An Intelligent Stock Forecasting System Using a Unify Model of CEFLANN, HMM and GA for Stock Time Series Phenomena

Dwiti Krishna Bebarta[1], T. Eswari Sudha[1], and Ranjeeta Bisoyi[2]

[1] Dept of CSE, GMR Institute of Technology, Rajam, AP, India
bebarta.dk@gmrit.org, sudha.eswari@gmail.com
[2] Multidisciplinary Research Cell, S.O.A. University, Bhubaneswar, Odisha, India
ranjeeta.bisoi@gmail.com

Abstract. The aim of this work to suggest and apply a unify model by combining the Computationally Efficient Functional Link Artificial Neural Networks (CEFLANN), Hidden Markov Model (HMM), and Genetic Algorithms (GA) to predict future trends from a highly uncertainty stock time series phenomena. We present a framework of an intelligent stock forecasting system using complete features to predict stock trading estimations that may consequence in better profits. Using CEFLANN architecture, the stock prices are altered to independent sets of values that become input to HMM. The trained and tested HMM output is used to identify the trends in the stock time series data. We apply different methods to generate complete features that raise trading decisions from stock price indices. We have used population based optimization tool genetic algorithms (GAs) to optimize the initial parameters of CEFLANN and HMM. Finally, the results achieved from the unified model are compared with CEFLANN and other conventional forecasting methods using performance assessment techniques.

Keywords: HMM, Genetic Algorithm, FLANN, CEFLANN, MAPE, AMAPE.

1 Introduction

The most important factor for being successful in trading in stock market is the ability to predict future market fluctuations appropriately. The goal of every investor is to buy stocks when market is low and sell when market trend is high to gain profit. Analyst's and researchers speaks related to the efficient market supposition, it is practically impossible to predict accurately based on historical stock market data. Professional traders use two major types of analysis to make accurate decisions in financial markets: fundamental and technical. Fundamental analysis is to consider company's overall condition of the economy, type of industry and overall financial strengths. Whereas technical analysis depends on charts, comparison tables, technical indicators and historical prices of stocks.

S.C. Satapathy et al. (eds.), *Emerging ICT for Bridging the Future – Volume 2*,
Advances in Intelligent Systems and Computing 338, DOI: 10.1007/978-3-319-13731-5_53

Presently forecasting technique has improved the accuracy by introducing vital forecasting methodologies. Though, the technical analysis traditionally started with various statistical models as a tool for forecasting future data with the help of historical data. Different models introduced like Auto Regressive Integrate Moving Average (ARIMA) [1], a flexible autoregressive conditional heteroskedasticity (ARCH) model [2] and Multiple Linear Regression (MLR) [3] are used for forecasting the time series phenomena. However such models are not good enough to predict efficiently when the stock time series data is considered as highly non-linear, high degree of vagueness, and volatile. Presently technical analysis is carry out by using advanced machine intelligence methods. Artificial Neural Network (ANN) [4], [5], [6] is suggesting one of the efficient soft computing methods for stock market prediction. ANN's are data driven model and are not efficient because of the multiple layers between the input and output layers. To improve further in accuracy and efficiency in forecasting researcher have also used Fuzzy logic, which is based on expert knowledge. Fuzzy logic can be used either autonomously [7], [8] or hybridized [9], [10] with other methods for forecasting stock data. These ANN's and hybrid network systems involves more computational complexity during training and testing for forecasting stock time series data. HMM [11], [12], [13] is a form of probabilistic finite state system used extensively for pattern recognition and classification problems. Using HMM for predicting future stock trend based on past data is not simple. HMM that is trained on the past dataset of the chosen stocks is used to search for the variable of interest data pattern from the historical dataset. In order to accomplish better prediction than the other models, the intellectual Functional Link Artificial Neural Network (FLANN) [14], [15], [16] is used. These networks are computationally efficient, involve less computational complexity and provide superior prediction performance compared to other standard models. In this paper we have proposed a unify model combining computationally efficient functional link artificial neural network (CEFLANN), Hidden Markov Model (HMM) and genetic algorithms (GAs) to achieve the better forecasting results. We have explored three different stock data for forecasting to exhibit our model. The prediction results obtained from our model is further compared with the fusion model of ANN, HMM, and GA discussed in paper [17].

