Financial Time Series Volatility Forecast Using Evolutionary Hybrid Artificial Neural Network

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Abstract. Financial time series forecast has been classified as standard problem in forecasting due to its high non-linearity and high volatility in data. Statistical methods such as GARCH, GJR, EGARCH and Artificial Neural Networks (ANNs) based on standard learning algorithms such as backpropagation have been widely used for forecasting time series volatility of various fields. In this paper, we propose hybrid model of statistical methods with ANNs. Statistical methods require assumptions about the market, they do not reflect all market variables and they may not capture the non-linearity. Shortcoming of ANNs is their process of identifying inputs insignificantly through which network produces output. The attempt for hybrid system is to outperform the forecast results and overcome the shortcomings by extracting input variables from statistical methods and include them in ANNs learning process. Further genetic algorithm is used for evolution of proposed hybrid models. Experimental results confirm the lesser root mean square error (RMSE) results obtained from proposed evolutionary hybrid ANN models EANN-GARCH, EANN-GJR, EANN-EGARCH than conventional ANNs and statistical methods.

Keywords: Evolutionary, Hybrid, ANN, GA, GARCH, EGARCH, GJR

1 Introduction

Financial forecasting has been challenging problem due to its non-linearity and high volatility [1]. Forecasting assumes that some aspects of past patterns will continue in future. Past relationship of it can be discovered through study and observation of data. Main idea behind forecasting has been to devise a system that could map a set of inputs to set of desired outputs [2]. There has always been risk involved with investment in financial market. ANNs have widely been used for the forecasting purpose because of their ability to learn linear and complex data [3]. ANNs is trained such as a set of inputs maps a set of desired output. These networks can hence automatically assume any shape that carries forward the task of determination of the outputs to the presented input.

The ANNs by their basic architecture represent the human brain [4]. They consist of a set of artificial neurons. The task of any fundamental artificial neuron may be divided into two parts. The first part does the weighted addition of the inputs presented to it. The second part of the neuron consists of an activation function. The weighted addition of the first part is passed through the activation function. This is the final output of the system [5]. Statistical methods such as GARCH, EGARCH and GJR also have been used extensively for volatility forecasting. GARCH model reflects the non-linear dependence of the conditional variance of the time series, which indicates the non-linear time series characteristics are from the conditional second-order moment of the distribution [6]. EGARCH model, which express conditional variance equation in the logarithm form, and relax the nonnegative restrictions on the parameters [7] . Genetic Algorithms (GA) can be used to optimize various parameters and to solve many problems in real time [8]. GA as a solution for optimization problems based on natural selection keeps an initial population of solution candidates and evaluates the quality of each solution candidate according to a specific cost function. Over successive generations, the population evolves toward an optimal solution [9].

2 Algorithms and Methods

2.1 Artificial Neural Network

General Backpropagation (BPA) Neural Network architecture as shown in figure 1, includes input layer, hidden layer and output layer. Each neuron in input layers are interconnected with neurons in hidden layers and each neuron of hidden layer in interconnected with output layer neuron with weights assigned to the connection [10]. On providing learning data to the network, the learning values are passed through input to hidden and finally to output layer where response for input data is obtained. For optimizing the error obtained, the error values are back propagated to make changes in weights of input to hidden layer and hidden to output layer. With error back propagation input response are made converged to desired response.

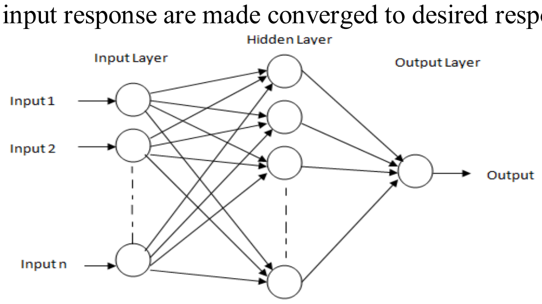

Fig. 1. General architecture of a Backpropagation Neural Network

BPA uses supervised learning in which trainer submits the input-output exemplary patterns and the learner has to adjust the parameters of the system autonomously, so that it can yield the correct output pattern when excited with one of the given input patterns [11].

