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Net Asset Value Prediction using FLANN Model

C. M. Anish[1], Babita Majhi[2]

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

[2]Dept. 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.

2. Development of Functional Link Artificial Neural Network (FLANN) model

The FLANN is a single layer, single neuron architecture, first proposed by Pao [8], with nonlinear input and a single neuron at the output. This network is structurally simple and involves fewer computations compared to the well known multilayer perception (MLP) [7]. In a FLANN, each input in a network undergoes functional expansion in a nonlinear manner. The functional link acts on an input generate a set of linearly independent function causes an increase in the input vector dimensionally. This enables FLANN to solve complex prediction problem by generating non-linear decision output. In this paper for net asset value prediction, Trigonometric expansion based financial model is developed.

A simplified FLANN model is shown in Fig. 1. In FLANN, firstly the nonlinear input element is functionally expanded to create more number of inputs. The main objective is to reduce the number of layers and the computational load by introducing nonlinearity to the input elements. Then compute the output in adaptive model with response to nonlinear input elements and comparing the estimated financial output of the model with the corresponding desired or target net asset value to generate an error signal. At last using a novel weight updating rule the weights are updated. The detailed structure of the generalized model is depicted in Fig. 2.

In the adaptive forecasting model the relevant features from the data corresponding to each day are extracted and tabulated. Let the set of input features pertaining to a given day is called an input pattern vector. Then each input pattern is functionally expanded in a nonlinear manner using trigonometric expansion such as sine and cosine expansion. During training process, each expanded input pattern $\underline{X}($ is sequentially applied to the model and the desired net asset value is supplied at the output. The model produces an output $\hat{d}()$ for a given input, which acts as an estimate of the desired value. The output of the linear part of the model is computed as

$$y(x) = X^T(x).\widehat{W}(x) + \widehat{w_b}(x) \quad (1)$$

where $\widehat{w_b}(x)$ represents the weighted bias input (may be positive or negative), $\widehat{W}(x)$ represents the weight vector and $X^T(x)$ represents T elements expanded each input pattern. This output is then passed through a nonlinear function (a sigmoid function) to produce the estimated output

$$\hat{d}(x) = f\{(y, x)\} = \frac{1-e^{-y(x)}}{1+e^{-y(x)}} \quad (2)$$

The error signal $err(n)$) is the difference between the desired response and the model output and is given by

$$err(x) = d(x) - \hat{d}(x) \quad (3)$$

To compute the correction weight vector $\underline{\Delta\widehat{w}}(x)$, error $err(x)$ and the input vector $\underline{X}(x)$ are employed to the weight update algorithm. Let the reflected error is given by

$$\delta(x) = err(x).\hat{d}'(x) = err(x).f'\{y(x)\} \quad (4)$$

where $f'\{y(x)\}$ represents the derivative of the activation function given in (2). Then the correction weight vector is given by

