Chapter -5

DEVELOPMENT AND PERFORMANCE EVALUATION OF RECURRENT RBF MODEL FOR LONG RANGE PREDICTION OF NET ASSET VALUE

DEVELOPMENT AND PERFORMANCE EVALUATION OF RECURRENT RBF MODEL FOR LONG RANGE PREDICTION OF NET ASSET VALUE

5.1 Introduction

Nowadays, investment is one of the most important economical activities in modern life. Mutual funds have become one of the major channels for investors. Mutual fund is fast becoming a source of investment as it is a common pool of money into which investors place their contributions that are to be invested in accordance with a stated objective. The growth of mutual funds is booming rapidly, due to its professional management of capital, stable profitability and low risk. The mutual funds have come a long way since its inception in 1964 and is growing further as a tool of investment. It is one of the reasons behind the popularity of late maturity of Indian capital market. Indian market has also drawn the attention of global investors. The retail investors are depending on mutual funds to take care of their investments due to the imminent risk in the equity market and low return from fixed income instruments. It is necessary for the mutual fund investors to know the net asset value (NAV) of the trade date for evaluating the future performance of the various schemes before deciding on investments. NAV plays a great role in mutual funds' buy and sell orders. NAV can be calculated as the value of a mutual fund's price per share value. The value of a fund's asset is the total value of all the securities in fund's portfolio. To compute the per-share dollar amount of the fund, the liabilities (if any) is subtracted from fund's asset value and the result is divided by the number of fund shares outstanding. In the perspective of mutual fund, NAV per share is computed once a day based on the closing market prices of the securities in the fund's portfolio. Therefore, the prediction of the net asset value of mutual funds is very important for investors and fund managers. Mutual fund on the other hand is not that much volatile by nature, as the diversification is very large and at a time 50-100 stocks are covered. Different kinds of stocks from different sectors and market capitalization are involved in mutual fund and the overall change in value is thus less volatile (other than extreme days). Mutual funds are dynamic financial institutions (FIs) which play an important role in an economy by mobilising savings and investing them in the stockmarket. This establishes a direct link between savings and the capital market. Therefore, the activities of mutual funds have both short-and long-term impact on the savings pattern, growth of capital markets and the economy. There is a general perception that this inter-relationship between the returns of the mutual funds and the economic variables has been strengthened in India in the recent past. Various data mining and soft computing techniques have been applied for accurate NAV forecasting. A brief review of literature in this area is presented here. Artificial neural network (ANN) has been used to predict the performance of equity mutual funds by using a multi-layer perceptron model GRG2 nonlinear optimizer. It has been observed that ANN generates better forecasting results than linear models for all styles of funds and a heuristic approach of variable selection via neural networks is compared with the stepwise selection method of linear regression [84]. An artificial neural network method is applied to mutual fund NAV forecasting to evaluate the effectiveness. Neural network forecasting model [85, 86, 87] have been developed to use for investigating the co-integrating relationship, relationship of macroeconomic factors to the returns of individual assets as well as forecasting in capital markets. A neural network with back propagation (BP) [88] has been used to forecast the end-of-year net asset value (NAV) of mutual funds in U. S. market. A non-linear technique like the Artificial Neural Network has been chosen to predict mutual fund net asset values on the basis of the selected variables like the interest rate, money supply, inflation rate and the equity market have considerable influence in the net asset value movement [89]. The interaction effects of the various economic factors influencing the Net Asset Values of the Indian Mutual Funds was evaluated and the future NAVs were forecasted for the following years using Regression Analysis and Artificial Neural Network[90].A mutual fund performance evaluation model, fast adaptive neural network classifier (FANNC) which combines the features of adaptive resonance theory and field theory fast adaptive neural network classifier (FANNC) [91] has been implemented and taking less time than the BPN approach to evaluate mutual fund performance. A genetic algorithm is used dynamically to select funds according to their past performances with the global trend indicator (GTI)[92] is defined for evaluating the price change trend of the funds in the future and the monitoring indicator (MI) based to measure whether the fund market is in the bull or bear state. Grey prediction, radial basis function neural network (RBFNN) and Grey-RBFNN [93] have been proposed to predict the net asset value of single nation equity funds. An unsupervised learning self-organizing map neural network (SOM-NN) [94] has also been used to establish a model to select the superior funds and also has a good predictive ability. It is reported that this model is more suitable for short-term and medium-term investment. Box-Jenkins autoregressive integrated moving average (ARIMA) [95] methodology has been employed to forecast the future NAV values of the mutual funds. A systematic method for guiding the investment in mutual funds, gene expression programming [96] has been used to generate trading rules to decide the buying timing, selling timing and the funds with higher sortino ratios are selected into the portfolio. There are two models for capital allocation, one allocates the capital equally (EQ) and the other allocates the capital with the mean variance (MV) model. A new fund trading strategy that combines turbulent particle swarm optimization (TPSO) [97] and mixed moving average techniques is used to find the proper content of technical indicator parameters to achieve high profit and low risk on a mutual fund. The time interval of moving average of the proposed method is adjustable and the trading model could avoid and reduce loss by providing several good buy and sell points.

In recent past recurrent radial basis function (RRBF) [98] neural network has been developed and applied for nonlinear system modeling [99], noise cancellation [100,101] and time series prediction [102]. This adaptive network possesses faster convergence [103] while it has better nonlinear modeling capability compared to conventional neural networks. In this chapter an attempt has been made to develop forecasting model for prediction of retail sales using RRBF neural network and its performance is compared with other neural network based models like multilayer artificial neural network (MLANN), functional link artificial neural network (FLANN), recurrent neural network (RNN) and radial basis function (RBF) neural network.

