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Forecasting of net asset value using modified Whale optimization algorithm based ensemble model

SarbeswaraHota, PranatiSatapathy, Debahuti Mishra

Abstract: ***Net Asset value (NAV) prediction is considered as a financial time series forecasting problem. Different linear and nonlinear time series forecasting models have been used in NAV prediction by various researchers. In this work, an ensemble model is proposed combining AMA as linear model and ANN and FLANN models as nonlinear models for forecasting of NAV data of TATA Dividend Yield Fund-Direct Growth and SBI Magnum Equity mutual funds. The individual models are trained with conventional LMS algorithm. It is a weighted linear ensemble model where the weights are optimized using a modified Whale Optimization Algorithm. The empiricalforecasting performance of the modified Whale Optimization Algorithm based ensemble model along with GA and PSO based ensemble models and the individual models are analyzed. The results demonstrate that the proposed ensemble model outperforms the other models.***

Index Terms:Functional Link Artificial Neural Network, Least Mean Square, Net Asset Value, Prediction performance,Whale Optimization Algorithm

I. INTRODUNCTION

A mutual fund acts like a bridge between the financial securities market and the investors [1]. It mobilizes the savings from the investors and invests in the securities market to earn returns. The retail investors have considered mutual funds as the means of investment and getting high return. Since the financial market is volatile and highly unpredicted in nature, it becomes essential for the common investors and brokers to analyze the performance of the mutual funds and to find some prediction mechanism. Net Asset value (NAV) plays a major role in analyzing the performance of a mutual fund [1]. NAV is calculated on a daily basis. The NAV prediction problem can be considered as one of the financial time series forecasting problem as the NAV data is nonlinear in nature. For the financial time series forecasting problem, researchers have used different soft computing techniques [2]. Artificial Neural Network (ANN) has been widely used model in financial time series data prediction due to its data driven and self-adaptive nature. Different researchers have used the traditional Artificial Neural Network (ANN) [3][4], Back Propagation Neural Network (BPNN) [5], Functional Link Artificial Neural Network (FLANN)[6] for the NAV Prediction problem. Ensemble methods have become popular in financial data forecasting domain [7]. From the literatures, it was found that predictions made by a combination of models are more accurate than the individual models. A common ensemble architecture is shown in figure 1 as found from the literature [8].

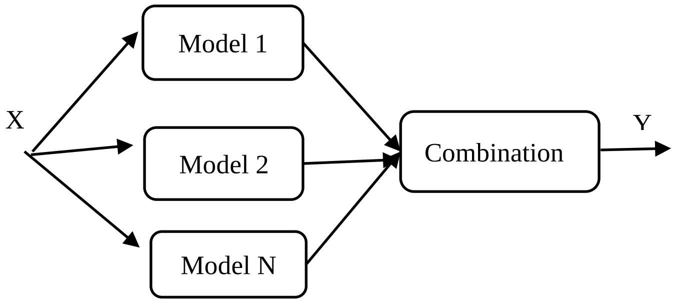

Fig.1. General Ensemble Architecture

The authors in [9] developed a weighted linearly combined ensemble method consisting of AARMA model, AMA model and FRBF model for the NAV prediction. The weights are optimized using PSO algorithm. It is found that the predicted results outperform the individual models. In [10], the AMA, AARMA and FLANN models have been combined using an adaptive model to forecast the NAV data. The results produced by the ensemble method was superior to the individual models.Different linear and nonlinear models can be combined together to produce more accurate predictions in financial domain [11, 12, 13].

From the literature, it is found that for the weighted ensemble method, different nature inspired algorithms can be used to optimize the weights associated with the outputs of individual models [9]. S. Mirjalili and A. Lewis proposed a novel bio inspired algorithm based on the hunting behavior of humpback whales [14]. It is called Whale Optimization Algorithm (WOA) and tested with different mathematical functions. The literature suggest that numerous works have been carried out based on WOA in different domains [15, 16]. Y. Sun *et al.*developed a modified WOA for large-scale global optimization problems to get out of local optima. In [17], the authors used the levy-flight strategy and a quadratic interpolation method to jump out of local optima. Some researchers have also proposedsome modifications and improvements to the WOA[18, 19, 20].

