Swarm and Evolutionary Computation 19 (2014) 25–42

Contents lists available at ScienceDirect

Swarm and Evolutionary Computation

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

Regular Paper

A self adaptive differential harmony search based optimized extreme learning machine for financial time series prediction

Rajashree Dash, P.K. Dash*, Ranjeeta Bisoi

Siksha 'O' Anusandhan University, Khandagiri Square, Bhubaneswar, Odisha, India

ARTICLE INFO

Article history:
Received 23 March 2014
Received in revised form
22 July 2014
Accepted 22 July 2014
Available online 6 August 2014

Keywords:
CEFLANN
RBF
ELM
Harmony search (HS)
Differential evolution (DE)
SADHS-OELM

ABSTRACT

This paper proposes a hybrid learning framework called Self Adaptive Differential Harmony Search Based Optimized Extreme Learning Machine (SADHS-OELM) for single hidden layer feed forward neural network (SLFN). The new learning paradigm seeks to take advantage of the generalization ability of extreme learning machines (ELM) along with the global learning capability of a self adaptive differential harmony search technique in order to optimize the fitting performance of SLFNs. SADHS is a variant of harmony search technique that uses the current to best mutation scheme of DE in the pitch adjustment operation for harmony improvisation process. SADHS has been used for optimal selection of the hidden layer parameters, the bias of neurons of the hidden-layer, and the regularization factor of robust least squares, whereas ELM has been applied to obtain the output weights analytically using a robust least squares solution. The proposed learning algorithm is applied on two SLFNs i.e. RBF and a low complexity Functional link Artificial Neural Networks (CEFLANN) for prediction of closing price and volatility of five different stock indices. The proposed learning scheme is also compared with other learning schemes like ELM, DE-OELM, DE, SADHS and two other variants of harmony search algorithm. Performance comparison of CEFLANN and RBF with different learning schemes clearly reveals that CEFLANN model trained with SADHS-OELM outperforms other learning methods and also the RBF model for both stock index and volatility prediction.

1. Introduction

Accurate forecasting of future behavior of the financial time series data with respect to its tremendous sudden variation and complex non-linear dimensionality is a big challenge for most of the investors and professional analysts. Indeed financial time series is highly volatile across time and is prone to fluctuation not only for economic factors but also for non economic factors like political conditions, investor's expectations based on actual and future economic etc. However, the benefits involved in accurate prediction have motivated researchers to develop newer and advanced tools and models. Forecasting financial time series is primarily focused on estimation of future stock price index and accurate forecasting of its volatility. The models used for financial time series forecasting fall into two categories. The first category involves models based on statistical theories, e.g. autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), autoregressive conditional heteroscedasticity (ARCH), and generalized autoregressive conditional heteroskedasticity (GARCH) models. 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. The second category includes models based on artificial intelligence, like ANN, Fuzzy set theory, Support Vector Machine, Rough Set theory etc. Due to the 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 application of ANN in modeling economic conditions is expanding rapidly. A survey of literature indicates that among different types of ANNs, i.e. Multi Layer Perception Network (MLP) [1–9], Radial Basis Function Neural Network (RBF) [10,11] and Functional Link Artificial Neural Network (FLANN) [12,13] are the most popular ANN tool used for predictions of financial time series.

The traditional back propagation algorithm with gradient descent method is the commonly used learning technique for ANNs. But it suffers from the issues of imprecise learning rate, local minimal and slow rate of convergence. To avoid the common drawbacks of back propagation algorithm and to increase the accuracy some scholars proposed several improved measures, including additional momentum method, self-adaptive learning rate adjustment

* Corresponding author. Tel.: +91 674 2727336.
E-mail address: pkdash.india@gmail.com (P.K. Dash).

http://dx.doi.org/10.1016/j.swevo.2014.07.003
2210-6502/

method, Recursive Least square method and various search algorithms like GA, PSO DE, HS algorithms [10,14–18], in the training step of the neural network to optimize the parameters of the network like the network weights and the number of hidden units in the hidden layer etc. To increase forecasting speed and accuracy, researchers have also tried to combine and optimize different