5.2 Development of Recurrent Radial Basis Function (RRBF) Neural Network based Forecasting Model

The architecture of recurrent radial basis (RRBF) neural network forecasting model is shown in Fig. 5.1. The model of RRBF is similar to RBF with additional input layer. In this network each output of the hidden neurons are fed back to their corresponding input through a delay. Let $x(n)$, ϕ and M represent the input to the network, the radial basis function that performs the nonlinear mapping and the total number of hidden units respectively. Each node has a center vector c_k and spread parameter σ_k, where $k = 1, 2, \ldots\ldots., M$.

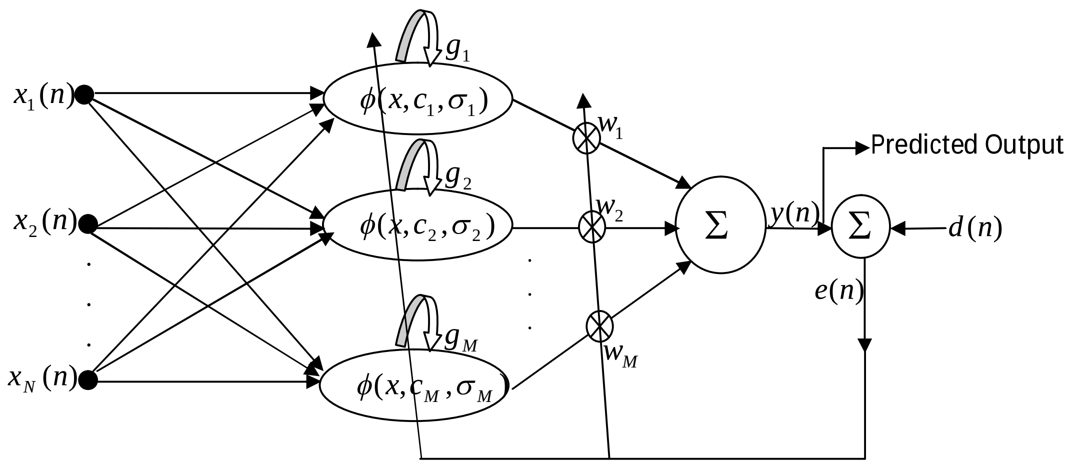

Fig. 5.1 Recurrent Radial Basis Function (RRBF) Neural Network based NAV forecasting model

The radial basis function is represented by $\phi\|x, c\|$, where $\|.\|$ represents the Euclidean norm.

The radial basis function employed is given as

$$\phi(r) = \exp\left(-\frac{r^2}{2\sigma^2}\right) \tag{5.1}$$

The estimated output of the network for nth pattern is

$$y(n) = \sum_{k=1}^{M} w_k(m)\phi(x(n), c_k(m), \sigma_k(m)) \tag{5.2}$$

where

$$\phi(x(n), c_k(m), \sigma_k(m)) = \exp\left(-\frac{\|x(n) - c_k(m)\|^2}{\sigma_k^2(m)} + g_k(m)\phi(x(n-1), c_k(m), \sigma_k(m))\right) \tag{5.3}$$

The error for the nth pattern is obtained by

$$e(n) = d(n) - \sum_{k=1}^{M} w_k(m)\phi(x(n), c_k(m), \sigma_k(m)) \tag{5.4}$$

where $d(n)$ is the target value. As the Gaussian function is chosen as the radial basis function (5.4) can be rewritten as

$$e(n) = d(n) - \sum_{k=1}^{M} w_k(m) \exp\left(- \frac{\|x(n) - c_k(m)\|^2}{\sigma_k^2(m)} \right) \tag{5.5}$$

The cost function is defined as

$$\xi = \frac{1}{2} \sum_{n=1}^{n_1} e^2(n) \tag{5.6}$$

where n_1 is the number of training patterns. It is required to adjust the free parameters such as weight, center and spread so as to minimize ξ. According to the gradient descent algorithm the free parameters at mth epoch are updated using

$$w_k(m+1) = w_k(m) - \mu_w \frac{\partial \xi}{\partial w_k(m)} \tag{5.7}$$

$$c_k(m+1) = c_k(m) - \mu_c \frac{\partial \xi}{\partial c_k(m)} \tag{5.8}$$

$$\sigma_k(m+1) = \sigma_k(m) - \mu_\sigma \frac{\partial \xi}{\partial \sigma_k(m)} \tag{5.9}$$

where μ_w, μ_c and μ_σ are learning parameters within the range of 0 to 1 and $k = 1, 2, \ldots\ldots\ldots\ldots, M$. Finally the update equations are defined as

$$w_k(m+1) = w_k(m) + \sum_{n=1}^{n_1} \mu_w e(n) \phi(x(n), c_k(m), \sigma_k(m)) \tag{5.10}$$

$$c_k(m+1) = c_k(m) + \sum_{n=1}^{n_1} \mu_c \frac{e(n) w_k(m)}{\sigma_k^2(n)} \phi(x(n), c_k(m), \sigma_k(m)) \, [x(n) - c_k(m)] \tag{5.11}$$

$$\sigma_k(m+1) = \sigma_k(m) + \sum_{n=1}^{n_1} \mu_\sigma \frac{e(n) w_k(m)}{\sigma_k^3(m)} \phi(x(n), c_k(m), \sigma_k(m)) \, [\|x(n) - c_k(m)\|^2] \tag{5.12}$$