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***Correspondence Author(s)**
SarbeswaraHota, Department of Computer Science & Engineering, Siksha O AnusandhanDeemed to be University, Bhubaneswar, India.
PranatiSatapathy, Department of Integrated MCA, Utkal University, Bhubaneswar, India.
Debahuti Mishra, Department of Computer Science & Engineering, Siksha O AnusandhanDeemed to be University, Bhubaneswar, India.

The basic goal of this work is to design different day ahead prediction models for the NAV prediction using modified WOA based ensemble model and compare its performance with the individual models as well as GA and PSO based ensemble model. The paper layout is as follows. The models are described in section II, III and IV. The datasets description and the experimental setup along with the experimental comparisons are discussed in section V.The conclusion of this work are described in section VI.

II. METHODOLOGIES

A. Adaptive Moving Average (AMA) Model

In AMA model, the input patterns are combined with weights to produce the desired output. The output of this model is computed as

$$y(n) = \sum_{i=1}^{n} x[n,i] \times w_i(n) \quad (1)$$

Here $x[n,i]$: nth input pattern

$w_i(n)$: Weights associated with the nth input sample.

The error is calculated as

$$err(n) = x(n) - y(n) \quad (2)$$

In this equation, $x(n)$ and $y(n)$ represent the actual NAV and the calculated NAV respectively.

After one iteration, the Mean Square Error (MSE) is evaluated. It is defined as: $MSE(n) = \frac{1}{N}\sum_{n=1}^{N} err^2\,(n)$ (3)

Where the total number of generated input samples is N.The Least Mean Square (LMS) algorithm is used to update the weights by minimizing the MSE values. When the MSE decreases to a lower possible value or remains constant, the weights are taken for the testing purpose.

B. Functional Link Artificial Neural Network (FLANN) Model

FLANN model is a single layer flat neural network model consisting of an input layer and one output node without any hidden layer. This model is suitable for nonlinear financial time series data prediction task as the functional expansion property provides nonlinearity. In this work, the input pattern is expanded through triginometric expansion to provide nonlinear elements. Various researchers have used trigonometric expnasion in FLANN model as expansion function scheme . The output of a node is calculated using the weighted linear combination of the expanded inputs and the activation function. The weighted sum is calculated as

$$p = f\,(b + \mathrm{W}.X^T) \quad (4)$$

Where p is the predicted output, b is the bias, W is the weight vector, X is the expanded input vector and f is the activation function used in the FLANN model. The error err is calculated as the difference between actual and predicted output. Using this error value, the weights are updated using LMS algorithm.

III. THE ENSEMBLE PREDICTION MODEL

In this work, the ensemble prediction model consists of one linear model i.e. AMA model and two nonlinear models i.e. ANN and FLANN model. From the literatures, it is found that linear ensemble is the most used method for most of the financial prediction tasks. So the linear ensemble of AMA, ANN and FLANN models are mathematically expressed as

$$y = w_1 y_1 + w_2 y_2 + w_3 y_3 = \sum_{i=1}^{3} w_i y_i \quad (5)$$

Here y is the final predicted output. Each $y_i(i = 1,2..3)$ is the predicted output and $w_i(i = 1,2 \ldots 3)$ is the weight associated with AMA, ANN and FLANN model respectively. It is the weighted sum of the individual prediction models. The ensemble weights associated with individual models are optimized by different bio inspired algorithms such as GA, PSO, WOA and a modified WOA. The constraints used in this optimization problem are:

$$w_i(i = 1,2 \ldots 3) > 0 \; and \; w_1 + w_2 + w_3 = 1$$

This proposed ensemble model is shown in fig.2.

