AN ADAPTIVE LOCAL LINEAR OPTIMIZED RADIAL BASIS FUNCTIONAL MODEL FOR FINANCIAL TIME SERIES PREDICTION USING NEURAL NETWORK

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Abstract: For financial time series prediction, the generation of fault bars on the point of prediction is important in order to calculate the corresponding risk. In some years, optimization techniques-driven artificial intelligence has been used to make time series concept more systematic and upgrade the forecasting performance. This paper contains a local linear radial basis functional neural network (LLRBFNN) model for classifying finance data from Yahoo Inc. The LLRBFNN model is learned by using the hybrid technique of back propagation and recursive least square algorithm. The LLRBFNN model uses a local linear model in between the hidden layer and the output layer in contrast to the weights connected from hidden layer to output layer in typical neural network models. The obtained prediction result is compared with multilayer perceptron and radial basis functional neural network with the parameters being trained by gradient descent learning method. The proposed technique provides a lower mean squared error and thus can be considered as superior to other models. The technique is also tested on linear data, i.e., diabetic data, to confirm the validity of the result obtained from the experiment.

***Keywords* – Artificial Neural Network (ANN), Functional Link Artificial Neural Network (FLANN), Radial Basis Function Network (RBFN), Wavelets Neural Network (WNN).**

I.INTRODUCTION

Financial markets data present a challenging and complex problem to understand and forecast. Forecasting is also a key element of financial and managerial decision making. The main purpose of forecasting is to reduce the risk in decision making that is important for financial organizations, firm and private investors. The common financial time series that need forecasting are stock prices, interest rates, price indices and currency exchange rates. These time series are known to be complex, difficult for econometric modeling, non-stationary, very noisy and badly fitted by linear models (Bodyanskiy & Popov, 2006)[1]. The problem of economic and financial forecasting has recently drawn the attention of many researchers. [2] The stock market is a very complicated dynamic system. Big disturbance, serious non- linearity and blindness of investor all make the stock market prediction very complicated and very hard.

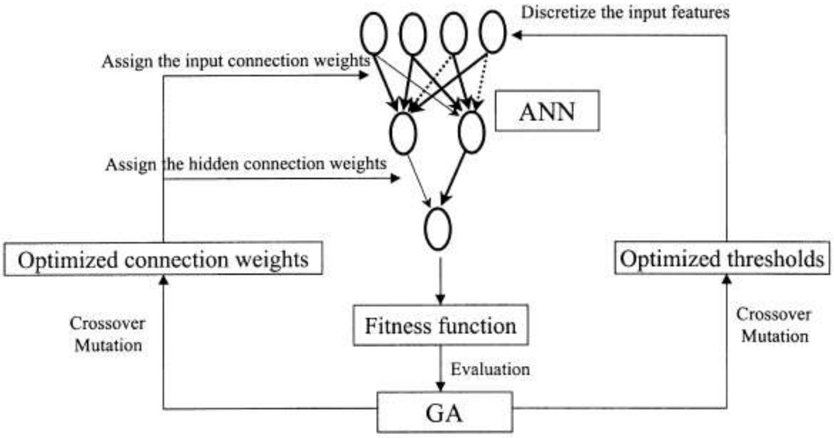
For example, it is a hard work to forecast the stock market, interest rate, exchange rate and bankruptcy. It has been observed to be a potential field of research due to its importance in financial and managerial decision making.

Many efforts of methods have been focused on traditional statistical economics. Limitation of traditional statistical economics consists of inflexibility in dynamic situation and complexity of modeling. Stock price, however, can be affected by various factors. In the long term, we have to admit that there are some essential fixed elements under change tendency as well as uncertainty in certain time. Change of stock price is perhaps a nonstandard economic fact.

So, forecasting of stock market very well is a very interesting problem for researchers and security analyzers.[3] Traditional statistical economics could only generally predict stock price in certain period time. Comparatively, artificial neural network, a massively parallel processing non-linear system with self-learning ability and adjustability, modeling on inherent relationship between data, has obtained satisfactory achievement on short term prediction on stock price. [4]

II.GA APPROACH TO FEATURE DISCRETIZATION FOR ANN:

. The overall framework of GAFD is shown in Fig. 1. The algorithms of GAFD consist of three phases. Phase 1. In the first phase, GA searches optimal or nearoptimal connection weights and thresholds for feature discretization. The populations, the connection weights and the thresholds for feature discretization, are initialized into random values before the search process. The parameters for searching must be encoded on chromosomes. This study needs three sets of parameters. The first set is the set of connection weights between the input layer and the hidden layer of the network. The second set is the set of connection weights between the hidden layer and the output layer.