The recurrent weights are updated as

$$g_k(m+1) = g_k(m) - \mu_g \frac{\partial \xi}{\partial g_k(m)} \tag{5.13}$$

where μ_g is the learning parameter and

$$\frac{\partial \xi}{\partial g_k(m)} = \sum_{n=1}^{n_1} w_k(m)\phi(x(n), c_k(n), \sigma_k(m))\phi(x(n-1), c_k(m), \sigma_k(m)) \tag{5.14}$$

From (5.13) and (5.14), the recurrent weights are adjustable as

$$g_k(m+1) = g_k(m) - \mu_g \sum_{n=1}^{n_1} w_k(m)\phi(x(n), c_k(m), \sigma_k(m))\,\phi(x(n-1), c_k(m), \sigma_k(m)) \tag{5.15}$$

where $k = 1, 2, ..., M$

5.3 Feature extraction and design of input data

The daily net asset value (NAV) of HDFC Top200(G), ICICI Top100(G), Birla Sunlife(G), India have been collected from the URL http//www.smctradeonline.com/mutual-fund-nav.aspx. The details of the data set collected are listed in Table 5.1.

Table 5.1 Data periods of NAV data sets

Mutual fund	**Data year**
Birla Sunlife Equity Fund-Growth	27/08/1998 to 31/12/2002
HDFC Top200- Growth	01/01/1997 to 31/12/2001
ICICI pro. Top100-Growth	19/06/1998 to 31/12/2002

The total numbers of samples available are 1225, 1097 and 1065 for HDFC Top200(G), ICICI Top100(G) and Birla Sunlife(G) NAV data sets respectively. As a first step the collected data is normalized so that each of those lies between 0 to 1. A moving window of size twelve is chosen to divide the total data set into 1214, 1086, 1054 blocks in case of HDFC Top200(G), ICICI Top100(G) and Birla Sunlife(G) respectively. Simple statistical features such as the mean and variance of each of the blocks are calculated. The 12^{th} number normalized value along with the mean and variance of the first block represent the first pattern. Subsequently the window is moved by one sample towards right and mean and variance of the new block is computed. This process is repeated in a sliding manner to extract features. In this way 1214, 1086, 1054 blocks has been formed for case of HDFC Top200(G), ICICI Top100(G) and Birla Sunlife net asset value data sets respetively. The corresponding target value is also chosen depending on the number of days’ ahead for prediction. Out of the 1214, 1086, 1054 input patterns, 1139, 1020, 990 patterns of HDFC Top200(G), ICICI Top100(G) and Birla Sunlife net asset value data sets respectively are used for training of the RRBF forecasting model and the remaining 30 patterns of all three net asset value data sets are used for validation of the model.

5.4 Simulation based experiments

Training of the model: After feature extraction from the NAV data, the proposed forecasting model is trained. For training of the model 1139, 1020, 990 input patterns are used for HDFC Top200(G), ICICI Top100(G) and Birla Sunlife(G) net asset value data sets respectively. Each input pattern is fed to the RRBF network. The outputs of the basis function are estimated and weighted to give the output. The output is then compared with the corresponding target value and the error value is computed. Each input features are applied to the model in sequence and the squared error is calculated in each case. After the application of all patterns the mean squared error (MSE) is obtained and used as the cost function. The weights, centers and variance associated with the Gaussian function and the network are updated using (5.10) – (5.12) and (5.15). The initial values of weights, center and variance are chosen to be random numbers between 0 to 1. The RRBF consists of three hidden neurons with Gaussian radial basis function and one output neuron. The values of learning parameters, μ_w, μ_c, μ_σ and μ_g are chosen as 0.01. Total number of epochs taken is 200 and in averaged over 10 runs. Once the MSE is minimized and attains the lowest magnitude the values of weights, center and variance are frozen for validation of the model. For comparison purpose other available models based on MLANN, FLANN, RNN and RBF are also simulated. The structures of MLANN, RBF and RNN used in the simulation study are chosen to be 3:3:1. The values of learning parameters are set as 0.1 for RNN and 0.05 for MLANN. The values of μ_w, μ_c, μ_σ are taken as 0.01 for RBF. In the FLANN model each of the input is expanded into five terms using trigonometric expansions and one neuron is used at output layer. The total number of weights are 16 including bias weight and the value of μ=0.08 and the momentum term is η=0.05. The RRBF prediction model is used to forecast 1, 3, 7, 15 and 30 days ahead of net asset value. The comparison of convergence characteristics of the forecasting models for 7, 15 and 30 days ahead prediction are shown in Figs. 5.2 – 5.4 for HDFC Top200(G), ICICI Top100(G) and Birla Sunlife(G) dataset respectively. From these Figures it is observed that the RRBF model at the completion of learning provides lowest MSE value in comparison to all other models. The comparison of actual and predicted values during training of the RRBF model for 7, 15 and 30 days ahead prediction are shown in Figs. 5.5 – 5.7 for HDFC Top200(G), ICICI Top100(G) and Birla Sunlife(G) data respectively.