$$\underline{\Delta\widehat{w}}(x) = \eta X(x).\delta(x). \quad (5)$$

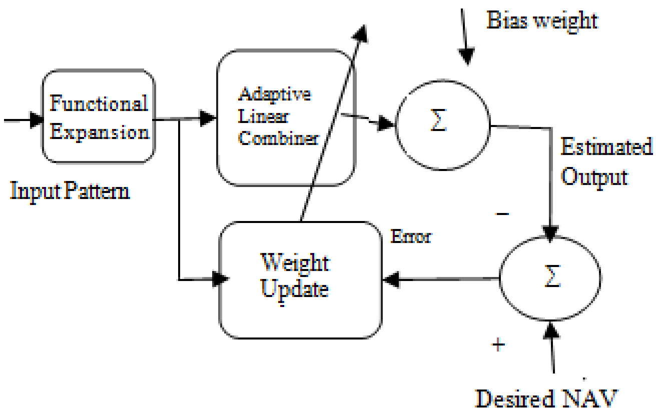

Figure 1:.Block diagram of FLANN financial forecasting based model

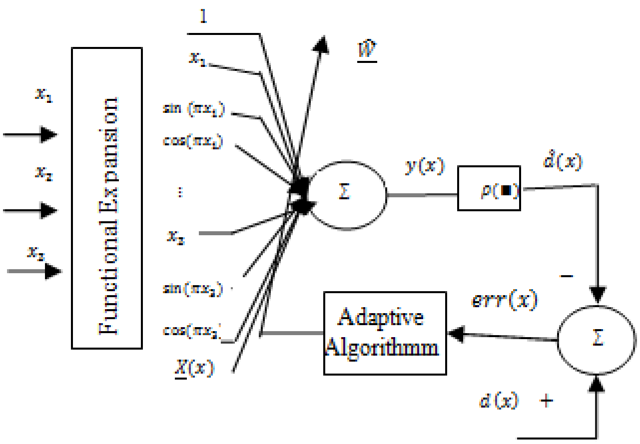

Figure 2: Detailed structure of FLANN based forecasting model

In the same way the change in bias weight can be obtained and is given by $\widehat{w_b}(x) = \eta\delta(x)$. A new known feature pattern is applied at the input and its corresponding $\underline{\Delta\widehat{W}}$ 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 $\underline{\Delta\widehat{w}}(x)$ are obtained. Then the average change of weight of the *k*th weight in the *i*th experiment is computed as

$$\Delta\widehat{w}a_k(i) = \frac{1}{N}\sum_{n=1}^{N}\Delta\widehat{w}_k(x) \quad (6)$$

The weights of the FLANN model is then updated according to the relation

$$\underline{\widehat{w}}(i+1) = \underline{\widehat{w}}(i) + \underline{\Delta wa}(i) \quad (7)$$

Similarly the bias weight for the ith iteration is given by

$$\Delta\widehat{w}a_b = \frac{1}{N}\sum_{n=1}^{N}\Delta\widehat{w}_b(x) \quad (8)$$

The bias weight is then updated according to equation defined as

$$\widehat{w}_b(i+1) = \widehat{w}_b(i) + \Delta\widehat{w}a_b \quad (9)$$

Experiments are then continued until the mean square error (MSE) in the ith experiment defined as

$$MSE(i) = \frac{1}{N}\sum_{n=1}^{N}err^2(x) \quad (10)$$

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

$$MAPE = \frac{\sum_{i=1}^{N}\left|\frac{A_i - P_i}{A_i}\right|}{N} \times 100$$

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.

(i) Root mean square error (RMSE)
It is calculated as

$$RMSE = \sqrt{\sum_{i=1}^{n}(A_i - P_i)^2/N}$$

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 1: Details of Mutual Fund data collection

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

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* $\cos \pi$, where 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, Ɛ 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 2: The comparative Results of performance

Models	*No. of weights*	*No. of sin/cos*	*No. of tanh()*	*No. of Adds.*	*No. of Muls.*
MLP	21	0	5	19	16
FLANN	10	3+3	1	9	10

