Researches indicated that artificial neural networks (ANNs) can forecast the future currency with up to 60% accuracy [22,23], and consequently are being widely used to model the behavior of financial data and to forecast future values for time series [24,25].

There are several features that make neural network the ideal technique over other traditional models of prediction. For example, since the majority of traditional models of prediction are linear, they fail to understand data patterns when the underlying relationship in time series is nonlinear. ANN has emerged as a powerful learning technique to perform complex tasks in highly nonlinear dynamical environments.

The advantage of using a neural network as a prediction tool is that it includes automatic learning of dependencies and it can be adapted to any type of data [21]. Utilizing a neural network to forecast financial time series such as a stock market has a number of advantages including: saving investors' time when making financial decisions, and aiding them to decrease investment loss and risk caused by stock market fluctuation [26]. Artificial neural networks (ANNs) have been widely used in both modern industries and scientific research to perform diverse and sophisticated tasks, such as data processing, pattern recognition, forecasting the exchange rates between currencies or forecasting the sign of price increments, capture the underlying information and rules of the movement in currency exchange rates [10,29,30,31]. In 1991, some banks started utilizing neural network models to help them make conclusions about loan application of financial prediction [19]. Several large investment banks (including Goldman Sachs and Morgan Stanley) currently have departments dealing exclusively with neural network for their business investment models [27].

MLP networks have powerful problem solving capability, however these networks suffer from various problems when dealing with temporal patterns. MLP represents static mapping between inputs and outputs. Therefore, MLP network does not consider the dependence of an individual input on others previous inputs [32,53,54].

In theoretical analysis, Herrera [33] assumed that time series are generated by dynamic systems. This means that their state changes over time. Prediction is considered a temporal signal processing problem. Therefore, using a temporal model such as recurrent neural network can achieve better prediction accuracy. Recurrent neural network can address the temporal relationship of the inputs by maintaining an internal state [28]. It is considered an alternative method of time series forecasting through the use of dynamic memory [34]. The memory of the previous values generated by the neural network is kept in the context layer; the values are then fed back to the neural network to predict the next values [35]. As result, the predicted values will rely on the current values as well as the previous neural network outputs. This can help the neural network to learn the dynamic information involved in time series.

Several models and techniques have already been developed to enhance the forecasting ability of neural networks [56], such as the regularization methods. This method is based on using weight decay in order to improve the training of the neural network. Mahdi [36] has used regularization technique in self-organized multilayer network inspired by the immune algorithm (SONIA) network in order to forecast physical time series data as well as financial time series data [37]. Their result demonstrated an improvement of the predication performance of SONIA network using the weight decay.

In this paper the regularization technique is applied with dynamic self-organized multilayer neural network which is inspired by immune algorithm (R-DSMIA). The aim is to improve the generalization capability of the DSMIA network for time series forecasting. To evaluate the forecasting performance of the proposed neural network, a number of simulation experiments have been preformed. The proposed R-DSMIA is used to predict 10 financial time series.

The remainder of this paper is organized as follows. Section 2 describes self-organized multilayer network inspired by the immune algorithm (SONIA). In Section 3, the proposed dynamic self-organized multilayer neural inspired by the immune algorithm is presented. Section 4 shows the application of the regularization technique in dynamic self-organized multilayer neural network inspired by the immune algorithm. Section 5 describes the set of data that has been used in this research. Section 6 includes the learning parameters, and performance measures. Section 7 presents the simulation results for the prediction of 10 signals using various neural network models. Finally, the conclusions of this paper are discussed in Section 8.

2. Self-organized multilayer network inspired by immune algorithm (SONIA)

Self-organized network inspired by the immune algorithm (SONIA) [38] is a single hidden layer neural network, which uses a self-organization hidden layer inspired by the immune and back-propagation algorithms for the training of the output layer. The immune algorithm is simulated as the nature immune system, which is based on the relationship between its components and involve antigens and cells (Recognition Ball). Thus, the immune system can allow its components to change and learn patterns by changing the strength of connections between individual components. The inspiration of the immune system in the self-organized neural network will provide hidden unit creation in back-propagation neural networks (BP-NN). The SONIA network was proposed to improve the generalization and recognition capability of the back-propagation neural network [38]. The input units are called antigens, while hidden units are called recognition balls (RBs). RBs in the immune system are used to create hidden units. The relation between the antigen and the RB is based on the definition of local pattern relationships between input vectors and hidden nodes. These relationships help SONIA to easily recognize and define the input data's local characteristics, which increases the networks ability to recognize patterns. The mutation process, which is biologically, a *B* cell, can be created and mutated to produce a diverse set of antibodies in order to remove and fight viruses that attack the body [39]. In SONIA, the mutated hidden nodes are designed to deal with unknown data, which is the test data, to develop the generalization ability of the network.

3. Dynamic self-organized multilayer network inspired by immune algorithm (DSMIA)

The dynamic self-organized multilayer network inspired by the immune algorithm (DSMIA) is used to predict financial time series. The structure of the DSMIA network is shown in Fig. 1. The DSMIA network has three layers: the input, the self-organized hidden layer, and the output layers with feedback connections from the output layer to the input layer. The input layer holds copies of the current inputs as well as the previous output produced by the network. This provides the network with memory. As such, the previous behavior of the network is used as an input affecting current behavior. Similar to the Jordan recurrent network [40], the