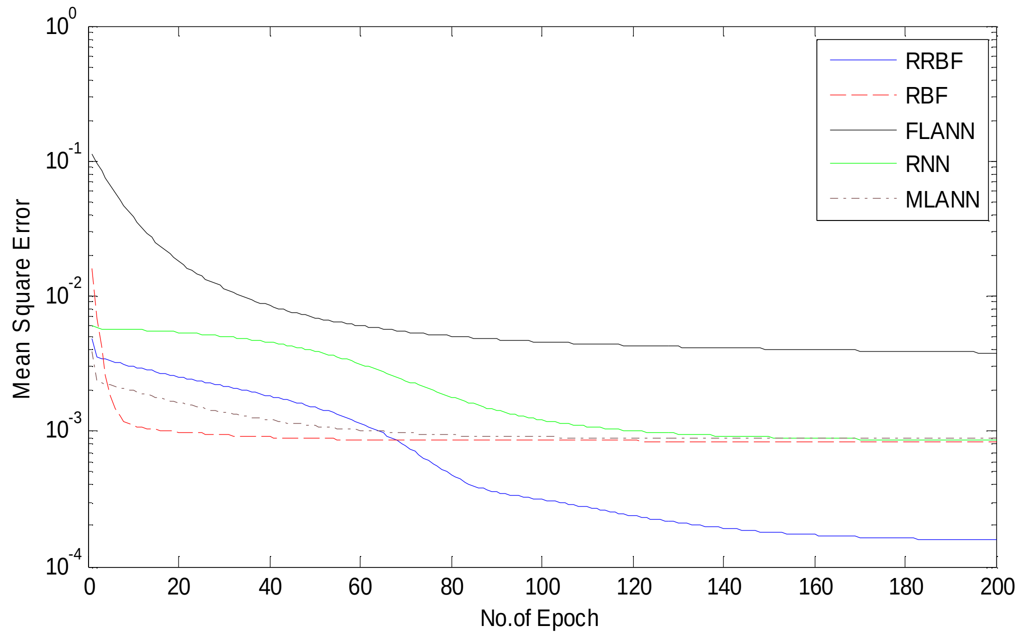

Fig. 5.2 Comparison of convergence characteristics for 7 days ahead prediction of HDFC Top200(G)

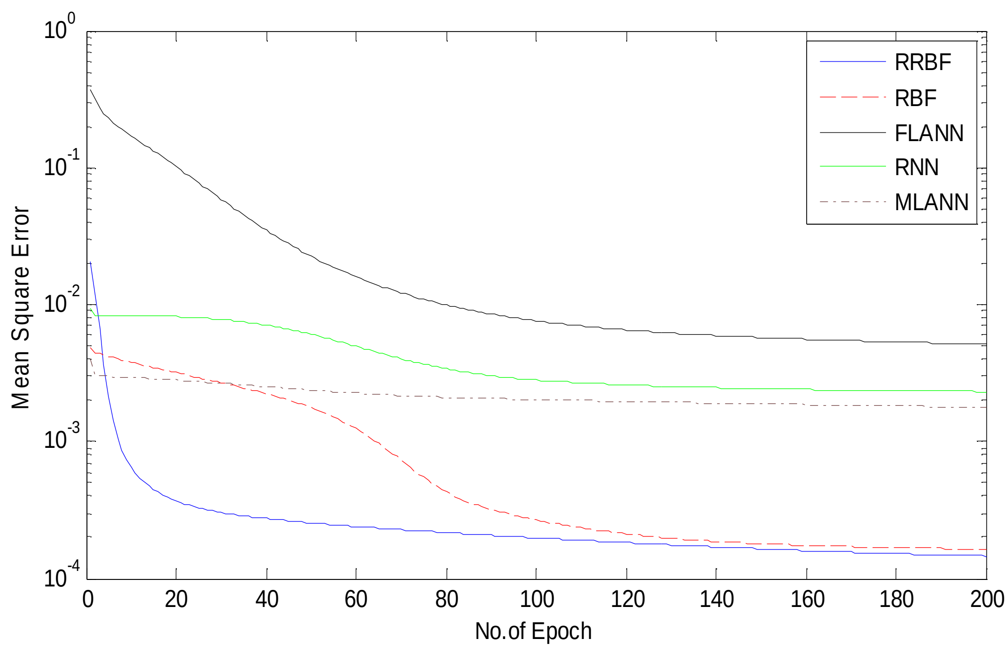

Fig. 5.3 Comparison of convergence characteristics for 15 days ahead prediction of ICICI Top100(G)

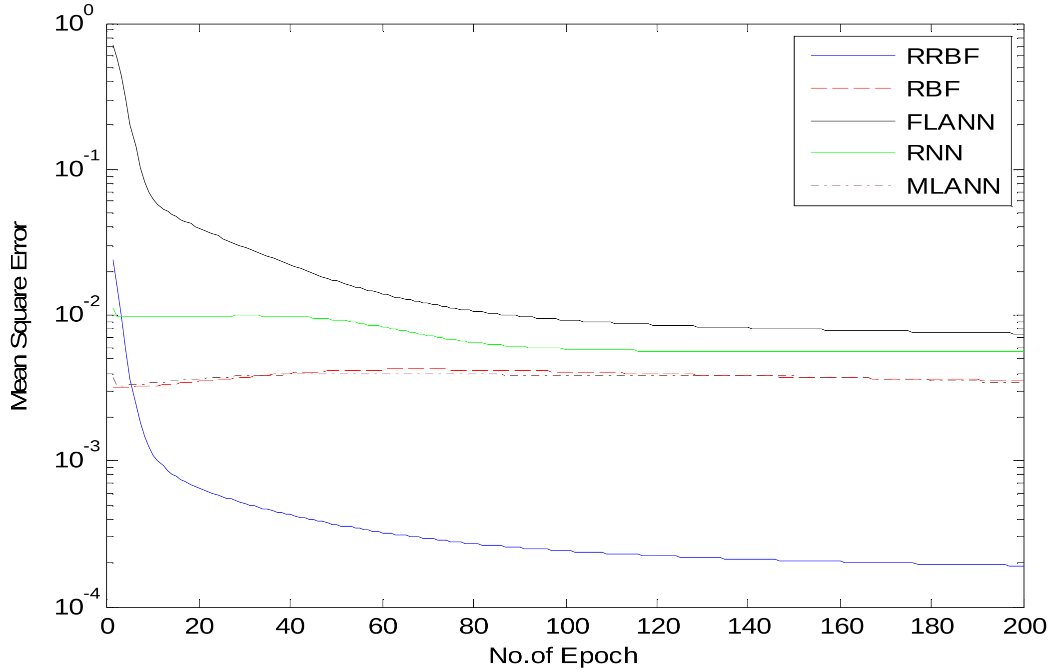

Fig. 5.4 Comparison of convergence characteristics for 30 days ahead prediction of Birla Sunlife(G)