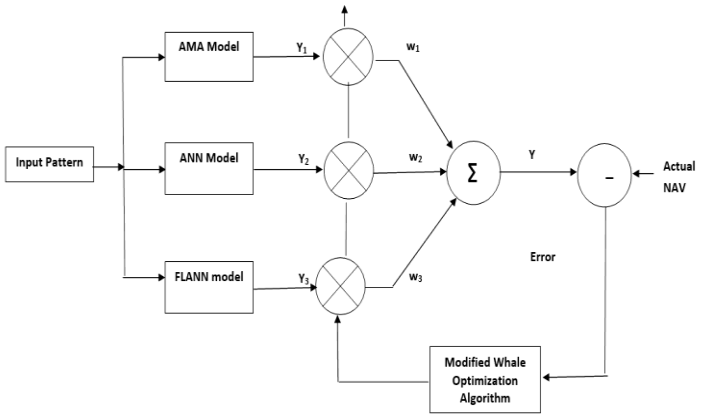

Fig. 2. Proposed ensemble model

IV. MODIFIED WHALE OPTIMIZATION ALGORITHM (MODIFIED WOA)

WOA is a very popular swarm based bio inspired algorithm developed by Mirjalili and Lewis [14]. This algorithm is based on the hunting mechanism of humpback whales. These whales search the krill and small fish herds and attack using bubble-net feeding approach. The hunting process consists of encircling prey, spiral bubble net move and search for prey. The whales search the prey and attack using encircling them or creating bubble nets.

The bubble-net behavior is simulated as a spiral movement. The position of the whale is updated in this process as

$$X_w(t+1) = D'.e^{bl}.\cos(2\pi l) + X_p(t) \quad (6)$$

Here $D' = |X_w(t) - X_p(t)|$ is the distance between a whale $X_w(t)$ and a prey $X_p(t)$, t refers to the current iteration number, l is the random number taken in the range [-1, 1], b is a constant that determines the shape of the logarithmic spiral.

In the encircling behavior, the position of the whales are updated as

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$$X_w(t+1) = X_p(t) - A.D \quad (7)$$

Here $D = |C.X_p(t) - X_w(t)|$ is the distance between the prey and the whale. A , C are the coefficient vectors formulated as

$$A = 2ar - a \quad (8)$$

$$C = 2r \quad (9)$$

Here a is linearly decreased from 2 to 0 with increasing iterations. $r$is a random number in the range of 0 and 1.The whales swim around the prey by shrinking encircling mechanism and performing spiral move simultaneously. To simulate the behavior, a probability of 50% is assumed to decide between the shrinking encircling mechanism and the spiral move to update the whale position. It can be modeled as

$$X_w(t+1) = \begin{cases} X_p(t) - A.D & if\ p < 0.5 \\ D'.e^{bl}.\cos(2\pi l) + X_p(t) & if\ p \geq 0.5 \end{cases} \quad (10)$$

Where p is a random number between 0 and 1.

The search for prey behavior can be simulated on the basis of A value. If the value of A is greater than 1, then the whale search randomly according to the position of each other. This can be expressed as

$$X_w(t+1) = X_{rand} - A.D \quad (11)$$

$$D = |C.X_{rand} - X_w(t)| \quad (12)$$

Here X_{rand} is a random whale chosen from the current whale population.

So the algorithm begins with a random whale positions that represent the initial random solutions. At each iteration, the updating of the whale position is performed depending on either a randomly chosen whale or the best whale position obtained so far. The random whale is chosen when A> 1 and the best whale position is chosen when A< 1. The value of p is used to switch between a spiral and circular movement. The best whale position is returned as the final solution when the termination criterion is satisfied.

Though WOA has proven its superiority in solving different optimization problems in engineering and other fields, like any other evolutionary algorithms, it also suffers from the problem of getting stagnant in local optima. A modified WOA is proposed that introduces a Mixed-Cauchy mutation into WOA in order to evade premature convergence in WOA by means of long jumps made by the Mixed-Cauchy mutation [21]. The objective behind using Cauchy mutation in WOA is to bring diversity to the population of WOA in each iteration and thereby enhance global search ability. Incorporating Mixed-Cauchy mutation to the whale updating equation help get out of the local search space by making them to jump to a better position in the search space. As because in Cauchy distribution there exist no expectation and variance for the same is infinite, so Cauchy mutation allows a whale to have a long jump.

Now the mixed Cauchy-pdf$MC - pdf$used in this work can be generated using the following equation.

$$MC - pdf = \propto Cauchy - pdf1 + (1 - \alpha)Cauchy - pdf2 \quad (13)$$

Here $\propto$ is a random number between 0 and 1.