Development of functional link artificial neural network(FLANN) model:

Different nonlinear expansions may be employed. These are trigonometric(sine and cosine), Chebyshev and power series. In this paper the trigonometric expansion based financial model is developed for exchange rate prediction as it offers better performance compared to when other expansions are used.

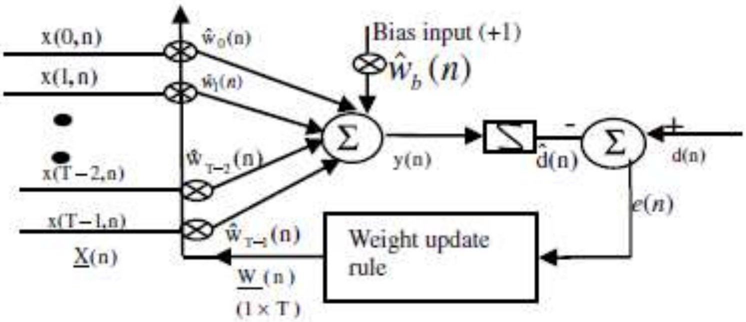


Fig. 2. Detailed structure of FLANN based forecasting model.

Development of cascaded FLANN model:

In this model two single layer FLANN structures are cascaded in series. Fig. 3
shows the block diagram representation of a two stage cascaded FLANN adaptive model. In this figure FL1 represents the first FLANN model as detailed in Fig. 2. This estimated value once again is expanded nonlinearly either by using trigonometric or exponential

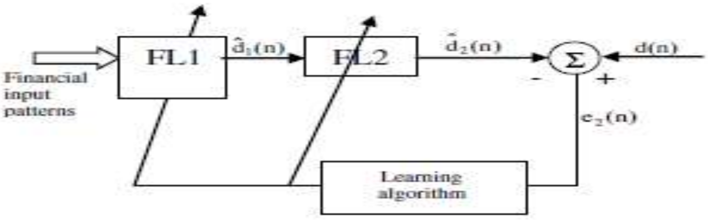


Fig. 3. Cascaded FLANN forecasting model.

functions.

Back Propagation Neural Network:

Through training, we can get weight matrix and then form a three-layer BP network prediction model. On the other hand, price increasing could give enterprises more benefits, so as to the investors' income, and then stock price will multiply.

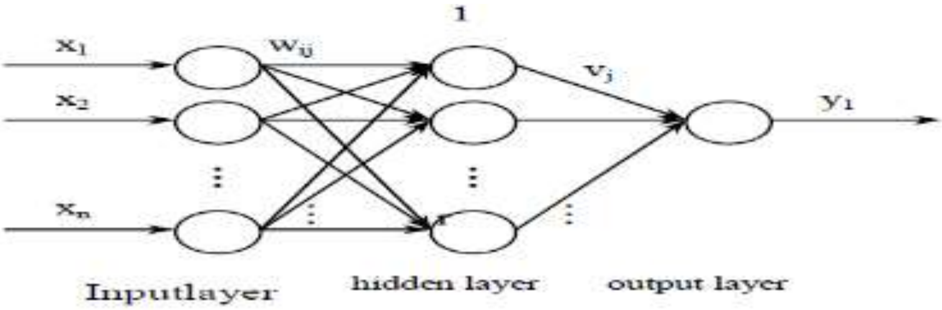


Fig-4 , n-r-1 Neural Network Structure

Radial Basis Function and AFSA:

Artificial fish swarm algorithm which based on research in intelligent behavior of animal groups is a new bionic optimization algorithm . Upon this algorithm, in this paper get an algorithm which is RBF Neural network artificial fish swarm algorithm. This algorithm is mainly used to optimize the RBFNN [4] in hidden layer node position and width value, this artificial fish need to determine the encoding and initialed, calculated to determine the fitness value of artificial fish behaviour, calculate the hidden layer to the output layer weights to determine RBFNN output error, the paper is divided into steps to address these issues.
The minimum value of the i-th column may be expressed as:

hidji=Ximin + rand(0,M),(Δi/M)