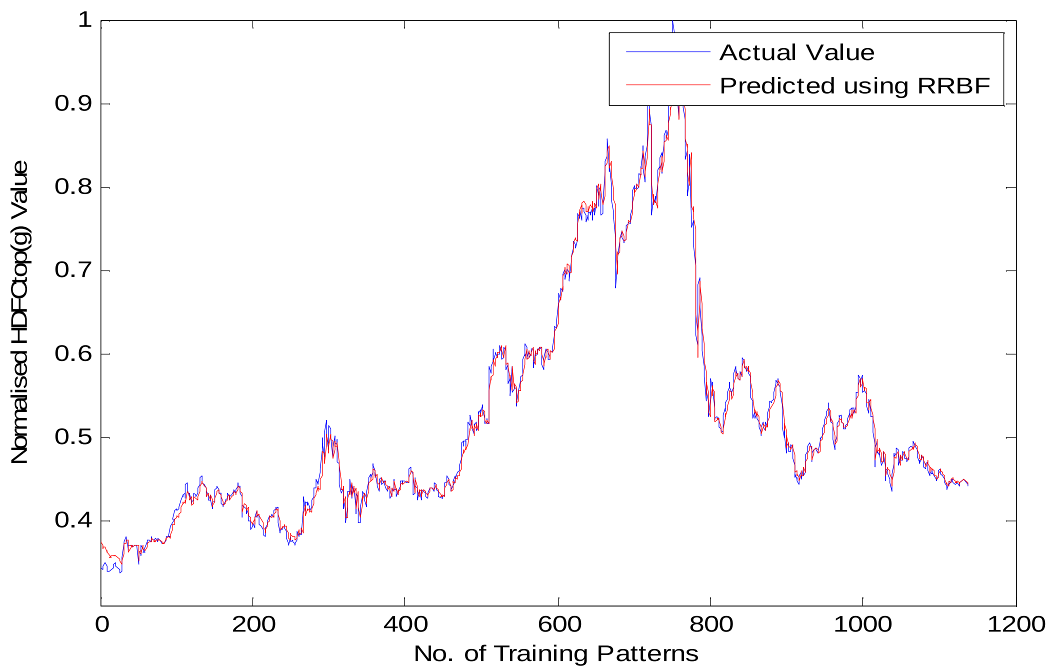

Fig. 5.5 Comparison of actual and predicted value for 7 days ahead prediction of HDFC Top200(G) using RRBF prediction model during training

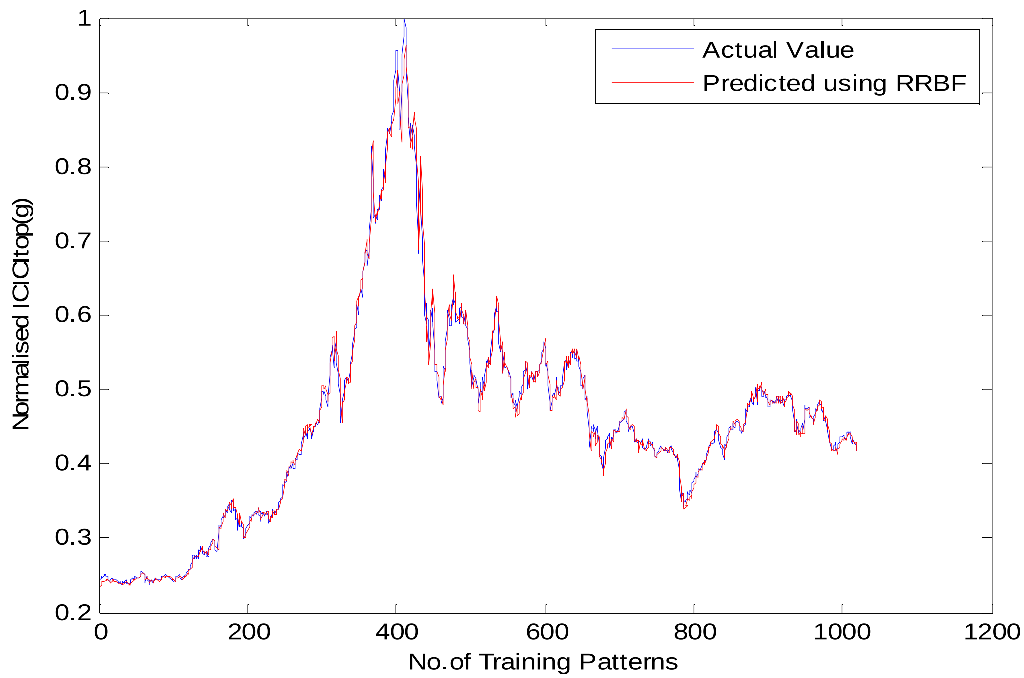

Fig. 5.6 Comparison of actual and predicted value for 15 days ahead prediction of ICICI Top100(G) using RRBF prediction model during training

