FINANCIAL TIME SERIES FORECAST USING SIMULATED ANNEALING AND THRESHOLD ACCEPTANCE GENETIC BPA NEURAL NETWORK

Anupam Tarsauliya, Ritu Tiwari and Anupam Shukla
Soft Computing and Expert System Laboratory, ABV-IIITM, Gwalior, 474010, India

Keywords: Simulated annealing, Threshold acceptance, Genetic, ANN, Time series, Financial forecast.

Abstract: Financial time series forecast has been eyed as key standard job because of its high non-linearity and high volatility in data. Various statistical methods, machine learning and optimization algorithms has been widely used for forecasting time series of various fields. To overcome the problem of solution trapping in local minima, here in this paper, we propose novel approach of financial time series forecasting using simulated annealing and threshold acceptance genetic back propagation network to obtain the global minima and better accuracy. Time series dataset is normalized and bifurcated into training and test datasets, which is used as supervised learning in BPA artificial neural network and optimized with genetic algorithm. Results thus obtained are used as seed for start point of simulated annealing and threshold acceptance. Empirical results obtained from proposed approach confirm the outperformance of forecast results than conventional BPA artificial neural networks.

1 INTRODUCTION

Forecasting is generally referred as the process of making statements about events whose actual outcomes have not yet been observed. Forecasting has got various applications in many situations such as weather forecasting, financial forecasting, flood forecasting, technology forecasting etc. Of these financial forecasting has been challenging problem due to its non-linearity and high volatility (Yixin and Zhang, 2010). 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 (Marzi, Turnbull and Marzi, 2008). ANNs have widely been used for the forecasting purpose because of their ability to learn non-linear and complex data (Eng et al., 2008). 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. Any problem has predefined inputs and outputs. The relation between the inputs and the outputs is done by a set of rules, formulae or known patterns. These networks do the task of predicting these rules such that the overall system performs better when any of the data from the historical database is again presented.

The ANNs by their basic architecture represent the human brain (Kumar et al., 2008). They consist of a set of artificial neurons. The various artificial neurons are joined or connected to each other by connections. These connections aid the flow of information or data between the neurons. Artificial neurons behave similar in concept to their biological counterparts. 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. Here each connection has a weight associated with it. As the input arrives through the connection, it is multiplied by the corresponding weight. The addition of all such inputs is performed. 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 (Zhao et al., 2010). The activation function is usually non-linear to enable the ANNs solve nonlinear problems.

GAs can be used to optimize various parameters and to solve many problems in real time; these solutions may otherwise not be possible in finite time. GA's are also used for various search-related

Tarsauliya A., Tiwari R. and Shukla A..
FINANCIAL TIME SERIES FORECAST USING SIMULATED ANNEALING AND THRESHOLD ACCEPTANCE GENETIC BPA NEURAL NETWORK.
DOI: 10.5220/0003492101720177
In *Proceedings of the 13th International Conference on Enterprise Information Systems* (ICEIS-2011), pages 172-177
ISBN: 978-989-8425-54-6

operations (Etemadi et al., 2009). Genetic algorithm is used for further optimization of the neural network. These algorithms model complex problems and return the optimal solution in an iterative manner. Genetic Algorithm 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. GA repeatedly modifies the population of individual solutions. At each step, the genetic algorithm selects individuals at random from the current population to be parents and uses them produce the children for the next generation. Over successive generations, the population evolves toward an optimal solution (Yang and Zhu, 2010).

Simulated Annealing is a Monte Carlo technique that can be used for seeking out the global minimum. The effectiveness of SA is attributed to the nature that it can explore the design space by means of neighbourhood structure and escape from local minima by probabilistically allowing uphill moves (Khosravi et al., 2010). Compared with traditional mathematical optimization techniques, SA offers a number of advantages: first, it is not derivative based, which means that it can be used for optimization of any cost function, regardless of its complexity or dimensionality, and secondly, it can explore and exploit the parameter space without being trapped in local minima (Suman and Kumar, 2006). Threshold acceptance uses a similar approach alike simulated annealing, but instead of accepting new points that raise the objective with a certain probability, it accepts all new points below a fixed threshold (Pepper, Golden and Wasil, 2002).

2 ALGORITHMS AND METHODS

2.1 Artificial Neural Network

The General BPA Neural Network architecture as shown in Fig. 1 includes input layer, hidden layer and output layer. Each neuron in input layers are interconnected with neurons in hidden layers with appropriate weights assigned to them (Shukla, Tiwari and Kala, 2010). Similarly each neuron of hidden layer in interconnected with output layer neuron with weights assigned to the connection. 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.

