Applied Soft Computing 12 (2012) 931–941

Contents lists available at SciVerse ScienceDirect

Applied Soft Computing

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

A PSO based integrated functional link net and interval type-2 fuzzy logic system for predicting stock market indices

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ARTICLE INFO

Article history:
Received 1 May 2010
Received in revised form 4 August 2011
Accepted 26 September 2011
Available online 22 October 2011

Keywords:
Functional Link Artificial Neural Network
Fuzzy logic system
Interval Type-2FLS
Backpropagation learning algorithm
Particle swarm optimization

ABSTRACT

This paper presents an integrated functional link interval type-2 fuzzy neural system (FLIT2FNS) for predicting the stock market indices. The hybrid model uses a TSK (Takagi–Sugano–Kang) type fuzzy rule base that employs type-2 fuzzy sets in the antecedent parts and the outputs from the Functional Link Artificial Neural Network (FLANN) in the consequent parts. Two other approaches, namely the integrated FLANN and type-1 fuzzy logic system and Local Linear Wavelet Neural Network (LLWNN) are also presented for a comparative study. Backpropagation and particle swarm optimization (PSO) learning algorithms have been used independently to optimize the parameters of all the forecasting models. To test the model performance, three well known stock market indices like the Standard's & Poor's 500 (S&P 500), Bombay stock exchange (BSE), and Dow Jones industrial average (DJIA) are used. The mean absolute percentage error (MAPE) and root mean square error (RMSE) are used to find out the performance of all the three models. Finally, it is observed that out of three methods, FLIT2FNS performs the best irrespective of the time horizons spanning from 1 day to 1 month.

1. Introduction

Financial time series is considered to be noisy, random and volatile. Stock exchange, in particular, is prone to fluctuations not only for economic factors but also for non-economic ones like political turmoil in a given country, terrorist attacks, and even individual investors' psychology [1] and hence prediction of stock market indices is a challenging task. However, the benefits involved in accurate prediction have motivated researchers to develop newer and advanced tools and models.

Out of the several techniques [2] available for stock market prediction, the statistical methods have been used extensively. The various statistical techniques include autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), autoregressive conditional heteroscedasticity (ARCH), and generalized autoregressive conditional heteroskedasticity (GARCH) models and all these models assume the linearity of previous and current variables. Generally the financial time series data, being chaotic and noisy in nature, do not necessarily follow a fixed pattern or linearity and thus the statistical approaches do not perform very well in predicting stock market indices accurately. However, their performance improves considerably with a large volume of data, although the computational overhead becomes higher [3].

In contrast to the statistical techniques, soft and evolutionary computing methods like Artificial Neural Network (ANN), fuzzy set theory, rough set theory, support vector machine (SVM) [4], and the evolutionary learning algorithms like genetic algorithm (GA), particle swarm optimization (PSO), bacterial foraging optimization (BFO), etc. can handle the uncertain, chaotic, and nonlinear nature of the stock markets and thus have been used widely for accurate prediction of stock market indices. A survey of literature indicates that among different types of ANNs, i.e. radial basis function (RBF) Neural Network, Recurrent Neural Network (RNN), etc., multilayer perceptron (MLP) is the most popular ANN tool used for predictions of financial time series. Two artificial neural network models, ANN1 and ANN2 [5] have used to predict weekly closing price of Bombay stock exchange (BSE). However, the models suffer from computational complexity because they need as many as 800 neurons in input layer and 600 neurons in hidden layers for predicting stock price indices. To overcome these limitations, more sophisticated ANNs like Local Linear Wavelet Neural Network (LLWNN), Functional Link Artificial Neural Network (FLANN) and hybrid models [6] have been developed. A local linear wavelet neural network [7] is proposed to predict Box-Jenkins and Mackey glass time series where a hybrid training algorithm of particle swarm optimization and gradient descent method were introduced to train the models. The same LLWNN model is used [8] to predict stock market indices like NASDAQ-100 index and S&P CNX NIFTY index. They have used estimation of distribution algorithm (EDA) to optimize the parameters of the model. Results show that the LLWNN model performs

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doi:10.1016/j.asoc.2011.09.013

marginally better than the conventional neural network models. Similarly, Functional Link Artificial Neural Network (FLANN) is used [9,10] to predict S&P 500 stock.

Though ANN is found to be a successful forecasting tool in large number of applications, it suffers from the limitations like black box technique [11], over fitting and gets trapped in local minima. To overcome these limitations, a combination of wavelet and Takagi–Sugeno–Kang (TSK) fuzzy rule based system [12,13] is applied to predict financial time series data of Taiwan stock market. Fuzzy logic based models are preferred because as they offer an efficient tool to handle uncertainties. A fuzzy neural network is used [14] to forecast financial time series where genetic algorithm and gradient descent learning algorithm are used alternatively in an iterative manner to adjust the parameters until the error is less than a certain threshold value. A hybrid neuro fuzzy architecture based on Kalman filter [15] has been applied to predict financial time series taking Mackey glass time series as experimental data. Fu-Yuan has adopted an improved PSO algorithm and fuzzy neural network [11] to predict Shanghai stock market indices and genetic fuzzy neural network [16] to forecast Shenzhen stock indices. A hybrid forecasting model [17] based on fuzzy time series and particle swarm optimization technique has been used to forecast Taiwan stock exchange. A survey of 100 published articles [18] related to prediction of stock market indices has concluded that neural networks and fuzzy models are most suitable for stock market prediction.