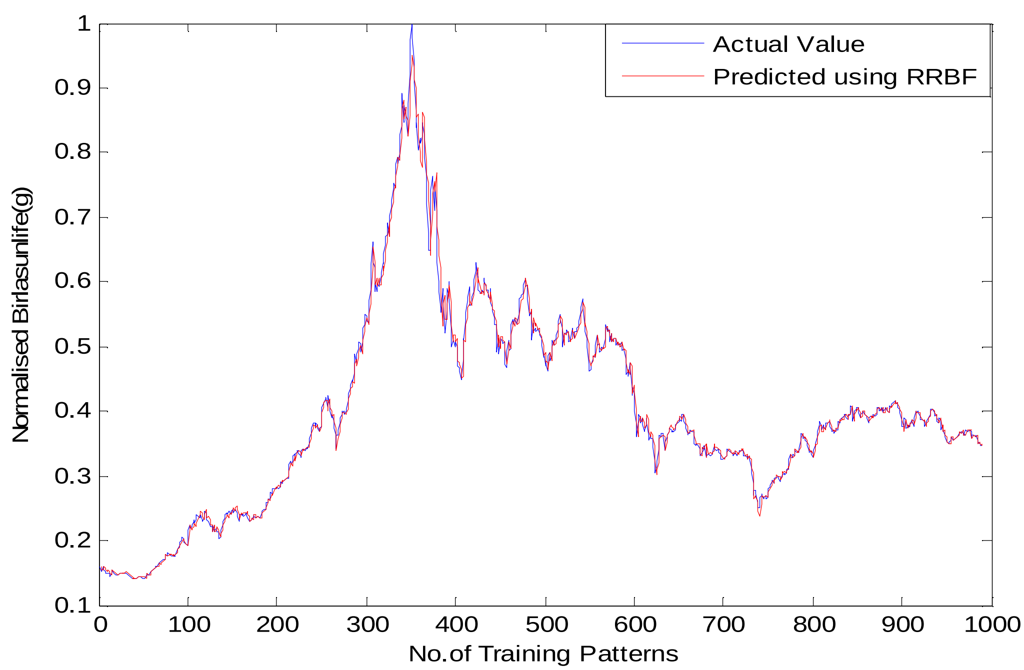

Fig. 5.7 Comparison of actual and predicted value for 30 days ahead prediction of Birla Sunlife(G) using RRBF prediction model during training

Testing the prediction performance of the proposed model: Validation of the prediction performance of the models is made by using 30 test patterns which have not been employed for training. The comparison of actual and predicted values during testing phase for 7, 15 and 30 days ahead prediction using the proposed RRBF model of HDFC Top200(G), ICICI Top100(G) and Birla Sunlife(G) net asset value data set is shown in Fig. 5.8, 5.9 and 5.10 respectively. In order to assess the prediction potentiality of the new model three performance measures defined in (5.15) - (5.17) such as root mean square error (RMSE), mean absolute percentage error (MAPE) and mean square deviation (MSD) are chosen. Although the comparison based on RMSE has been criticised [104, 105, 106], it is often chosen by practitioners for its simplicity and ease of computation [107]. The MAPE criterion is less sensitive than RMSE to large errors. The formulae are given as

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|A_i - F_i|}{A_i}\times 100 \tag{5.15}$$

$$MSD = \frac{1}{n}\sum_{i=1}^{n}(A_i - F_i)^2 \tag{5.16}$$

$$RMSE = \sqrt{MSD} \tag{5.17}$$

where A_i = actual value, F_i = predicted value and n = total number of testing patterns.

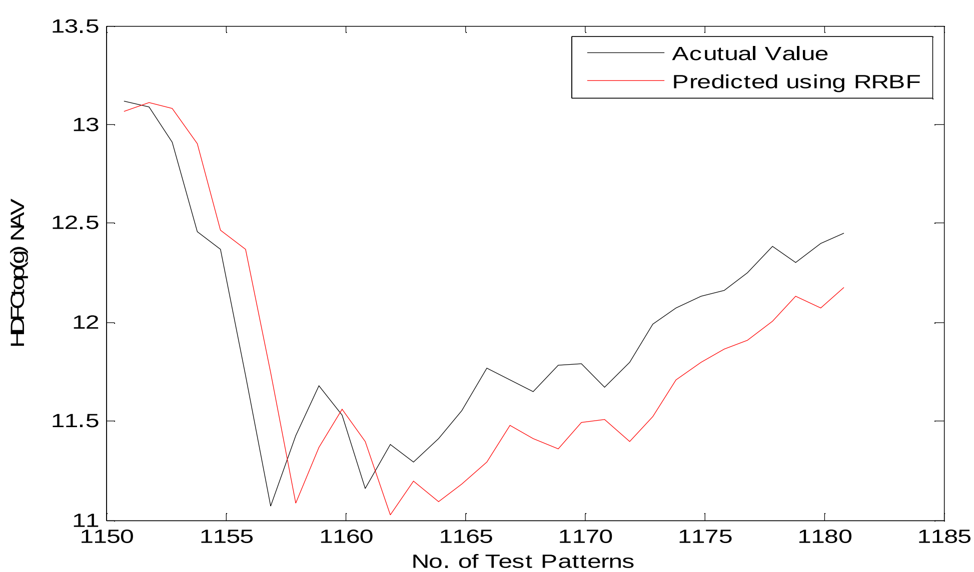

Fig. 5.8 Comparison of actual and predicted value for 7 days ahead prediction of HDFC Top200(G) using RRBF prediction model during testing