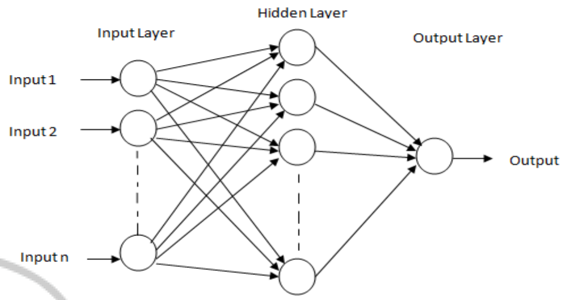

Figure 1: General Architecture of an ANN.

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 (Lee, 2008).

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 (Shopova et al., 2006). Such assumptions are required for efficient use of traditional optimization strategies. Since many practical design problems involve nonlinear and multimodal problem spaces, the GA approach is attractive.

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 (Altunkaynak, 2009) as shown in Fig. 2.

The fitness function is derived from two categories of errors: (1) the error of pattern k, which is the difference between the actual and the forecast values at any current pattern k, and (2) the total error of all patterns.

$$\text{Fitness} = \text{error}\,[k] + \text{error}\,[\text{total}]$$

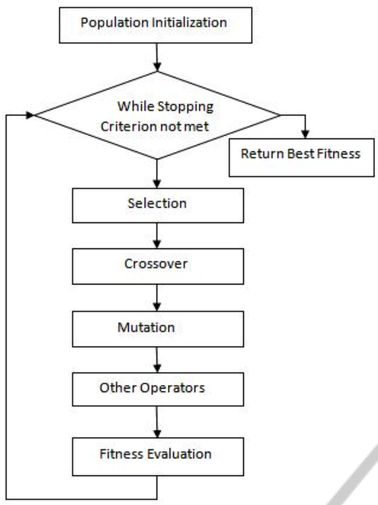

Figure 2: Flow Chart for working of Genetic Algorithm.

Once the GA reaches its optimal state and terminates as per the stopping criterion, we get the final values of the weights and biases. We then create the ANN with these weights and bias values; which is then regarded as the most optimal ANN to result from the ANN training. We can then use the evolved ANN for testing.

2.3 Simulated Annealing & Threshold Acceptance

Simulated annealing (Kirkpatrick, Gelatt and Vecchi, 1983) is a method for solving unconstrained and bound-constrained optimization problems. The method models the physical process of heating a material and then slowly lowering the temperature to decrease defects, thus minimizing the system energy.

At each iteration of the simulated annealing algorithm (Zain, Haron and Sharif, 2011), a new point is randomly generated. The distance of the new point from the current point, or the extent of the search, is based on a probability distribution with a scale proportional to the temperature. The algorithm accepts all new points that lower the objective, but also, with a certain probability, points that raise the objective. By accepting points that raise the objective, the algorithm avoids being trapped in local minima, and is able to explore globally for more possible solutions. The annealing schedule is the rate by which the temperature is decreased as the algorithm proceeds. The slower the rate of decrease, the better the chances are of finding an optimal solution, but the longer the run time (Liu and Zhu, 2010). An annealing schedule is selected to systematically decrease the temperature as the algorithm proceeds. As the temperature decreases, the algorithm reduces the extent of its search to converge to a minimum.

Threshold acceptance uses a similar approach alike simulated annealing, but instead of accepting new points that raise the objective with a certain probability, it accepts all new points below a fixed threshold (Pepper, Golden and Wasil, 2002). The threshold is then systematically lowered, just as the temperature is lowered in an annealing schedule. Because threshold acceptance avoids the probabilistic acceptance calculations of simulated annealing, it may locate an optimizer faster than simulated annealing (Lidia and Carr, 1985).

The following is an outline of the steps performed (Liu and Zhu, 2010) for both the simulated annealing and threshold acceptance algorithms as shown in Fig. 3:

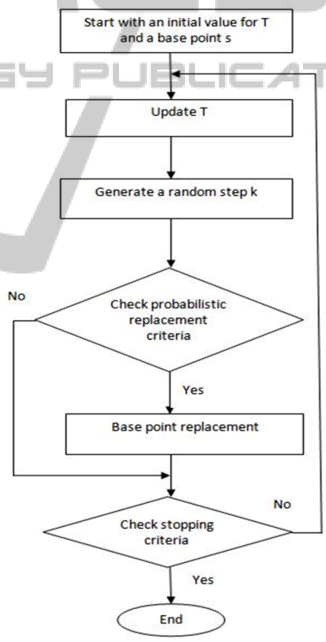

Figure 3: Flow Chart for working of Simulated Annealing and Threshold Acceptance.