In this paper, we imply and develop a unify model consisting of computationally efficient Functional Link Artificial Neural Network (CEFLANN) structural design [18], [19] with HMM and a population based optimization tool genetic algorithms (GAs) [20] for better prediction of prices of leading stock market phenomena. The structure of CEFLANN model is simple and with proper jumbles of technical and fundamental parameters prediction accuracy is improved. A Hidden Markov Model (HMM), which is built on the probabilistic structure for modeling time series annotations to predict stock prices. Further by using population based optimization tool GAs for initializing the parameters of the CEFLANN and HMM.

The rest of the paper is planned as follows: section 2, the details of the unify model provided; section 3, study of datasets; section 4, experimental setup, performance estimation and results; and lastly section 5 tenders a brief conclusion and advance researches are given.

2 Overview of the Unify Model

2.1 Computationally Efficient Functional Link Artificial Neural Network (CEFLANN) Model

The architecture of CEFLANN described in the paper [18], [19] is a nonlinear adaptive model and can approximate stock time series phenomena through a supervised learning. The algorithm used in the CEFLANN is an optimum method for computing the gradients of the error by the help of back-propagation learning method. This algorithm usually treated as robust with respect to annoyance or unstable data. Fig. 1 shows the block diagram representation of CEFLANN architecture.

This CEFLANN architecture uses a functional expansion block where all the inputs are used to enhance the dimension of input space as described below.

$$\underset{Input\,Vector}{X = [x_1, x_2, ..., x_m, x_0, x_{p+1}, ...x_{p+m}]} \qquad \underset{Desired\,Vector}{[x_{m+1}]} \tag{1}$$

Where $[x_1, x_2, ..., x_m]$ are from real stock data, $[x_{p+1}, ...x_{p+m}]$ enhanced input using Functional Expansion Block (FEB) and x_{m+1} is target data taken from real stock data.

The trigonometric basic function used to enhance the input pattern is based on tan hyperbolic as specified below.

$$\begin{aligned}
x_{p+1} &= \tanh(a_{01} + a_{11}x_1 + a_{21}x_2 + a_{31}x_3 + ... + a_{m1}x_m) \\
x_{p+2} &= \tanh(a_{02} + a_{12}x_1 + a_{22}x_2 + ... + a_{m2}x_m) \\
&.. \\
x_{p+m} &= \tanh(a_{0m} + a_{1m}x_1 + a_{2m}x_2 .... + a_{mm}x_m)
\end{aligned} \tag{2}$$

Where, the associate parameter given in matrix [A] eq. (3) and input matrix X in eq. (1) is used in above eq. (2)

$$A = \begin{bmatrix} a_{01} & a_{11} & a_{21} .... & a_{m1} \\ a_{02} & a_{12} & a_{22} .... & a_{m2} \\ .... & & & \\ a_{0m} & a_{1m} & a_{2m} .... & a_{mm} \end{bmatrix} \tag{3}$$

$$\begin{aligned}
&O = W * X^T \\
&where \\
&W = [w_1, w_2, w_3, ..., w_m, w_0, w_{p+1}, ..., w_{p+m}] \\
&X = [x_1, x_2, ..., x_m, x_0, x_{p+1}, ...x_{p+m}]
\end{aligned} \tag{4}$$