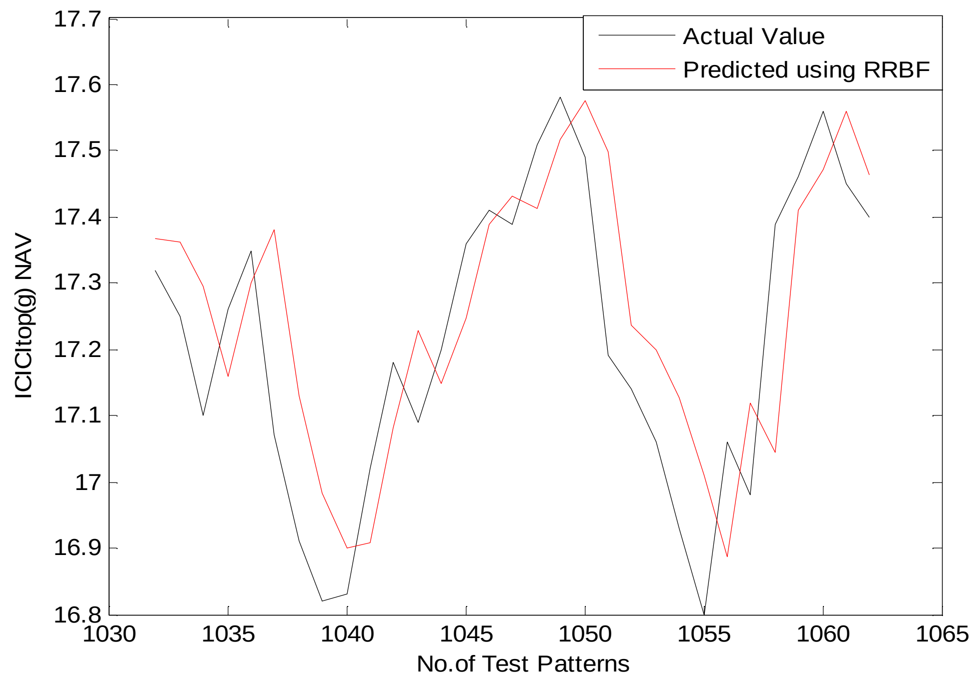

Fig. 5.9 Comparison of actual and predicted value for 15 days ahead prediction of ICICI Top100(G) using RRBF prediction model during testing

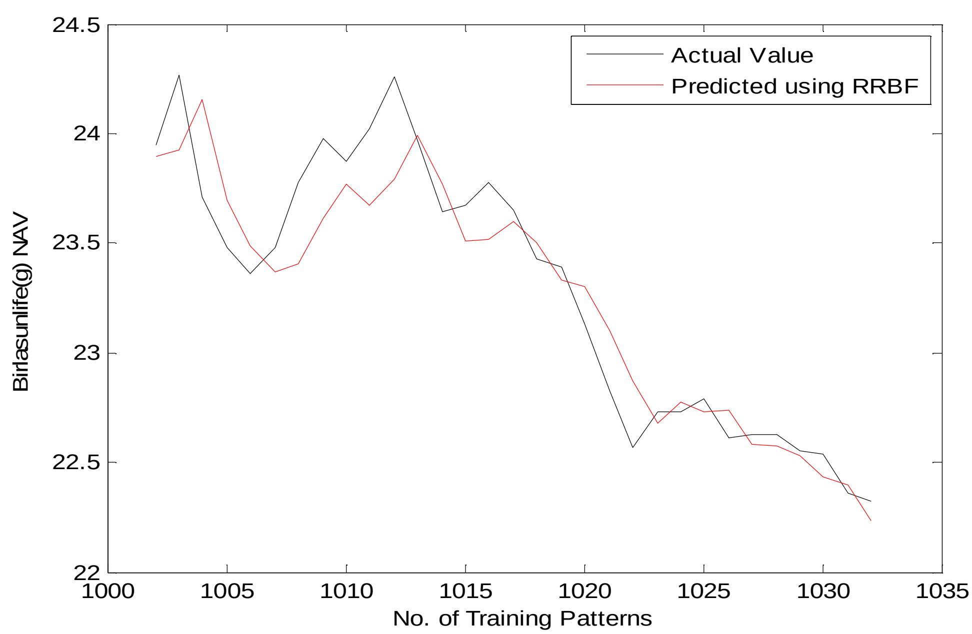

Fig. 5.10 Comparison of actual and predicted value for 30 days ahead prediction of Birla Sunlife(G) using RRBF prediction model during testing

Table 5.2 Comparison of MAPE and RMSE of different forecasting models using Birla Sunlife(G) NAV data set

No. of days ahead	**RRBF**		**RBF**		**RNN**		**FLANN**		**MLANN**	
	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE
1	0.6930	0.2109	0.8619	0.2413	0.6964	0.2122	7.3556	1.7900	0.9730	0.2406
3	1.1778	0.3399	1.6062	0.4369	1.3178	0.3627	8.0396	1.9347	1.3607	0.3689
7	1.8771	0.5203	2.4278	0.6648	1.9418	0.5354	8.5505	2.0451	2.3125	0.5629
15	3.7110	0.9940	4.2472	1.2059	4.0261	1.0444	8.9846	2.2611	4.1712	1.1210
30	3.2798	0.8794	5.0970	1.4771	4.8252	1.3597	6.1477	1.8187	6.1687	1.8337

Table 5.3 Comparison of actual and predicted net asset value for 30 days ahead prediction of Birla Sunlife(G) data using RRBF neural network model

Actual Value	**Predicted Value**
23.6500	23.6009
23.4300	23.5028
23.3900	23.3346
23.1300	23.3042
22.8300	23.1046
22.5700	22.8721
22.7300	22.6761
22.7300	22.7768

Table 5.4 Comparison of MSD of different forecasting models using net asset value of Birla Sunlife(G) data