2.2 Genetic Algorithm

Genetic algorithms (GA) function by optimizing an objective function. They exploit the structure of the error surface. GAs does not assume that the error surface is unimodal, or even that its derivative exists [12]. A genetic algorithm performs a parallel stochastic search. It is parallel in the sense that many solutions in the population are considered simultaneously and the fittest solutions are chosen for reproduction. It is stochastic in the sense that the solutions are randomly selected for refinement and the likelihood of a solution being selected is enhanced by the quality of the solution or its fitness, and the search direction is also chosen randomly. Genetic Algorithm evolves ANNs by fixing the values and the weights and biases of the various nodes i.e. the GA optimizes the network parameters for better performance.

Steps followed for evolution of ANN are problem encoding, creation of random initial state, fitness evaluation, and genetic operator including selection, crossover, mutation and elite, generate next generation, testing and verification [13] are shown below in figure 2 below.

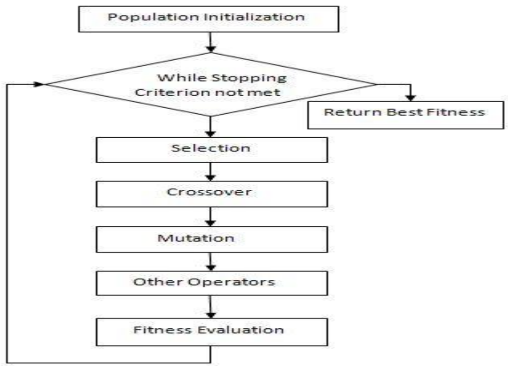

Fig. 2. Flow Chart of a working of Genetic Algorithm

3 Proposed Evolutionary Hybrid Neural Networks

3.1 EANN-GARCH

GARCH stands for generalized autoregressive conditional heteroscedasticity. It is a mechanism that includes past variances in the explanation of future variances. More specifically, GARCH is a time series technique used to model the serial dependence of volatility. The general GARCH (P, Q) model [14], [16] for the conditional variance of innovations is

$$\sigma_t^2 = k + \sum_{i=1}^{P} G_i\, \sigma_{t-i}^2 + \sum_{j=1}^{Q} A_j\, \varepsilon_{t-j}^2 \tag{1}$$

With constraints: $\sum_{i=1}^{P} G_i + \sum_{j=1}^{Q} A_j < 1$, $k > 0$, $G_i \geq 0$, $A_j \geq 0$

The basic GARCH (P, Q) model is a symmetric variance process, in that it ignores the sign of the disturbance [15]. ANN-GARCH model can be created by extracting the input variables based on above variables. After including these variables in ANN learning process, model can be used to forecast volatility. The newly extracted variables are as follows:

$$\sigma'^2_{t-1} = \sum_{i=1}^{P} G_i \, \sigma^2_{t-i} \qquad \varepsilon'^2_{t-1} = \sum_{j=1}^{Q} A_j \, \varepsilon^2_{t-j}$$

3.2 EANN-GJR

The general GJR (P, Q) model [16] for the conditional variance of innovations with leverage terms is

$$\sigma_t^2 = k + \sum_{i=1}^{P} G_i \, \sigma^2_{t-i} + \sum_{j=1}^{Q} A_j \, \varepsilon^2_{t-j} + \sum_{j=1}^{Q} L_j S_{t-j} \, \varepsilon^2_{t-j} \tag{2}$$

Where $S_{t-j} = 1 \; if \; \varepsilon_{t-j} < 0, S_{t-j} = 0 \; otherwise$

With constraints

$$\sum_{i-1}^{P} G_i + \sum_{j-1}^{Q} A_j + \frac{1}{2} \sum_{j-1}^{Q} L_j < 1$$

$$k \geq 0, \; G_i \geq 0, \; A_j \geq 0, \; A_j + L_j \geq 0$$

The lag lengths P and Q, and the magnitudes of the coefficients Gi and Aj, determine the extent to which disturbances persist. These values then determine the minimum amount of pre-sampled data needed to initiate the simulation and estimation processes. ANN-GJR model can be created by extracting the input variables based on above variables. After including these variables in ANN learning process, model can be used to forecast volatility. The newly extracted variables are as follows:

$$\sigma'^2_{t-1} = \sum_{i=1}^{P} G_i \, \sigma^2_{t-i}, \qquad \varepsilon'^2_{t-1} = \sum_{j=1}^{Q} A_j \, \varepsilon^2_{t-j}, \qquad \varepsilon''^2_{t-1} = \sum_{j=1}^{Q} L_j S_{t-j} \, \varepsilon^2_{t-j}$$