The weight vector [W] and associated parameters [A] are updated in the direction of the negative gradient of the performance function using back-propagation learning algorithm by computing the error between the target output and the expected output is written in eq. (5)

$$e = x_{m+1} - O \tag{5}$$

By taking gradient of the error with respect to the weights, the weight adjustment is obtained in eq. (6)

$$W(t+1) = W(t) + \frac{\mu \tanh(\beta e) * X}{\lambda + X^T X}$$

$$\mathrm{a}_{j+m-1} = \mathrm{a}_{j+m-1} + P \tag{6}$$

$$where$$

$$P = \mathrm{C} * \mathrm{P1} * \mathrm{x}_{j+m}$$

$$where$$

$$P1 = (\mathrm{sech}(\mathrm{a}_{j-1} + \mathrm{a}_j * \mathrm{x}_j + \mathrm{a}_{j+1} * \mathrm{x}_{j+2} + \ldots + \mathrm{a}_{j+m-1} * \mathrm{x}_{j+m-1})^2$$

2.2 Hidden Markov Model

A Hidden Markov Model (HMM) is like a finite state machine that represents the statistical regularities of sequences. In HMMs, the states are hidden and observations are probabilistic function of state. Steps to define HMM more formally:

Step-1: N, the number of states in the model.

$$S = \{s_1, s_2 \ldots s_N\}$$

Step-2: M, the number of distinct observation sequences.

$$Q = \{q_1, q_2 \ldots q_m\}$$

Step-3: The state transition probability distribution matrix, $T = \{t_{ij}\}$

Where,

$$t_{ij} = \Pr ob(c' = s_j \; or \; c = s_i)$$

$$where \quad 1 \le i \; and \quad j \le N$$

Where, c' is the next state, c is the current state, and S_j is the jth state.

Step-4: Observation Probability distribution matrix, $B = [b_{s_j}(q_t)]$

Where,

$$b_{s_j}(q_t) = \Pr ob(q_t \,\mathrm{I}\, c = s_j)$$

$$where \quad 1 \le j \le N \; and \quad 1 \le t \le M$$

Step-5: The initial state distribution vector [π] and

$$\pi_i = \Pr ob(q_0 = s_i)$$

Where, $i \le N$ and q_0 is initial state

Step-6: The final HMM model is λ= (T, B, π)

In this study, the Baum–Welch algorithm [13] is attempted to re-estimate the HMM parameters A, B and π so that the HMM model best fits in the training data set. An algorithm Forward- Backward method is used to compute the probability $P(Q/\lambda)$ of observation sequence $Q= q_1, q_{2,\ldots..} q_m$ for the given model λ, where $\lambda = (A, B, \pi)$.

2.3 Integration of CEFLANN with HMM

The proposed unify model consisting of CEFLANN and HMM cascaded as shown in given Fig. 1 to forecast stock prices. We have employed CEFLANN as a tool to bring out an observed sequence. These observed sequences are further introduced to HMM to improve a better accuracy in the prediction result. The GA is used to find out optimal initial parameters for both CEFLANN and HMM.

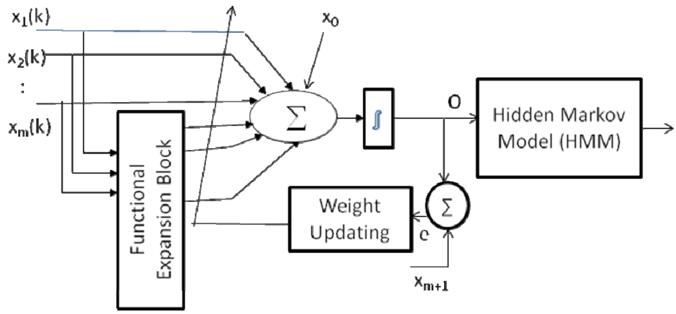

Fig. 1. The UNIFY MODEL

To combine CEFLANN and HMM to make our unify model the integration method states below:

a. We have created the structure of the CEFLANN having ‘m’ inputs of real historical data and ‘m’ number of enhanced input using FEB. One bias term is also introduced for reducing error during training the network.

b. We have initialized the respective parameters of the network.

c. The output of the network ‘O’ resulted from CEFLANN is fed into the HMM as input to get the final output ‘Y’.

d. GA method is used to optimize the initial parameters of CEFLANN and HMM since performance of these methods depends on the initial values.