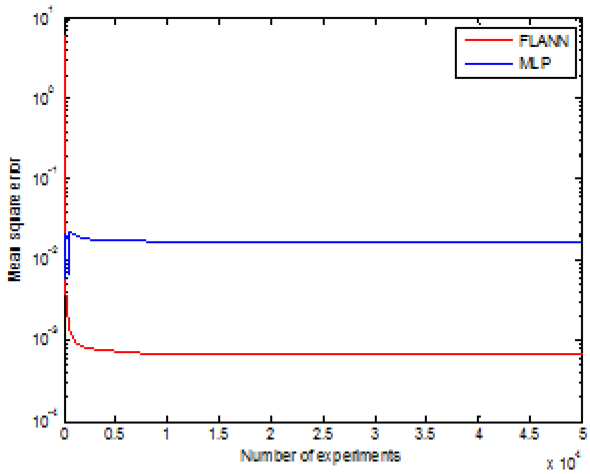

Figure 3(a): Convergence characteristic of BirlaSunlife Equity Fund-Growth

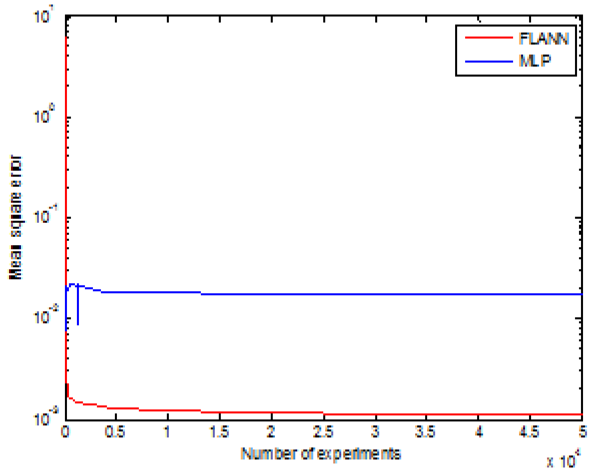

Figure 3(b): Convergence characteristic of Franklin India Bluechip Fund –Growth

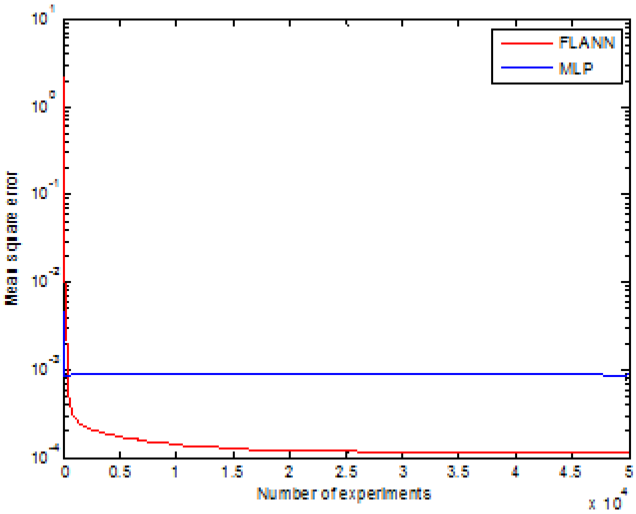

Figure 3(c): Convergence characteristic of for HDFC Top200- Growth

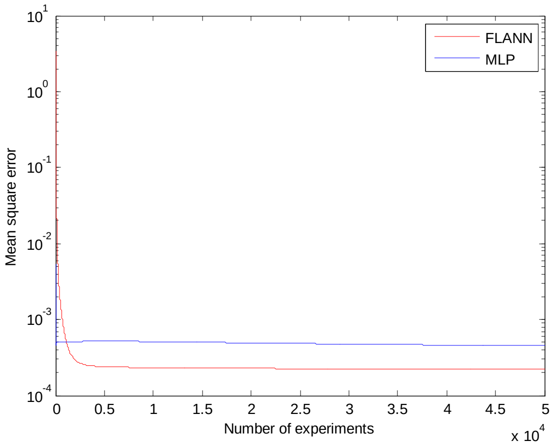

Figure 3(d): Convergence characteristic of for ICICI Pro.Top100 -Growth

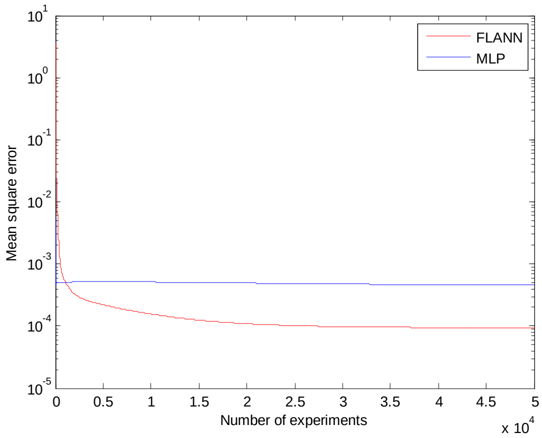

Figure 3(e): Convergence characteristic of for UTI Equity Fund- Growth

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.

The values of various performance measures for five NAV 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.

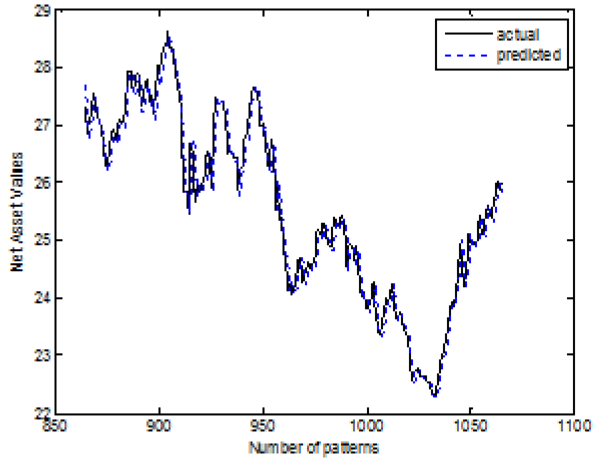

Figure 4(a): Performance of FLANN model during Testing for BirlaSunlife Equity Fund-Growth