3.3 EANN-EGARCH

The general EGARCH (P, Q) model [15], [16] for the conditional variance of the innovations, with leverage terms and an explicit probability distribution assumption is

$$\log \sigma_t^2 = k + \sum_{i=1}^{P} G_i \log \sigma^2_{t-1} + \sum_{j=1}^{Q} A_j \left[\left| \frac{\varepsilon_{t-j}}{\sigma_{t-j}} \right| - \sqrt{\frac{2}{\pi}} \right] + \sum_{j=1}^{Q} L_j \left(\frac{\varepsilon_{t-j}}{\sigma_{t-j}} \right) \tag{3}$$

EGARCH models are fundamentally different from GARCH and GJR models in that the standardized innovation, serves as the forcing variable for both the conditional variance and the error. EANN-EGARCH model can be created by extracting the input variables based on above variables. After including these variables in ANN learning process, model can be used to forecast volatility. The newly extracted variables are as follows:

$$\log \sigma'^2_{t-1} = \sum_{i=1}^{P} G_i \log \sigma^2_{t-1}$$

$$Levergae\ Effect = \sum_{j=1}^{Q} A_j \left[\left|\frac{\varepsilon_{t-j}}{\sigma_{t-j}} - \sqrt{\frac{2}{\pi}}\right|\right]$$

$$Levergae\ = \sum_{j=1}^{Q} L_j \left(\frac{\varepsilon_{t-j}}{\sigma_{t-j}}\right)$$

4 Experiment and Results

4.1 Research Data

We have used two different data (un-normalized) have been collected from Prof. Rob J Hyndman's website http://robjhyndman.com/TSDL/ . Data sets analyzed are as: Daily closing price of IBM stock, Jan. 01 1980 - Oct. 08 1992. [17], Daily S & P 500 index of stocks, Jan. 01 1980 - Oct. 08 1992. [17].

Table 1. Time Series Data Sets Description

Time Series	Standard Deviation	Mean	Count
Daily IBM	28.76493	105.6183	3333
Daily S&P	97.01113	236.1225	3333

4.2 Methodology

We analyze the above discussed statistical forecasting models (P=1, Q=1) and extract the best suited input variables of these models. We divide the dataset into training and testing dataset. A random dataset division is followed to result 80% of dataset as training dataset and remaining 20% as testing dataset.

Supervised learning is followed for learning of the neural network with target prediction series given. Artificial neural network thus obtained is evolved using genetic algorithm. Genetic algorithm optimizes the weights and biases of neural network based on the given training dataset for better accuracy forecast.

Testing dataset thus obtained is used for simulating the evolutionary neural network, checking the error or accuracy of the trained network. We compare the output data as given by the network with the testing data set with the target dataset.

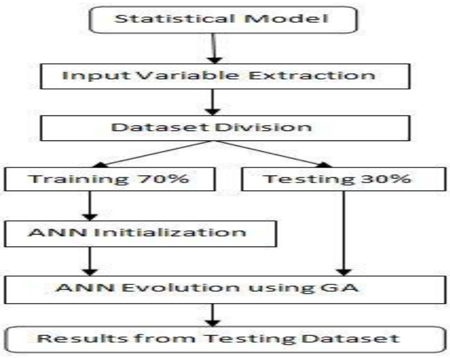

Fig. 3. Flow Chart of used Methodology

4.3 Empirical Results

Table 2. Results Obtained for Time Series

Methodology	Daily IBM (Mean RMSE)	Daily S&P (Mean RMSE)
BPA-ANN	0.00232	0.0027
EANN-GARCH	0.000287	0.000312
EANN-GJR	0.000242	0.000253
EANN-EGARCH	0.000198	0.000217

4.4 Graphical Analysis

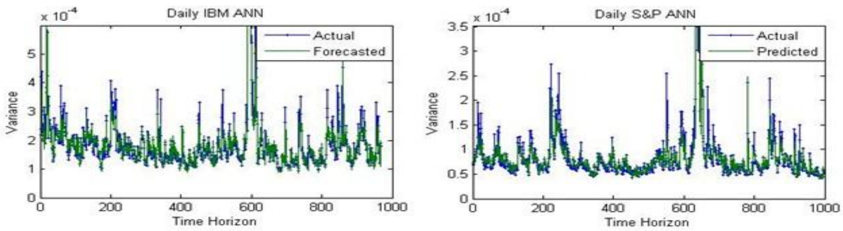

Fig. 4. Graphs for Actual and Predicted Values for Daily IBM and Daily S&P using traditional Backpropagation Algorithm with variance value is taken on Y-Axis and Day of Index is on X-Axis, with mean RMSE = 0.00232 and 0.0027 respectively.