2.4 Using GA to Optimize the Parameters of HMM

There are three parameters in HMM (T, B, π) which are needed to optimize by using GA instead of considering random values. The initial parameters of GA are chosen suitably. The initial parameters of GA are as follows:

For Observation probability distribution and Transition probability matrix

Chromosome size	16
Population type	Double
Population size	20
Elite parent selection	2
Crossover fraction	0.8
Migration fraction	0.2
Generation	100
Fitness limit	-infinity
Initial Population	Random
Fitness scaling	Rank Scaling
Selection	Stochastic Uniform

For Initial probability distribution

Chromosome size	4
Population type	Double
Population size	20
Elite parent selection	2
Crossover fraction	0.8
Migration fraction	0.2
Generations	100
Fitness limit	-infinity
Initial Population	Random
Fitness scaling	Rank Scaling
Selection	Stochastic Uniform

3 Construction of Stock Data Indices

3.1 Historical Data Set

For investigating the efficiency of the proposed model we have used stock data collected from different industries share market price. The Reliance Industries Limited (RIL), Tata Consultancy Services (TCS), and Oracle Corporation (ORACLE) historical prices of stock data used to analyze the results. More than 2000 data patterns considered which consists of open price, high price, low price, close price and volume of the stocks. The proposed model which is designed to forecast the next day closing price by taking input as each day's close price in the stock index of datasets. Following 80:20 ratio, we have used closing price of 200 days for training and next 30 days of closing price is used for testing the model. The MATLAB implementation has done for forecasting using the proposed unify model.

3.2 Data Normalization

To form an input vector for the unify model to learn, the range of values is 0 to 1. The historical past data collected from web is used for training and testing the model. The normalization formula in the following equation (7) is shaping by stating the data in terms of maximum and minimum values of the stock data.

$$NV = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{7}$$

Where, NV is normalized value and x_i is actual value, x_{min} and x_{max} represents minimum and maximum values of original stock data set.

4 Experiments and Results

4.1 Simulation Results

The comparison of target vs. predicted stock closing price of RIL stock during testing of CEFLANN only and with HMM is given in Figs. 2 & 3. The stock market indices for one day in advance for a period of 30 days are showcased.

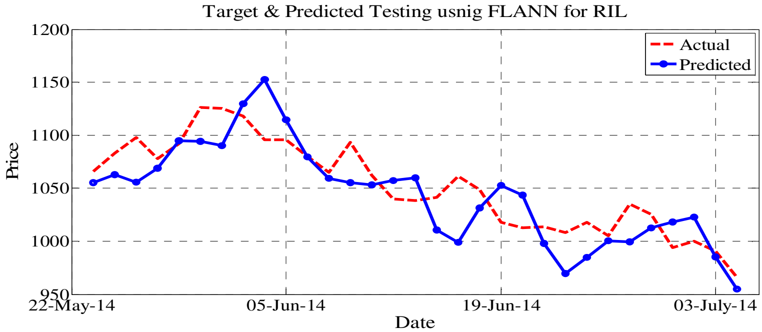

Fig. 2. Testing results of RIL using CEFLANN

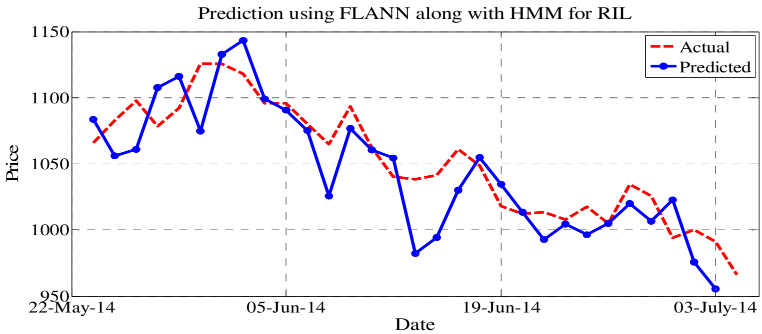

Fig. 3. Testing results of RIL using UNIFY MODEL

The comparison of target vs. predicted stock closing price of TCS stock during testing of CEFLANN only and with HMM is given in Figs. 4 & 5. The stock market indices for one day in advance for a period of 30 days are showcased.