In this paper, a hybrid functional link and interval type-2 fuzzy neural system (FLIT2FNS) [19–23] is used to forecast stock market indices. Interval Type-2FLS is a simplified version of Type-2FLS. A type-2 fuzzy set [24] is more capable to incorporate uncertainties compared to type-1 fuzzy logic system. Due to computational complexity of type-2 fuzzy logic system, Liang and Mendel proposed interval Type-2FLS, i.e. a simplified version of Type-2FLS which possesses all the advantages of Type-2FLS *sans* its computational complexity. This has been dealt with in Section 3. However, a detailed discussion can be seen in ref. [25] Further, the interval Type-2FLS used in this paper belongs to TSK (Takagi–Sugano–Kang) type [26–28] yielding an easier defuzzification procedure for forecasting stock market indices.

The parameters of all three models (FLIT2FNS, FLANN and Type-1FLS, and LLWNN) are optimized by the commonly used backpropagation (BP) learning algorithm. Further, to overcome two major limitations of backpropagation learning algorithm, i.e. slowness in error convergence speed and its inability to escape local optima, particle swarm optimization (PSO) [29,30], a population based, self-adaptive search optimization technique is used to optimize the parameters of all the models. PSO will be discussed in details in Section 5.2.

Three stock market indices Standard's & Poor's 500 (S&P 500), Dow Jones industrial average (DJIA) and the Bombay stock exchange (BSE) are used as the experimental data. The S&P 500 is an index of the prices of 500 large publicly held companies publishing its stock market fluctuations since 1957. The DJIA known as "the barometer of stock market" began publishing the composite list of stocks of major companies in the year 1984. In 1997, it appeared in Wall Street Journal. In the beginning, it averaged the stocks of 12 companies with the idea of giving a picture of the trend in the stock market which can help in the forecasting. The BSE is the oldest stock exchange in Asia and on August 2007 as many as 4700 companies were listed in the Exchange which is the largest stock exchange in the world [31].

This paper is organized as follows: In Section 2, a comparative analysis is made between Type-1FLS and interval Type-2FLS. Section 3 deals with the proposed FLIT2FNS model. A brief note on LLWNN model is given in Section 4. Section 5 deals with both backpropagation (BP) and particle swarm optimization (PSO) learning algorithms. Section 6 provides the original datasets and an overview of input selection for all the three models. In Section 7, empirical results are given and they are discussed and analyzed in Section 8. Finally, Section 9 draws the conclusion.

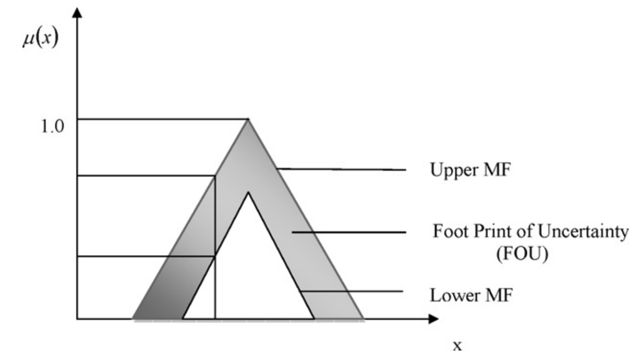

Fig. 1. FOU and interval type-2 membership functions (MFs).

2. Type-1 fuzzy logic system vs. interval type-2 fuzzy logic system

Both type-1 and type-2 fuzzy logic systems are considered as efficient tools to handle uncertainty in real life decision-making process. Out of these two types, type-1 fuzzy sets express the belongingness of a crisp value x' of a base variable x in a fuzzy set A by a crisp membership value $\mu_A(x')$, and thus they cannot capture the uncertainties due to imprecision in identifying membership functions. In other words, the membership function (MF) of a traditional FLS, i.e. type-1 fuzzy set has no uncertainty associated with it. To overcome this limitation, Type-2FLS [20] has been introduced to minimize the effects of the uncertainty in the rule base and is used in the areas like control of mobile robots, fuzzy granulation, image processing, pattern recognition, and speech recognition, etc. But in recent years, because of its computational complexity, interval type-2 fuzzy logic system (IT2FLS) [21], where the computation is more similar with the Type-1FLS is preferred. Symbolically, type-2 and IT2FLS are different from Type-1FLS by a tilde symbol putting over the symbol for the fuzzy set. For example, if A denotes a type-1 fuzzy set, than $\tilde{A}$ denotes the interval type-2 fuzzy set or type-2 fuzzy set.

A type-2 fuzzy set, denoted $\tilde{A}$, is characterized by a type-2 membership function (MF) $\mu_{\tilde{A}}(x, u)$, where $x \in X$ and $u \in J_x \subseteq [0, 1]$, that is

$$\tilde{A} = \{((x, u), \mu_{\tilde{A}}(x, u)) | \forall x \in X, \forall u \in J_x \subseteq [0, 1]\} \tag{1}$$

where $0 \le \mu_{\tilde{A}}(x, u) \le 1$

This means that at a specific value of x, say x', there is no longer a single value as for the type-1 membership function (u'); instead, the type-2 membership function takes on a set of values named the primary membership of x', $u \in J_x \subseteq [0, 1]$. It is possible to assign an amplitude distribution to all of these points and this amplitude is named a secondary grade of type-2 fuzzy set. When the values of secondary grade are the same and equal to 1, then it results in an interval type-2 membership function. Thus for all $\mu_{\tilde{A}}(x, u) = 1$, then $\tilde{A}$ is an interval type-2 fuzzy set.

In interval Type-2FLS there are two membership functions: lower membership function $\underline{\mu}_{A(x)}$ and upper membership function $\bar{\mu}_{A(x)}$. Each of the two membership functions can be represented by a type-1 fuzzy set membership function. The interval between these two membership values represents the foot print of uncertainty (FOU), which is the union of all primary membership functions and consists of a bounded region shown in Fig. 1. Most of the steps for type-1 and interval type-2 fuzzy sets are similar except