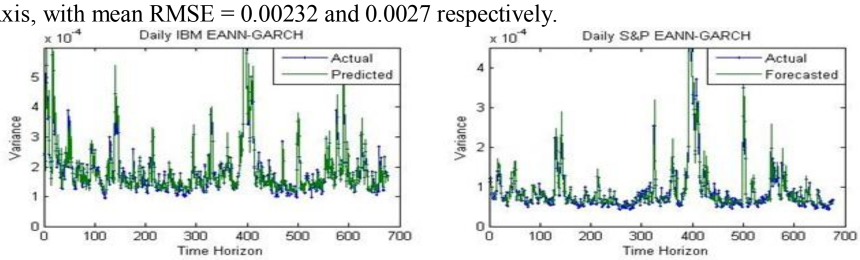

Fig. 5. Graphs for Actual and Predicted Values for Daily IBM and Daily S&P using EANN-GARCH with variance value is taken on Y-Axis and Day of Index is on X-Axis, with mean RMSE = 0.000287 and 0.000312 respectively.

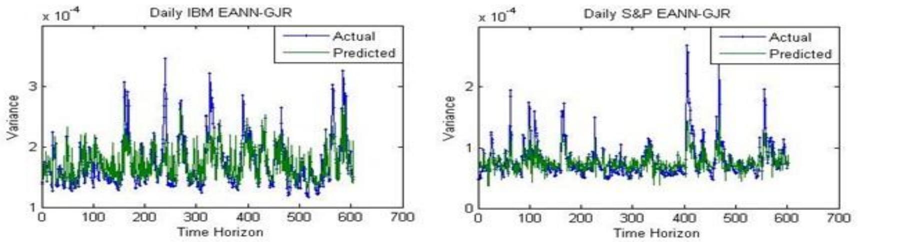

Fig. 6. Graphs for Actual and Predicted Values for Daily IBM and Daily S&P using EANN-GJR with variance value is taken on Y-Axis and Day of Index is on X-Axis, with mean RMSE = 0.000242 and 0.000253 respectively.

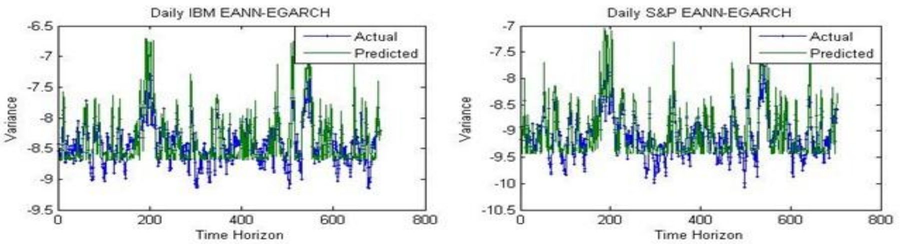

Fig. 7. Graphs for Actual and Predicted Values for Daily IBM and Daily S&P using EANN-EGARCH with variance value is taken on Y-Axis and Day of Index is on X-Axis, with mean RMSE = 0.000198 and 0.000217 respectively.

5 Conclusions

The Evolutionary Hybrid Artificial Neural Network has been proposed in order to improve the financial forecast accuracy. It is based on the hybridization concept of using best features of different models for better result. We have extracted the input variables out of statistical forecast models GARCH, GJR and EGARCH, which optimizes the best input variable feed for artificial neural network initialization and learning. A hybrid model thus obtained from statistical model and artificial neural network is evolved using genetic algorithm. Genetic algorithm optimizes the artificial neural network parameters such as weights and biases as per the given training dataset, in order to improve the forecast accuracy of hybrid model. Accuracy results and plotted comparison graph of actual and predicted values shows the better performance by these proposed evolutionary hybrid artificial neural network over conventional artificial neural network forecasting. Order of performance can be adjudged as EANN-EGARCH > EANN-GJR > EANN-GARCH > ANN.

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