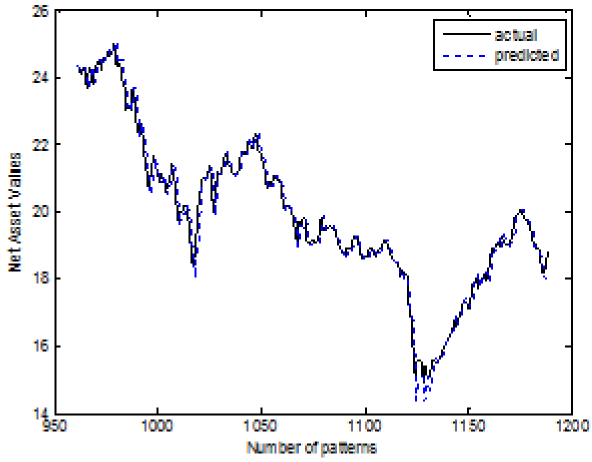

Figure 4(b): Performance of FLANN model during Testing for of Franklin India Bluechip Fund –Growth

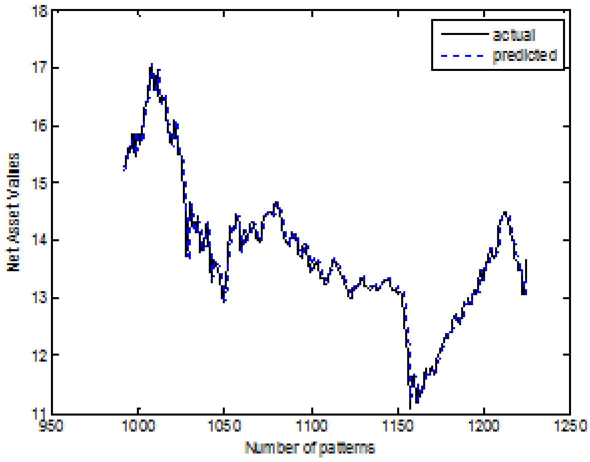

Figure 4(c): Performance of FLANN model during Testing for HDFC Top200- Growth

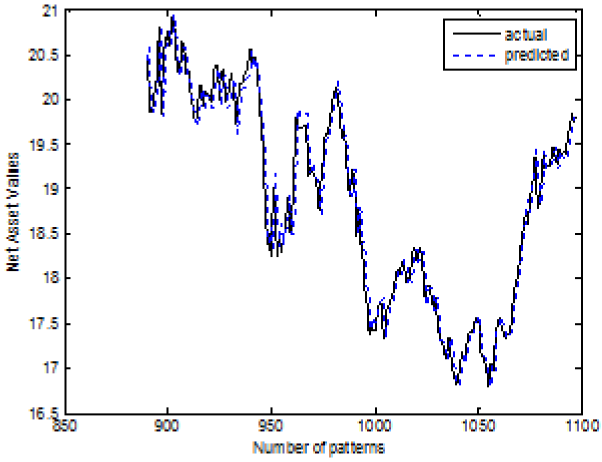

Figure 4(d): Performance of FLANN model during Testing for ICICI Pro.Top100 –Growth

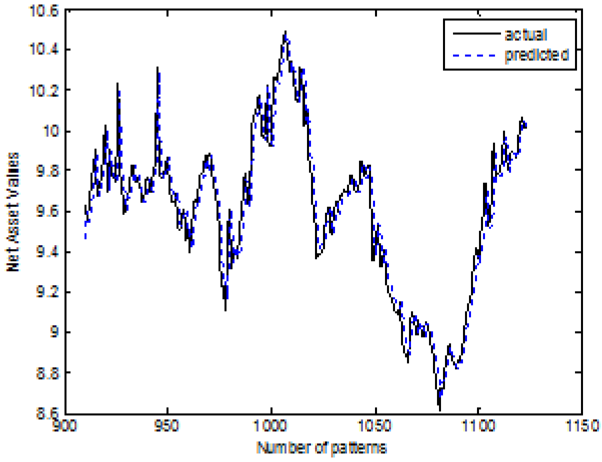

Figure 4(e): Performance of FLANN model during Testing for UTI Equity Fund- Growth

Table 3: The comparative results of performance measure value for five Indian mutual funds.

	MLP Model		*FLANN Model*	
	RMSE	*MAPE*	*RMSE*	*MAPE*
Birla Sunlife Equity Fund(G)	0.065	2.442	0.3123	0.9352
Franklin India Bluechip Fund(G)	0.032	3.852	0.3434	1.2042
HDFC Top 200(G)	0.082	4.851	0.2111	1.1141
ICICI Pro.Top 100 (G)	0.038	2.544	0.2453	0.9927
UTI Equity Fund(G)	0.034	2.896	0.1285	0.9538

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 solved with various hybrid models or multiobjective evolutionary algorithms.

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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, bhilai 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, Bhubaneswar, 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.