The value of the width of the i-th hidden unit can be expressed as:

σ i = σ min + rand(0,M).(Δσ/M)

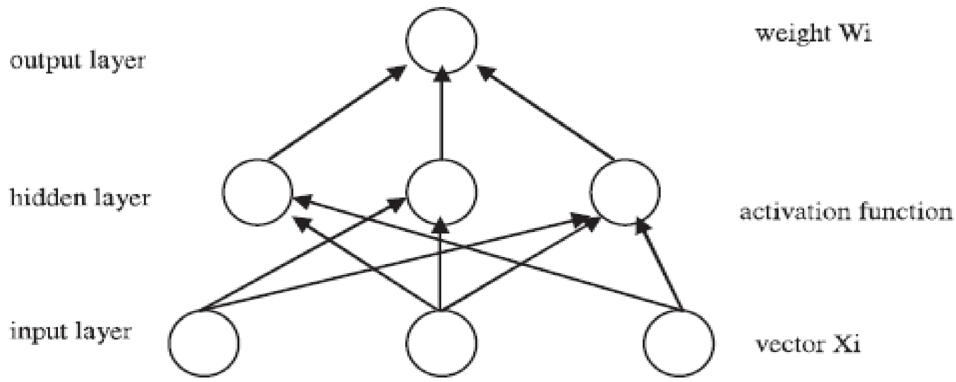


Fig-5 , Structure of RBF

DataSet

The dataset containing 1500 samples is divided into two parts: One is for training and other is for testing of the network. Approximately 64 % of the whole data are used as training data and rest 36 %data are used as testing data. The actual data are in the form of large whole numbers, so they have been normalized and converted to the value range between [0, 1] with the help of min–max normalization. The formula is given by:

$$X_{norm} = \frac{X_{original} - X_{min}}{X_{max} - X_{min}}$$

Result and comparative study:

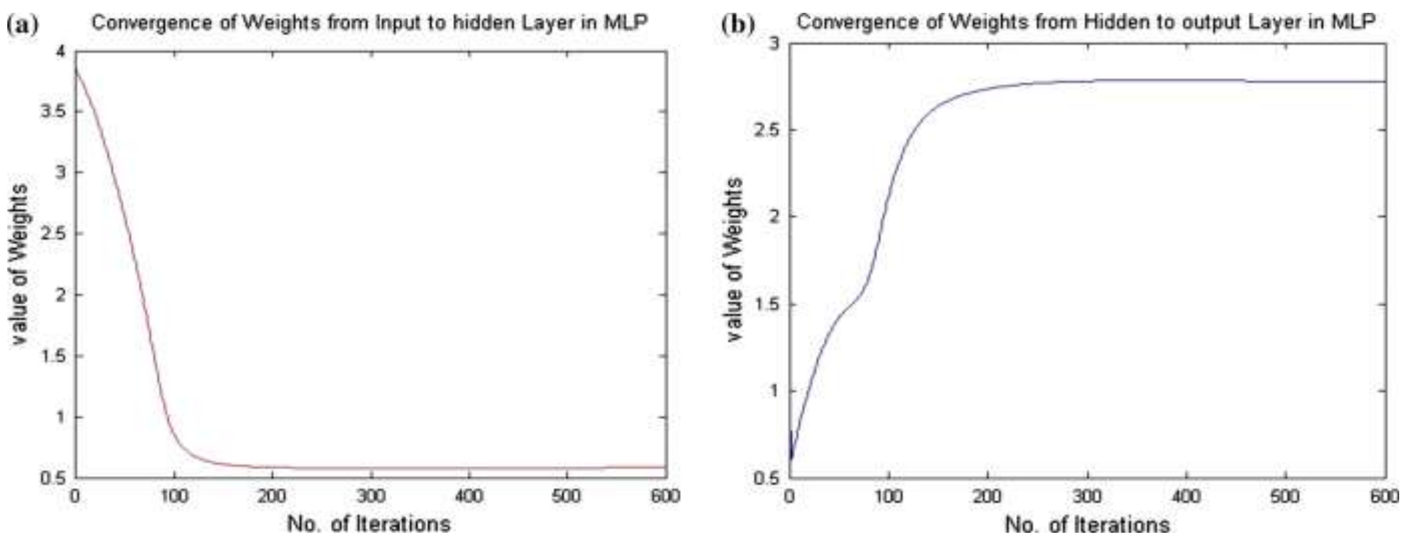


Fig-6 Weight convergence between input and hidden layer of MLP and b weight convergence between hidden and output layer of MLP

LLRBFNN, RBFNN and MLP. Figure-7 shows the comparison between forecasted and the actual index value of the stock market during training and testing phase of the model using LLRBFNN. Figure-8 shows the comparison between forecasted and actual index value of the stock market obtained during the training and testing phase of the model using RBFNN. In the same manner, Figure-9 gives us idea about the forecasted and actual index value of the stock market of the model using MLP.

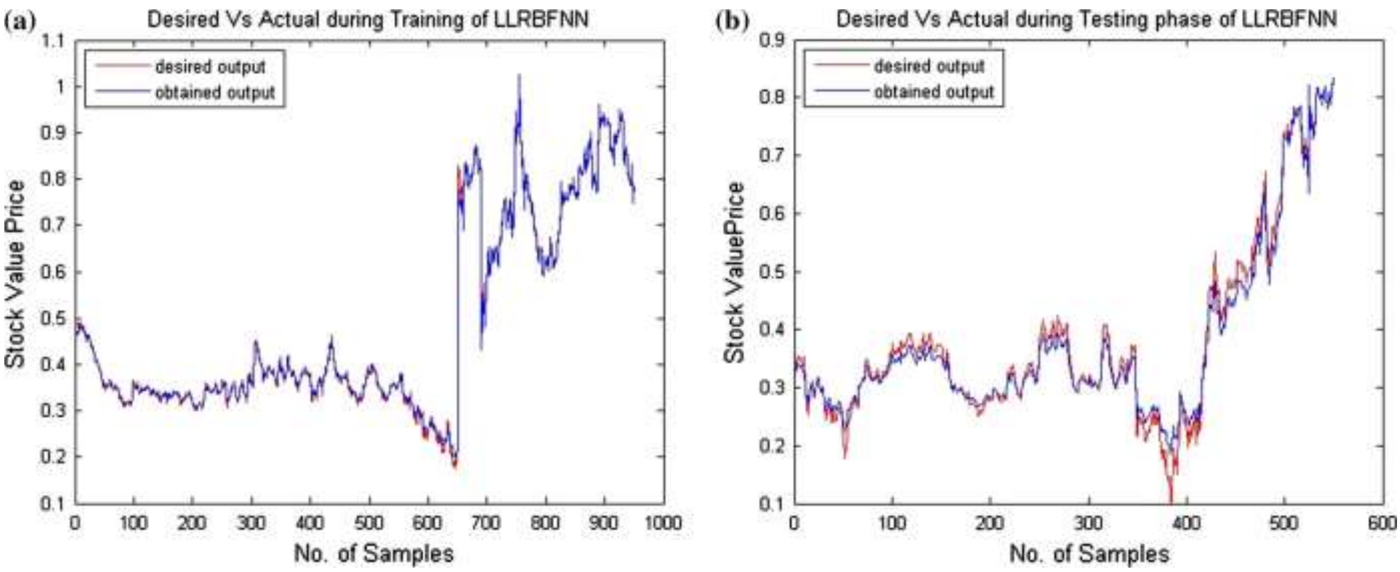


Fig-7 Desired verses actual LLRBFNN (training) and b desired verses actual LLRBFNN (testing)