The equation for $Cauchy - pdf1$ and $Cauchy - pdf2$ are given in equation (14) and (15)

$$Cauchy - pdf1 = \frac{1}{\pi\gamma\left[1+\left(\frac{x-y_1}{\gamma}\right)^2\right]} \quad (14)$$

$$Cauchy - pdf2 = \frac{1}{\pi\gamma\left[1+\left(\frac{x-y_2}{\gamma}\right)^2\right]} \quad (15)$$

Where y_1 and y_2 represents the location parameters and x in our case represents the current best position of the whale.

Algorithm: **Modified WOA**

1. Initialize the whale population X_{w_i} $(i = 1,2, \dots n)$
2. Evaluate the fitness of each whale.
3. Let X_{w_b}represent fittest whale
4. Repeat steps 5 to 17 for *t*=1 to *TotalNoofItearation*
5. {
6. Repeat steps 6 to 14 for *I* =1 to *n*
7. {
8. Set the values of *a, A, C, l, p*
9. If (*p* < 0.5)
10. then if (*A*< 1)
11. then update the whale position using equation (7)
12. else if (*A*>= 1)
13. then update the whale position using equation (11)
14. else if (*p*>= 0.5)
15. Then update the whale position using equation (6)
16. }
17. Evaluate the fitness of each whale and find the fittest whale position.
18. Perform mixed-Cauchy mutation over fittest whale position according to equation (13)
19. Compare it with the existing fittest whale to determine the best whale position.
20. }
21. Return the best whale position.

A. Modified WOA based weighted linear ensemble model

Our proposed model consists of four phases. The phases are described as follows:

Phase 1: Individual prediction models i.e. AMA, ANA and FLANN models are trained independently using the training dataset.

Phase 2: Each input pattern is applied to the three models to generate three different predicted NAV.

Phase 3: The outputs of these three models are associated with three different weights and then linearly combined to produce the final predicted NAV. The weights are optimized using anmodified WOA and compared with GA and PSO. So our proposed work is known as modified WOA ensemble model.

Phase 4: The performance of this proposed model is measured using the test dataset.

Procedure: Modified WOA based ensemble NAV Prediction

1. Each input pattern is processed through AMA, ANN and FLANN model to generate three different output NAV.
2. This predicted NAV is compared with the actual NAV to produce the error. Thus the MSE is calculated.

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3. The modified WOA is used to minimize the MSE.
4. After each iteration, the MSE values are plotted to generate the convergence characteristics.
5. When the MSE reaches the lowest value i.e. the curve converges, training is stopped and the best whale position refers to the optimal weights.

Using these optimal weights, the test datasets are taken for performance comparison

V. EXPERIMENTAL STUDY

The simulation of the proposed ensemble model is conducted for the 1-day, 3-day, 5-day and 7-day ahead NAV prediction of two Indian Mutual funds. The performance comparison between the individual models and the ensemble model is depicted using different measures.

A. Dataset Preparation

The NAV data of the two Indian Mutual funds i.e. TATA Dividend Yield Fund-Direct Growth and SBI Magnum Equity mutual funds are collected for this simulation study. The NAV data of SBI Magnum Equity mutual fund are collected from 1st March 2007 to 1st March 2017. Similarly, the NAV data of TATA Dividend Yield Fund-Direct Growth are collected from 2nd January 2013 to 1st December 2017. A running window of size 12 is taken to determine the input pattern. For each window, the mean, standard deviation, kurtosis and skewness are calculated. The input pattern now consists of the current NAV and these four statistical components. The window is moved down by one NAV and the next window is used to decide the second input pattern and the process continues to prepare the training dataset. In this case 80% of NAV are taken for training the models and rest 20% is used for measuring the performance of the model.