No. of days ahead	**RRBF**	**RBF**	**RNN**	**FLANN**	**MLANN**
1	0.0445	0.0582	0.0450	3.2040	0.0716
3	0.1249	0.1908	0.1316	3.7429	0.1423
7	0.2607	0.4420	0.2866	4.1826	0.3807
15	0.9880	1.4542	1.0907	5.1125	1.3446
30	0.7734	2.1819	1.8488	3.3077	3.3625

Table 5.5 Comparison of MAPE and RMSE of different forecasting models using net asset value of HDFC Top200(G) data

No. of days ahead	RRBF		RBF		RNN		FLANN		MLANN	
	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE
1	1.9643	0.2984	2.4108	0.3584	2.3734	0.3215	6.3966	1.0529	5.5796	0.7275
3	2.4600	0.3306	3.1727	0.5203	2.9778	0.4993	5.7286	1.0186	5.4772	0.7095
7	3.0940	0.5020	4.2597	0.7507	4.8064	0.7250	5.7911	0.9663	8.2182	1.0392
15	3.0348	0.4713	5.2700	0.6853	5.0889	0,6625	4.8022	0.7668	9.1259	1.3052
30	3.2325	0.5846	8.4492	1.3220	4.0725	0.7036	6.0099	0.8208	5.2518	0.8493

Table 5.6 Comparison of actual and predicted net asset value for 30 days ahead prediction of HDFC Top200(G) data using RRBF neural network model

Actual Value	Predicted Value
13.1200	13.0633
13.0900	13.1098
12.9100	13.0792
12.4600	12.9042
12.3700	12.4682
11.7300	12.3661
11.0700	11.7440
11.4300	11.0882

Table 5.7 Comparison of MSD of different forecasting models using net asset value of HDFC Top200(G) NAV data

No. of days ahead	RRBF	RBF	RNN	FLANN	MLANN
1	0.0891	0.1284	0.1034	1.1085	0.5292
3	0.1093	0.2707	0.2493	1.0375	0.5034
7	0.2520	0.5636	0.5257	0.9280	1.0799
15	0.2221	0.4697	0.4389	0.5879	1.7036
30	0.3417	1.7477	0.4950	0.9060	0.7214

Table 5.8 Comparison of MAPE and RMSE of different forecasting models using ICICI Top100(G) NAV data set

No. of days ahead	RRBF		RBF		RNN		FLANN		MLANN	
	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE
1	0.7803	0.1680	0.7541	0.1527	0.9716	0.2036	5.5031	0.9932	1.1793	0.2486
3	1.0745	0.2357	1.2915	0.2734	1.4107	0.2891	5.2372	0.9999	1.6184	0.3331
7	1.4338	0.3174	1.8952	0.3835	1.9267	0.3715	5.1609	1.0186	2.0878	0.4106
15	2.9828	0.5982	2.9770	0.6365	2.6620	0.7261	6.0044	1.2533	2.7902	0.7058
30	3.9512	0.8971	7.0985	1.5284	5.8362	1.2574	9.8741	1.9929	5.0527	1.1352

Table 5.9 Comparison of actual and predicted net asset value for 30 days ahead prediction of ICICI Top100(G) data using RRBF neural network model

Actual Value	Predicted Value
17.3200	17.3034
17.2500	17.2886
17.1000	17.2087
17.2600	17.0538
17.3500	17.1770
17.0700	17.2489
16.9100	16.9880
16.8200	16.8293

Table 5.10 Comparison of MSD of different forecasting models using ICICI Top100(G) NAVdata

No. of days ahead	RRBF	RBF	RNN	FLANN	MLANN
1	0.0282	0.0233	0.0414	0.9864	0.0618
3	0.0555	0.0747	0.0836	0.9998	0.1110
7	0.1007	0.1471	0.1380	1.0338	0.1686
15	0.3579	0.4015	0.5273	1.5707	0.4981
30	0.8048	2.3359	1.5811	3.9717	1.2887

Comparison of MAPE and RMSE metrics for different forecasting models for 1, 3, 7, 15 and 30 days ahead prediction are shown in Tables 5.2, 5.5 and 5.8 for Birla Sunlife(G), HDFC Top200(G), ICICI Top100(G) net asset values respectively. The actual and predicted net asset values for 30 days ahead prediction for Birla Sunlife(G), HDFC Top200(G), ICIC Top100(G) are also depicted in Tables 5.3, 5.6 and 5.9 respectively. Tables 5.4, 5.7 and 5.10 represent the MSD value between the actual and predicted value for different days ahead obtained from different forecasting models. From these tables it is evident that the proposed RRBF model provides the least MAPE value for all three net asset value data sets. The mean square deviation (MSD) value between the predicted and actual value is also the least in case of the proposed RRBF model in comparison to all other neural network models.

5.5 Summary

The literature survey on net asset value forecasting reveals that few works has been reported on long range forecasting of net asset values. On the other hand there is a need of such longer interval forecasting of net asset data to devise suitable capital management. The existing soft computing based forecasting models provide comparatively poor prediction performance. Keeping this in view a new soft computing model is developed and utilized for prediction of net asset value up to 30 days ahead. The simulation results of real life data show excellent prediction performance compared to that of four other soft computing models.

5.6 Conclusion

This chapter proposes a recurrent radial basis function (RRBF) neural network model for efficient long term prediction of net asset values. Prediction of three different net asset value data sets for 1, 3, 7, 15 and 30 days ahead are carried out and compared with four other existing forecasting models. From the simulation study it is demonstrated that the RRBF model exhibits better performance from among other four forecasting models for the NAV data used for simulation study.

****