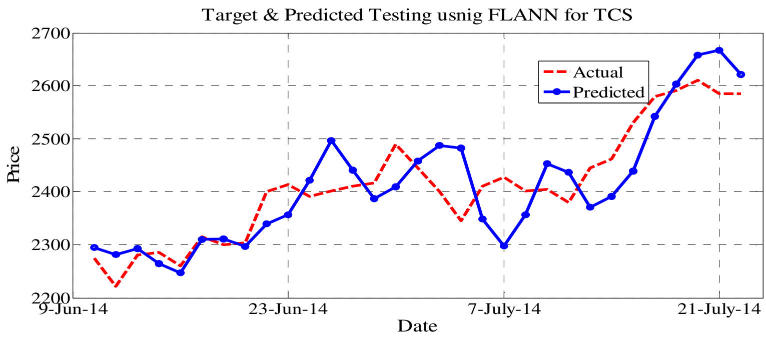

Fig. 4. Testing results of TCS using CEFLANN

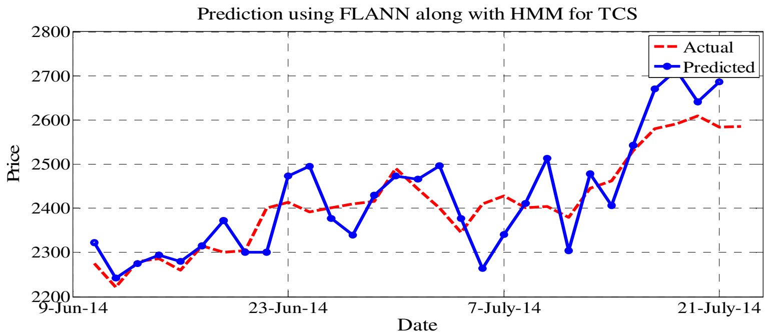

Fig. 5. Testing results of TCS using UNIFY MODEL

The comparison of target vs. predicted stock closing price of ORACLE stock during testing of CEFLANN only and with HMM is given in Figs. 6 & 7. The stock market indices for one day in advance for a period of 30 days are showcased.