3 EXPERIMENT AND RESULTS

3.1 Research Data

We have used two different data sets for our research. The 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. Daily S & P 500 index of stocks, Jan. 01 1980 - Oct. 08 1992. (Hipel and McLeod, 1994)

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

3.2 Methodology

We adopted and performed the following steps for training and testing the data series as shown in Fig. 4. The brief description of each step is as follows:

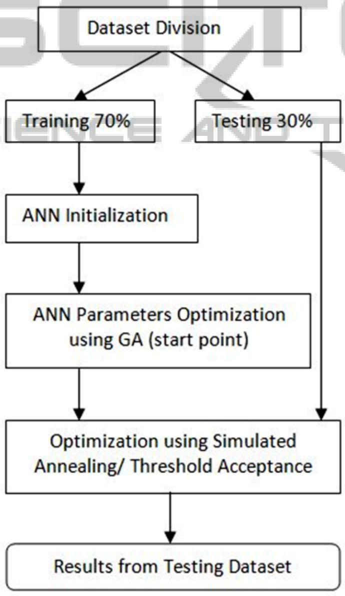

Figure 4: Flow Chart for Adopted Methodology.

We first load the given time series data set, which is divided into training and testing dataset. A random dataset division is followed to result 70% of dataset as training dataset and remaining 30% as testing dataset. Training dataset outcome of random data set division followed is used for defining and building the architecture of artificial neural network. Training dataset is used for learning of the neural network using supervising learning. Testing dataset is used for validation and testing of the learned neural network. Simulated output of the neural network for testing dataset is compared against the target output. Thus it is used in formulating accuracy of the neural network.

After the network defined is optimized using genetic algorithm. Process of genetic algorithm as described before is followed. First an initial random population is generated. Various genetic operation selection, crossover and mutation are followed. Population is then evaluated using fitness function. If stopping criteria is met or goal is met, the algorithm is stopped else next generation process is followed.

Thus obtained optimized artificial neural network is further optimized using Simulated Annealing/ Threshold Acceptance algorithm. Optimized parameters value obtained from genetic optimization is used as start initial point for the algorithms. Process as described in section 2.3 is followed. Optimized parameter values after simulated annealing/ threshold acceptance is used for formulating final artificial neural network. This neural network is thus used for final simulation of results and formulating the accuracy of the system.

3.3 Empirical Results

ANN Parameters used:
Neurons (Input, Hidden, Output) = (10, 05, 01)
Learning Rate: 0.3
Momentum: 0.7

Table 2: Mean RMSE for different algorithms and data.

Algorithm Used	Mean RMSE Daily IBM	Mean RMSE Daily S&P
BPA	3.7106	6.0846
Simulated Annealing Genetic BPA	2.5426	5.4519
Threshold Acceptance Genetic BPA	2.5321	5.6382

It can be seen from the table 2 that estimation are better for simulated annealing and threshold acceptance algorithms approach than BPA algorithm. It can also be drawn that from above results that performance of simulated annealing and threshold acceptance is financial time series specific, as simulated annealing estimates better for Daily S&P while threshold acceptance for Daily IBM.

3.4 Graphical Analysis

Below described graphs are drawn for actual vs. Predicted values with Index Value on Y-Axis and Days on X-Axis.

Fig. 5 and Fig. 6 shown below are comparison graph plotted between desired output and simulated output using conventional BPA for dataset of Daily IBM and Daily S&P respectively. It is observed that trends are well learned by network but volatilities in data are not well predicted with some vertical and horizontal lags present. It can also be observed that network lacks generalization ability.

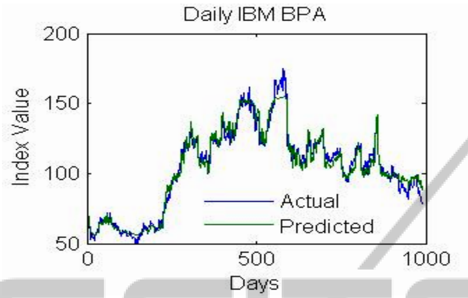

Figure 5: Graph for Daily IBM using traditional BPA Algorithm. Daily IBM Mean RMSE = 3.7106.

