Net Asset Value Prediction using FLANN Model

C. M. Anish, Babita Majhi

1Dept. of Computer Science and IT, Guru Ghasidas Vishwavidyalaya, Central University, Bilaspur, Chattisgarh, India
cmanish1124@gmail.com

2Dept. of Computer Science and IT, Guru Ghasidas Vishwavidyalaya, Central University, Bilaspur, Chattisgarh, India
babita.majhi@gmail.com

Abstract: Financial forecasting which includes the financial data such as interest rate, exchange rate, stock market, mutual fund asset value and bankruptcy is the hottest topic for the researcher due to its importance in financial and managerial decision making. Survey of existing literature disclose that there is a demand for efficient forecasting capability model involving less computational load and fast forecasting capability. This paper fulfills this objective by developing functional link artificial neural network (FLANN) based forecasting model involving nonlinear inputs. Simulation study exhibits, the predicting model is effective and applicable in mutual fund NAV forecasting.

Keywords: Net asset Value (NAV), Mutual Funds, Functional link artificial neural network (FLANN) and prediction.

1. Introduction

Mutual Fund is the popular investment tool for the investors. However, the financial market is so complex with dynamic and chaotic data series, thus it is usually of much risk. Generally the mutual fund is an investment management with benefit and risks. Investors enjoy the benefit but also perceived risk present in the equity market. It is difficult for the investors who have lacks investment information to manage high return with low risk. To get high return from the market many researchers had applied the machine learning techniques and soft computing methods such as support vector regression (SVR) [1][2], support vector machine (SVM) [1][6] artificial neural network (ANN) [3][4], genetic algorithm (GA) [3][5] and so on. In recent years researcher applied neural network based techniques to predict NAV of investment fund such as classical neural network [11], back propagation neural network (BPNN) [12]. Also, auto regressive integrated moving average (ARIMA) based prediction is applied for Indian mutual funds [10].

The literature review revels that there is a need to develop a low complexity and fast forecasting capability model to forecast the NAV data as multilayer artificial neural network (MLANN) and GA are very time consuming.

This paper presents a FLANN based net asset value predicting technique for digging out the patterns hidden in the mutual funds. Through analyzing and training the asset data which has been disposed the assets of Indian Mutual fund prediction.

The rest of the paper is organized into following sections. In section 2, we will develop a FLANN based model for prediction and some background knowledge. Different performance measures used for the prediction are shown in Section 3. In section 4 simulation based study and the results of the experiment have been carried out. Finally the conclusion is carried out in section 5.
is computed as
\[ y(x) = \tilde{X}(x), \tilde{w}_b(x) + \tilde{w}_b(x) \tag{1} \]
where \( \tilde{w}_b(x) \) represents the weighted bias input (may be positive or negative), \( \tilde{W}(x) \) represents the weight vector and \( \tilde{X}(x) \) represents \( T \) elements expanded each input pattern. This output is then passed through a nonlinear function (a sigmoid function) to produce the estimated output
\[ \hat{d}(x) = f(\tilde{y}(x)) = \frac{1}{1+e^{-\tilde{y}(x)}} \tag{2} \]
The error signal \( \text{err}(n) \) is the difference between the desired response and the model output and is given by
\[ \text{err}(x) = \hat{d}(x) - \tilde{d}(x) \tag{3} \]
To compute the correction weight vector \( \Delta \tilde{w}(x) \), error \( \text{err}(x) \) and the input vector \( \tilde{X}(x) \) are employed to the weight update algorithm. Let the reflected error is given by
\[ \delta(x) = \text{err}(x), \hat{d}(x) = \text{err}(x), f'(y(x)) \tag{4} \]
where \( f'(y(x)) \) represents the derivative of the activation function given in (2). Then the correction weight vector is given by
\[ \Delta \tilde{w}(x) = \eta \tilde{X}(x), \delta(x) \tag{5} \]

Figure 1: Block diagram of FLANN financial forecasting based model

Figure 2: Detailed structure of FLANN based forecasting model

In the same way the change in bias weight can be obtained and is given by \( \tilde{w}_b(x) = \eta \hat{d}(x) \). A new known feature pattern is applied at the input and its corresponding \( \Delta \tilde{w} \) is computed using (1) through (5). This procedure is repeated until all the training patterns are applied. Application of all the \( N \) patterns constitutes one experiment and at the end of each experiment \( N \) sets of \( \Delta \tilde{w}(x) \) are obtained. Then the average change of weight of the \( k \)th weight in the \( i \)th experiment is computed as
\[ \Delta \tilde{w}_k(i) = \frac{1}{N} \sum_{n=1}^{N} \Delta \tilde{w}_k(x) \tag{6} \]
The weights of the FLANN model is then updated according to the relation
\[ \tilde{w}(i + 1) = \tilde{w}(i) + \Delta \tilde{w}(i) \tag{7} \]
Similarly the bias weight for the \( i \)th iteration is given by
\[ \tilde{w}_b(i + 1) = \tilde{w}_b(i) + \Delta \tilde{w}_b(i) \tag{8} \]
Experiments are then continued until the mean square error (MSE) in the \( i \)th experiment defined as
\[ \text{MSE}(i) = \frac{1}{N} \sum_{n=1}^{N} \text{err}^2(x) \tag{9} \]
attains a minimum value. When the training process is complete, the connecting weights of the model are frozen to their final values. The model so developed is then used for testing with known Net asset values and for future prediction.