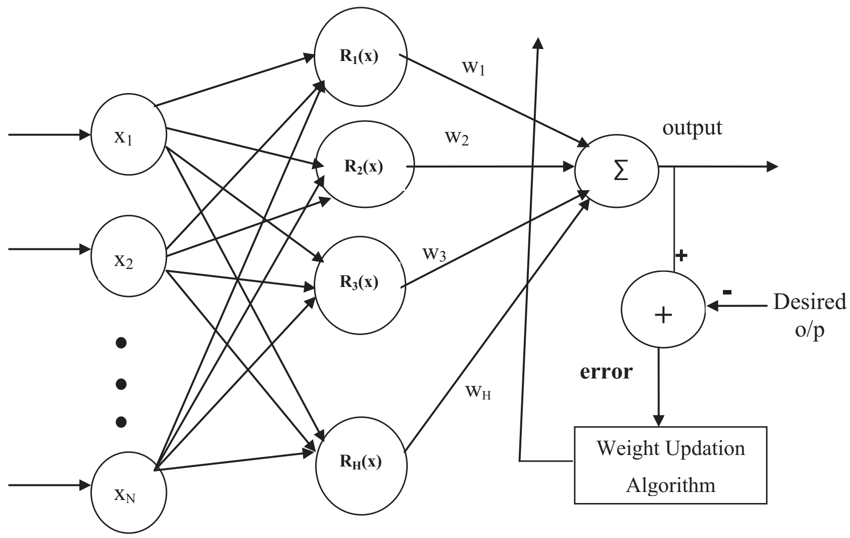

Fig. 1. Architecture of radial basis function network.

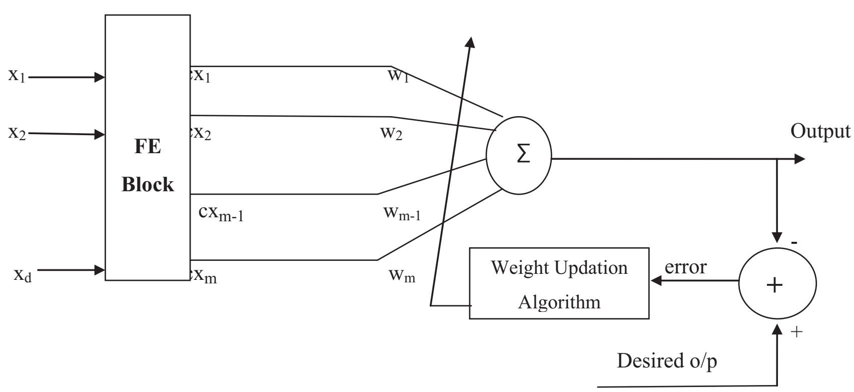

Fig. 2. Architecture of computational efficient FLANN (CEFLANN).

Table 1
Descriptive statistics of closing price.

Descriptive statistics	BSE Sensex	CNX Nifty	Nikkei 225	FTSE 100	S&P 500
Mean	1.8014e+004	5.3839e+003	9.7451e+003	5.6982e+003	1.2882e+003
Minimum	1.5175e+004	4.5442e+003	8.1600e+003	4.8058e+003	1.0226e+003
Maximum	2.1005e+004	6.3124e+003	1.3926e+004	6.5294e+003	1.5976e+003
Standard deviation	1.2352e+003	366.7439	1.0415e+003	339.0059	133.6663
Skewness	0.1411	0.2615	1.2970	0.0039	0.1491
Kurtosis	2.2326	2.4604	5.1992	2.7171	2.2666
Jarque–Bera test statistics	23.1765 (h=1)	17.7373 (h=1)	393.2247 (h=1)	2.7991 (h=0)	21.8353 (h=1)

Table 2
Descriptive statistics of daily return.

Descriptive Statistics	BSE Sensex	CNX Nifty	Nikkei 225	FTSE 100	S&P 500
Mean	0.0126	0.0185	0.0323	0.0213	0.0412
Minimum	−4.2129	−4.1689	−11.1534	−4.7792	−6.8958
Maximum	3.5181	3.5546	5.5223	5.0323	4.6317
Standard deviation	1.0699	1.1108	1.3243	1.0918	1.1324
Skewness	0.0293	0.0139	−0.8074	−0.1442	−0.4505
Kurtosis	3.5700	3.4826	9.5766	4.9304	6.9439
Jarque–Bera test statistics	11.3691 (h=1)	7.3303 (h=1)	1.5573e+003 (h=1)	133.0163 (h=1)	569.3927 (h=1)