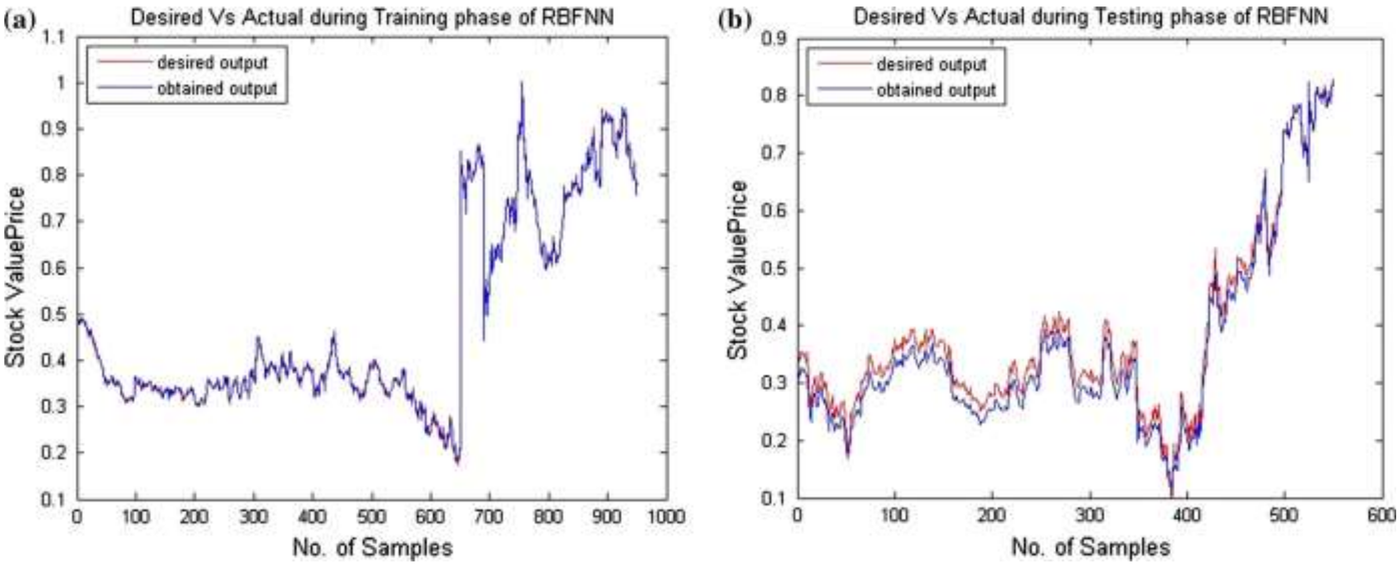


Fig-8 Desired verses actual RBFNN (training) and b desired verses actual RBFNN (testing)

Comparison with linear (diabetic) dataset :

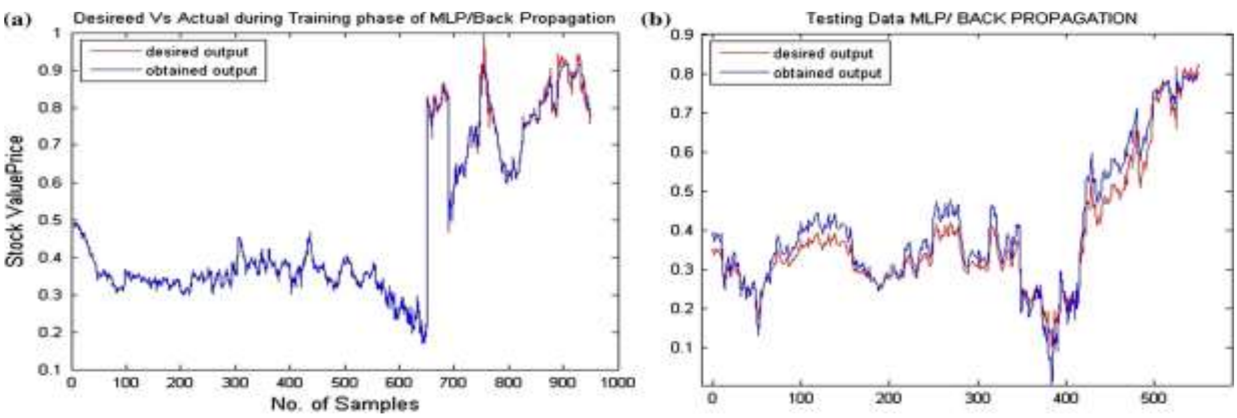


Fig-9 Desired verses actual MLP (training) and b desired verses actual MLP (testing)

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