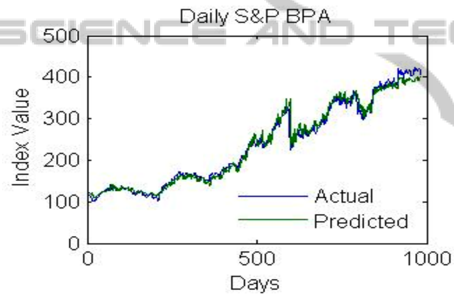

Figure 6: Graph for Daily S&P using traditional BPA Algorithm. Daily S&P Mean RMSE = 6.0846.

Fig. 7 and Fig. 8 shown below are comparison graph plotted between desired output and simulated output using simulated annealing genetic BPA neural network for dataset of Daily IBM and Daily S&P respectively. It can be observed from the graphs when compared to graphs drawn for conventional BPA in Fig. 5 and Fig. 6 that trend in the series are better learned and approximated.

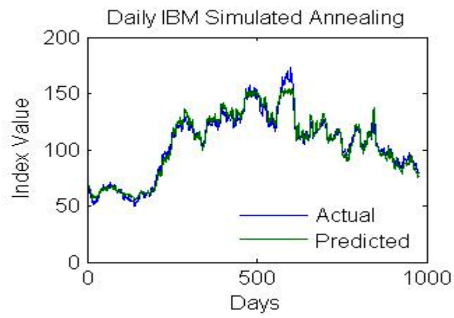

Figure 7: Graph for Daily IBM using Simulated Annealing Genetic BPA network. Daily IBM Mean RMSE = 2.5426.

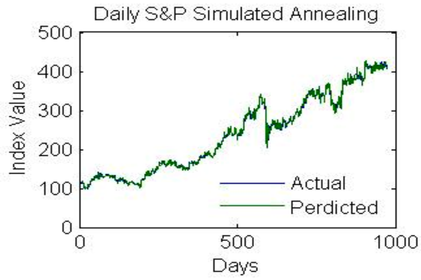

Figure 8: Graph for Daily S&P using Simulated Annealing Genetic BPA network. Daily S&P = 5.4519.

Fig. 9 and Fig. 10 shown below are comparison graph plotted between desired output and simulated output using threshold acceptance genetic BPA neural network for dataset of Daily IBM and Daily S&P respectively. It can be observed from the graphs when compared to graphs drawn for conventional BPA in Fig. 5 and Fig. 6 that trend in the series are better learned and approximated.

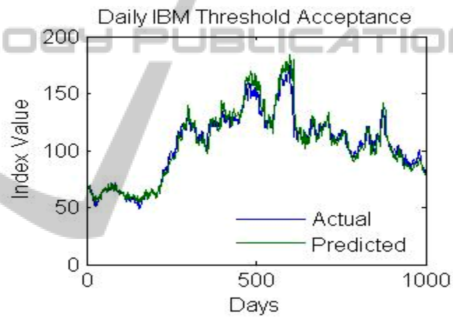

Figure 9: Graph for Daily IBM using Threshold Acceptance Genetic BPA network. Daily IBM Mean RMSE = 2.5321.

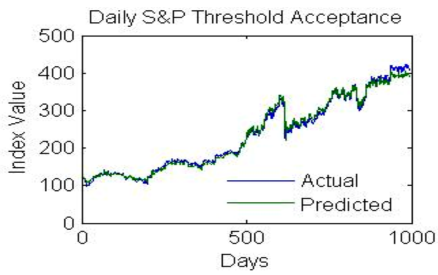

Figure 10: Graph for Daily S&P using Threshold Acceptance Genetic BPA. Daily S&P = 5.6382.

4 CONCLUSIONS

A novel approach of financial forecasting using simulated annealing and threshold acceptance is proposed in this paper in order to obtain better forecast results. Model is based on starting with initialization of neural network and optimizing the network parameter using traditional genetic algorithm. Obtained network parameter is used as starting seed point for simulated annealing and threshold acceptance algorithm for further optimizing the parameters in order to get global optima. The proposed methodology comes out to be an efficient as it gives better estimation of index values. Proposed approach was compared with traditional BPA algorithm. Empirical results obtained as illustrated in section 3.3 for two of the different financial time series concludes that proposed approach gives a better results than traditional BPA algorithm as can be seen in from results in terms of average root mean square error. It can also be drawn that from above results that performance of simulated annealing and threshold acceptance is financial time series specific, as simulated annealing estimates better for Daily S&P while threshold acceptance for Daily IBM.