3. Performance Measure Used

The forecasting problem conventionally considered as a single objective optimization problem in which mean square error (MSE) of the adaptive model is taken as the cost function. The performance evaluation is assessed by comparing the measuring forecast error criteria via the mean absolute percentage error (MAPE) and root of the mean squared error (RMSE).

(i) Mean absolute percentage error (MAPE)
It is calculated as
\[ \text{MAPE} = \frac{\sum_{i=1}^{N} \left| \frac{A_i - P_i}{A_i} \right|}{N} \times 100 \]
where \( A_i \) is the actual and \( P_i \) is the predicted value for \( i \)th pattern. \( N \) is the total number of testing patterns.

(ii) Root mean square error (RMSE)
It is calculated as
\[ \text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (A_i - P_i)^2}{N}} \]

4. Simulation Based Study and Results

4.1 Data Collection

For the purpose of simulating the experiment for prediction performance of the proposed model, we choose data from five top rated Indian Mutual Funds as rated by value research, India. The data collection from various mutual funds is shown in Table 1.

4.2 Feature Extraction

Out of the total input vector a window size of 12 data is used...
at a time for the feature extraction. The 12th number data mean of 12 data and variance of 12 data is calculated to form one pattern. Then the window size is slide by one position and in the same way the next data pattern is calculated. In this way we generate 1065 data patterns for Birla sunlife equity fund (growth). Similar method is used to calculate the data pattern for other mutual funds. Out of the total data patterns 80% is used for training of the model and rest 20% is used for testing.

<table>
<thead>
<tr>
<th>Mutual fund</th>
<th>Data year</th>
<th>Total data patterns</th>
</tr>
</thead>
<tbody>
<tr>
<td>Birla Sunlife Equity Fund-Growth</td>
<td>27/08/1998 to 31/12/2002</td>
<td>1065</td>
</tr>
<tr>
<td>Franklin India Bluechip Fund</td>
<td>01/01/1997 to 31/12/2001</td>
<td>1188</td>
</tr>
<tr>
<td>HDFC Top200- Growth</td>
<td>01/01/1997 to 31/12/2001</td>
<td>1225</td>
</tr>
<tr>
<td>ICICI pro. Top100-Growth</td>
<td>19/06/1998 to 31/12/2002</td>
<td>1097</td>
</tr>
<tr>
<td>UTI Equity Fund-Growth</td>
<td>01/01/1998 to 31/12/2002</td>
<td>1123</td>
</tr>
</tbody>
</table>

4.3 Training of FLANN model

In the adaptive model each input feature of each pattern is expanded to three terms \( x, \sin \pi x \) and \( \cos \pi x \), where \( x \) is the input feature. Out of which two are trigonometric expansion and one is the input itself. For 3 inputs of a pattern we get 9 expanded terms. These 9 inputs multiplied with 9 weights and sum together to produce an output. A bias weight is added to the output and the output passes through tanh activation function to produce the final output. The output of the model is then compared with the corresponding desired value and an error value is obtained for each input pattern. Then MSE is calculated according to (10). After finding the MSE, the value of the MSE is stored and plotted against the corresponding experiment number to show the convergence characteristics of the model during training period. After each input pattern the change in weights is noted and the weight vectors are updated, once using (7) and (9) after each experiment. When the training process is complete, the connecting weights of the model are frozen to their final values. The weights are updated using the RLS algorithm. The initialization constant, \( E \) for the RLS is set at 0.01. The number of experiment is taken as 50000.

4.4 Testing of FLANN model

After achieving the minimum level of the MSE the training of the proposed network is terminated and the final weights of the model are frozen. The remaining 20 percent of the data patterns are passed to the proposed model and the output is calculated in the same way as done during training time. The percentage of the error is calculated for each data pattern. The performance evaluation is assessed by comparing the measuring forecast error criteria via the mean absolute percentage error (MAPE) and root of the mean squared error (RMSE), which are discussed in section 3.