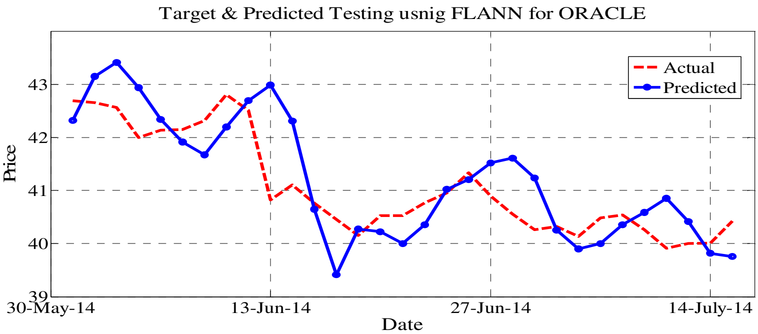

Fig. 6. Testing results of ORACLE using CEFLANN

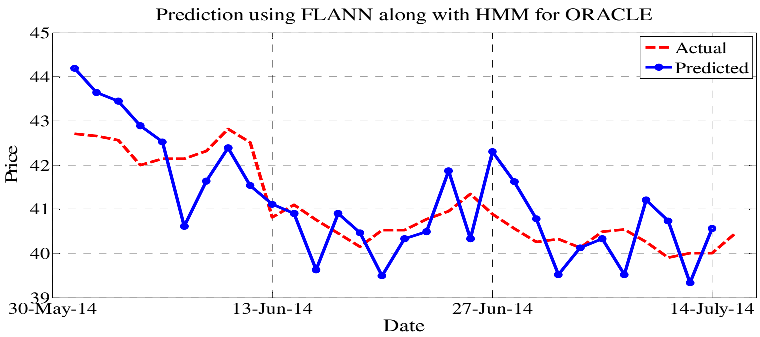

Fig. 7. Testing results of ORACLE using UNIFY MODEL

4.2 Performance Metric

To evaluate the performance of the proposed model there are various criterions can be used. Popularly the accuracy measures like Mean Absolute Percentage Error (MAPE) and Average Mean Absolute Percentage Error (AMAPE) is used to study the accuracy of the model. The above named error calculation methods are mentioned below in eq. (8) and eq. (9).

$$MAPE = \left(\frac{1}{N} \sum_{j=1}^{N} \frac{abs(e_j)}{y_t} \right) \times 100\% \tag{8}$$

$$AMAPE = \left(\frac{1}{N} \sum_{j=1}^{N} \left[\frac{abs(e_j)}{\bar{y}} \right] \right) \times 100\%$$

$$where \quad \bar{y} = \frac{1}{N} \sum_{j=1}^{N} [\, y_t \,] \tag{9}$$

Where $e = y_t - y$, y_t & y represents the actual and forecast values; $\bar{y}$ is the average value of actual price.

4.3 Results

Table 1. Performance Comparison on daily closed price of various stocks by using simple ANN-HMM-GA

Stock	Duration (30 Days)	Performance Assessments	
		MAPE	AMAPE
RIL	22/05/2014 to 03/07/2014	9.1720	9.3324
TCS	09/06/2014 to 21/07/2014	10.3611	10.3810
ORACLE	30/05/2014 to 14/07/2014	6.9921	7.3630

Table 2. performancecomparison on daily closed price of various stocks by using only CEFLANN

Stock	Duration (30 Days)	Performance Assessments	
		MAPE	AMAPE
RIL	22/05/2014 to 03/07/2014	8.7212	8.7324
TCS	09/06/2014 to 21/07/2014	7.2600	7.2814
ORACLE	30/05/2014 to 14/07/2014	5.8512	5.8669

Table 3. Performance Comparison on daily closed price of various stocks by using unify model

Stock	Duration (30 Days)	Performance Assessments	
		MAPE	AMAPE
RIL	22/05/2014 to 03/07/2014	6.1854	6.1795
TCS	09/06/2014 to 21/07/2014	5.6401	5.662
ORACLE	30/05/2014 to 14/07/2014	5.6569	5.6713

5 Conclusion

The main idea of this paper was to build a unify model that can be used in predicting the stock time series phenomena in the decision making process and that would execute similar to an actual investor. We have proposed a high-tech method that can forecast one-day ahead market values by using our unify model. Our experimental analysis concluded that, by implementing and testing the proposed method on real stock data, we could estimate the market trend and make acceptable decisions. Our unify model consists an adaptive CEFLANN, a HMM and GAs to forecast stock data indices. We find the performance of the unify model is better than that of the basic models (Hassan, Baikunth and Michael, 2007) and our adaptive model (D K Bebarta, Birendra Biswal and P K Dash, 2012). The adaptive CEFLANN based on back propagation learning method used combining with HMM by the help of optimized parameter using GAs to forecast three different stocks. The results obtained from all models suggested our unify model gives best accuracy over other methods. Further this work can be suitably extended to get prediction result with improved MAPE by using high end learning methods like case based dynamic window and adaptive evolutionary optimized method differential evolution (DE) algorithm.