REFERENCES

Zhou Yixin, Jie Zhang, "Stock Data Analysis Based on BP Neural Network," *ICCSN*, pp.396-399, 2010 Second International Conference on Communication Software and Networks, 2010

Marzi, H.; Turnbull, M.; Marzi, E.; , "Use of neural networks in forecasting financial market," Soft Computing in Industrial Applications, 2008. *SMCia '08. IEEE Conference on*, vol., no., pp.240-245, 25-27 June 2008

Ming Hao Eng; Yang Li; Qing-Guo Wang; Tong Heng Lee; "Forecast Forex with ANN Using Fundamental Data," Information Management, Innovation Management and Industrial Engineering, 2008. *ICIII '08. International Conference on* , vol.1, no., pp.279-282, 19-21 Dec. 2008

P.Ram Kumar, M.V.Ramana Murthy , D.Eashwar , M.Venkatdas, “Time Series Modeling using Artificial Neural Networks”, *Journal of Theoretical and Applied Information Technology* Vol no.4 No .12, pp.1259-1264, © 2005 - 2008 JATIT.

Zhizhong Zhao; Haiping Xin; Yaqiong Ren; Xuesong Guo; , "Application and Comparison of BP Neural Network Algorithm in MATLAB," Measuring Technology and Mechatronics Automation (ICMTMA), *2010 International Conference on* , vol.1, no., pp.590-593, 13-14 March 2010

Hossein Etemadi, Ali Asghar Anvary Rostamy, Hassan Farajzadeh Dehkordi, A genetic programming model for bankruptcy prediction: Empirical evidence from Iran, *Expert Systems with Applications*, Volume 36, Issue 2, Part 2, March 2009, Pages 3199-3207

Cheng-Xiang Yang; Yi-Fei Zhu; "Using genetic algorithms for time series prediction," Natural Computation (ICNC), 2010 *Sixth International Conference on,* vol.8, no., pp.4405-4409, 10-12 Aug. 2010

Anupam Shukla, Ritu Tiwari, Rahul Kala, Real Life Application of Soft Computing, CRC Press 2010.

Tsung-Lin Lee, Back-propagation neural network for the prediction of the short-term storm surge in Taichung harbor, Taiwan, *Engineering Applications of Artificial Intelligence*, Volume 21, Issue 1, February 2008, Pages 63-7

Elisaveta G. Shopova, Natasha G. Vaklieva-Bancheva, BASIC--A genetic algorithm for engineering problems solution, *Computers & Chemical Engineering,* Volume 30, Issue 8, 15 June 2006, Pages 1293-1309

Abdusselam Altunkaynak, Sediment load prediction by genetic algorithms, *Advances in Engineering Software*, Volume 40, Issue 9, September 2009, Pages 928-934

B. Suman, P. Kumar, A Survey of Simulated Annealing as a Tool for Single and Multiobjective Optimization, *The Journal of the Operational Research Society,* Vol. 57, No. 10 (Oct., 2006), pp. 1143-1160

S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi, “Optimization by simulated annealing,*” Science, vol. 220*, pp. 671–680, 1983.

Lidia, Steve; Carr, Roger; "Faster magnet sorting with a threshold acceptance algorithm,*" Review of Scientific Instruments* , vol.66, no.2, pp.1865-1867, Feb 1995

Hung-Jie WANG, Ching-Jung TING, A Threshold Accepting Algorithm for the Uncapacitated Single Allocation p-Hub Median Problem, *Journal of the Eastern Asia Society for Transportation Studies*, Vol.8, 2009, pp. 802-814

Hipel and McLeod *Time Series Modelling of Water Resources and Environmental Systems*, 1994, Elsevier.

Pepper, J.W.; Golden, B.L.; Wasil, E.A.; "Solving the traveling salesman problem with annealing-based heuristics: a computational study," *Systems, Man and Cybernetics, Part A: Systems and Humans*, IEEE Transactions on , vol.32, no.1, pp.72-77, Jan 2002

Abbas Khosravi, Saeid Nahavandi, Doug Creighton, Construction of Optimal Prediction Intervals for Load Forecasting Problems, *IEEE Transactions on Power Systems*, vol.25, no. 3, pp. 1496-1503, Aug 2010

Jun Liu; Jiang Zhu; "Intelligent Optimal Design of Transmission of Cooling Fan of Engine," Information and Computing (ICIC), 2010 *Third International Conference on* , vol.4, no., pp.101-104, 4-6 June 2010

Azlan Mohd Zain, Habibollah Haron, Safian Sharif, Estimation of the minimum machining performance in the abrasive waterjet machining using integrated ANN-SA, *Expert Systems with Applications*, Volume 38, Issue 7, July 2011, Pages 8316-8326