4.5 Results and Discussion

The aim of the experiment is to obtain the performance of FLANN model for NAVs prediction. To assess the prediction performance of FLANN model, it is compared with the results obtained by the MLP based prediction model. The MLP model that is use for the simulation is 3:4:1 structure. Where 3:4:1 is the number of neuron in input layer, hidden layer and output layer respectively. The comparison of computational complexity by FLANN and MLP are given in Table 2[9]. From the table it is clear that the number of computation in case of FLANN model is less in comparison to MLP. Thus FLANN model reduces the computational load for the prediction.

The convergence characteristics of FLANN based forecasting model and MLP model are shown in the Figs 3(a)-(e). These plots clearly indicate that error is minimizing as the number of experiments increase and at a particular point the error is constant for further experiments. It shows successful training is done by the FLANN model for NAVs. It also exhibits that the error is low in case of FLANN in comparison to MLP.

<table>
<thead>
<tr>
<th>Models</th>
<th>No. of weights</th>
<th>No. of ( \sin/\cos )</th>
<th>No. of ( \tanh() )</th>
<th>No. of Adds.</th>
<th>No. of Muls.</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLP</td>
<td>21</td>
<td>0</td>
<td>5</td>
<td>19</td>
<td>16</td>
</tr>
<tr>
<td>FLANN</td>
<td>10</td>
<td>3+3</td>
<td>1</td>
<td>9</td>
<td>10</td>
</tr>
</tbody>
</table>

The convergence characteristic of Franklin India Bluechip Fund –Growth

The convergence characteristic of BirlaSunlife Equity Fund-Growth

The convergence characteristic of Franklin India Bluechip Fund –Growth
values are given in Table 3. The results show that the MAPE value is below 1.3% for all NAVs in the proposed model. Table 3 also shows that FLANN model is a better prediction model than MLP.

The values of various performance measures for five NAV

Figure 3(c): Convergence characteristic of for HDFC Top200- Growth

Figure 3(d): Convergence characteristic of for ICICI Pro.Top100 -Growth

Figure 3(e): Convergence characteristic of for UTI Equity Fund- Growth

The performance of the FLANN model for NAV prediction of various Indian mutual funds at the time of testing is shown in the Figs 4(a)-(e). From these figures, it is clear that the actual and predicted value is almost overlap, indicates the accuracy of the model. It is clear from the figures that the model successfully predicts the actual net asset value with an accuracy of more than 98.5% for five mutual funds.

Figure 4(a): Performance of FLANN model during Testing for BirlaSunlife Equity Fund-Growth

Figure 4(b): Performance of FLANN model during Testing for Franklin India Bluechip Fund –Growth

Figure 4(c): Performance of FLANN model during Testing for HDFC Top200- Growth
one layer as compare to multilayer neural network (MLP) simulation, same set of data is passing to the MLP and the works well for prediction of various mutual funds. During where one or more layer is present. The same model also formulated as a hybrid or multiobjective problem and will be solved with various hybrid models or multiobjective evolutionary algorithms.

5. Conclusion

This paper develops an improved nonlinear FLANN based prediction model for net asset value (NAV) of Indian mutual funds which incorporates fewer computational load and fast forecasting capability. The FLANN architecture is computationally efficient as its backbone consists of only one layer as compare to multilayer neural network (MLP) where one or more layer is present. The same model also works well for prediction of various mutual funds. During simulation, same set of data is passing to the MLP and the FLANN model for the comparison. FLANN shows better results in terms of complexity, convergence, MAPE and RMSE. All these unique features make the proposed model a promising alternative scheme for net asset value prediction for the future work the NAVs prediction task will be formulated as a hybrid or multiobjective problem and will be

References


Author Profile

C.M. Anish is a Ph.D student in the Guru Ghasidas Vishwavidyalaya, central university, Bilaspur. He has received his Master degree in Master of computer application from Chattisgarh Swami Vivekanand Technical University, bhillai in 2009. His research interest s are Soft-Computing, Evolutionary Computing, Computational Finance and Data Mining.

Babita Majhi did her Ph.D. degree in 2009 from National Institute of Technology Rourkela and Post Doctoral research work at the University of Sheffield, UK (December 2011–2012), specializing in evolutionary algorithms and its applications. She is presently working as an Assistant Professor in the department of Computer Science and Information Technology, G.G. Vishwavidyalaya, Central University, Bilaspur, India. Prior to this she was working as an Assistant Professor in the CSIT department of ITER, Siksha ‘O’ Anusandhan University, Bhubaneshwar, Odisha. She has published number of research papers in various referred international journals and conferences papers in a number of International journals and conferences. She is a Member of IEEE. She received the prestigious BOYSCAST Fellowship of DST, Govt. of India for pursuing postdoctoral work for the year 2010-2011 and the best Ph.D. thesis award from IEEE NaBIC in 2009. Her research interests are Adaptive Signal Processing, Soft -Computing, Evolutionary Computing, Computational Finance, Distributed Signal Processing and Data Mining.