References

1. Zhang, G.P.: Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing 50, 159–175 (2003)
2. Cheong, C.W.: Modeling and forecasting crude oil markets using ARCH-type models. Energy Policy 37, 2346–2355 (2009)
3. Jahandideh, S., Jahandideh, S., Asadabadi, E.B., Askarian, M., Movahedi, M.M., Hosseini, S., Jahandideh, M.: The use of artificial neural networks and multiple linear regression to predict rate of medical waste generation. Waste Management 29, 2874–2879 (2009)
4. Chen, A.S., Leung, M.T., Daouk, H.: Application of Neural Networks to an emerging financial market: Forecasting and trading the Taiwan Stock Index. Comput. Operations Res. 30, 901–923 (2003)
5. Chang, P.-C., Liu, C.-H., Lin, J.-L., Fan, C.-Y., Ng, C.S.P.: A neural network with a case based dynamic window for stock trading prediction. Expert Systems with Applications 36(3, Pt 2), 6889–6898 (2009)
6. Giles, C.L., Lawrence, S., Tsoi, A.C.: Noisy Time Series Prediction using Recurrent Neural Networks and Grammatical Inference. Machine Learning 44, 161–183 (2001)
7. Dostál, P.: Forecasting of Time Series with Fuzzy Logic. In: Zelinka, I., Chen, G., Rössler, O.E., Snasel, V., Abraham, A. (eds.) Nostradamus 2013: Prediction, Model. & Analysis. AISC, vol. 210, pp. 155–162. Springer, Heidelberg (2013)
8. Karnik, N.N., Mendel, J.M.: Applications of type-2 fuzzy logic systems to forecasting of time-series. Information Sciences 120, 89–111 (1999)
9. Teoh, H.J., Chen, T.-L., Cheng, C.-H., Chu, H.-H.: A hybrid multi-order fuzzy time series for forecasting stock. Expert Systems with Applications 36, 7888–7897 (2009)
10. Castillo, O.: Hybrid Intelligent Systems for Time Series Prediction Using Neural Networks, Fuzzy Logic, and Fractal Theory. IEEE Transactions on Neural Networks 13, 1395–1408 (2002)

11. Rafiul, M., Nath, B.: StockMarket Forecasting Using Hidden Markov Model: A New Approach. In: IEEE Conference on Intelligent Systems Design and Applications (ISDA 2005), pp. 192–196 (2005), doi:10.1109/ISDA.2005.85
12. Park, S.-H., Lee, J.-H., Song, J.-W., Park, T.-S.: Forecasting Change Directions for Financial Time Series Using Hidden Markov Model. In: Wen, P., Li, Y., Polkowski, L., Yao, Y., Tsumoto, S., Wang, G. (eds.) RSKT 2009. LNCS, vol. 5589, pp. 184–191. Springer, Heidelberg (2009)
13. Rabinar, L.R.: A tutorial on hidden Markov models and selected applications in speech recognition. Proceedings of IEEE 77, 257–285 (1989)
14. Pao, Y.H., Takefji, Y.: Functional-Link Net Computing. IEEE Computer Journal, 76–79 (1992)
15. Majhi, R., Panda, G., Sahoo, G.: Development and performance evaluation of FLANN based model for forecasting of stock markets. Experts Systems with Applications An International Journal (2008)
16. Bebarta, D.K., Biswal, B., Rout, A.K., Dash, P.K.: Forecasting and classification of Indian stocks using different polynomial functional link artificial neural networks. In: IEEE Conference, INDCON, pp. 178–182 (2012), doi:10.1109/INDCON.2012.6420611
17. Hassan, M.R., Nath, B., Kirley, M.: A fusion model of HMM, ANN and GA for stock market forecasting. Expert Systems with Applications 33, 171–180 (2009)
18. Bebarta, D.K., Biswal, B., Dash, P.K.: Comparative study of stock market forecasting using different functional link artificial neural networks. Int. J. Data Analysis Techniques and Strategies 4(4), 398–427 (2012)
19. Rout, A.K., Biswal, B., Dash, P.K.: A hybrid FLANN and adaptive differential evolution model for forecasting of stock market indices. International Journal of Knowledge-Based and Intelligent Engineering Systems 18, 23–41 (2014)
20. Chau, C.W., Kwong, S., Diu, C.K., Fahrner, W.R.: Optimization of HMM by a genetic algorithm. In: IEEE International Conference on Acoustics, Speech, and Signal Processing, pp. 1727–1730 (1997)