B. Training the model

The training process of the proposed ensemble model is performed in three phases. In the first phase, the individual linear and nonlinear models are trained individually with respect to their objective functions by taking the input patterns from the training NAV dataset. In the second phase, the individual output NAV data are multiplied with three weight values and linearly combined to generate the predicted NAV. The error between the actual NAV and predicted NAV are used to calculate the MSE. In the third phase, these weight values are optimized using a modified WOA so that the MSE will be minimum and converge after certain iterations. The MSE values are plotted at each iteration and the comparison of the error curves with other nature inspired algorithms i.e. GA and PSO are given in fig.3 for SBI Magnum Equity mutual fund in 1-day, 3-day and 5-day ahead prediction.It is found that Modified WOA achieves minimum MSE values for different day ahead prediction of both the Indian mutual funds. After completion of the training process, the weight values are taken for the testing phase. For simulating this proposed work, the population size is 50 and 100 number of iterations are considered. The Value of location parameters are y_1=2 and y_2= 6 respectively and scale parameter γ=1. The mutation coefficient α=0.2.

C. Testing the model

The test NAV dataset used to measure the prediction performance. The Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) are computed for measuring the performances of the propose ensemble models. These two measures are defined as follows:

$$MAPE = \frac{\sum_{i=1}^{S}\left|\frac{X_i - Y_i}{X_i}\right|}{S} \times 100 \qquad (16)$$

$$RMSE = \sqrt{\frac{1}{S}\sum_{i=1}^{S}(X_i - Y_i)^2} \qquad (17)$$

Here X_i and Y_i represent the actual NAV and the Calculated NAV of the *i*th input pattern respectively. The total number of test dataset is represented as S. The actual and predicted NAV are plotted for each test pattern as shown in fig. 4 using proposed ensemble model for SBI Magnum Equity mutual fund.

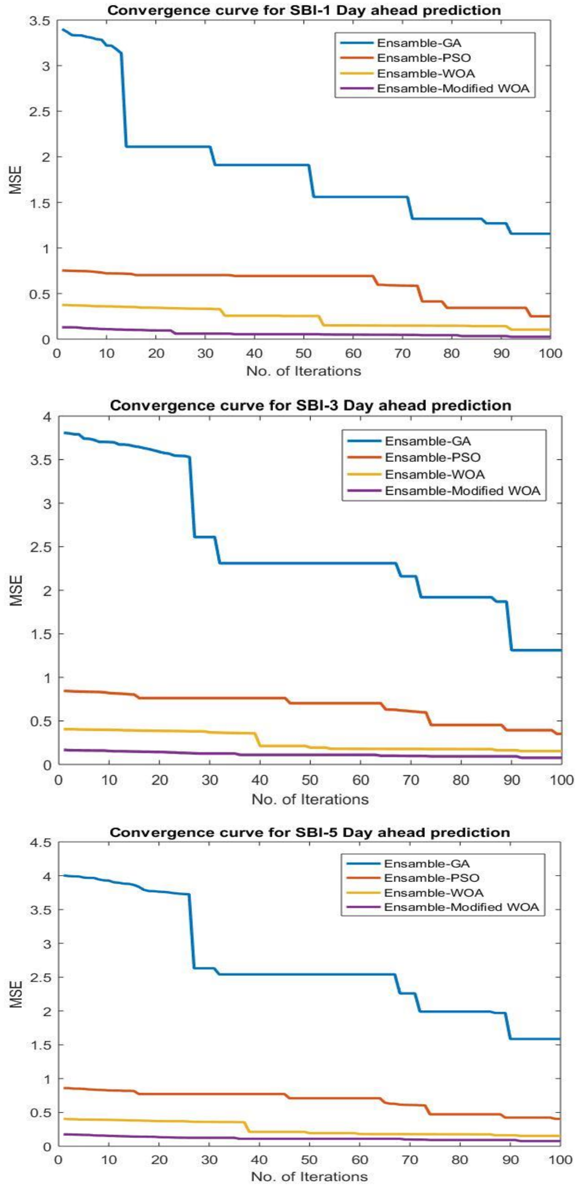

Fig.3. Comparison of Convergence Curves of different Bio Inspired algorithms in ensemble method.

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D. Analysis of the results

The RMSE and MAPE values are compared with the individual models i.e. AMA, ANN and FLANN models as well as other bio-inspired ensemble model. From the prediction graphs of different day ahead NAV prediction, it is found that the actual and predicted NAV of the two Indian mutual funds closely overlap with each other.

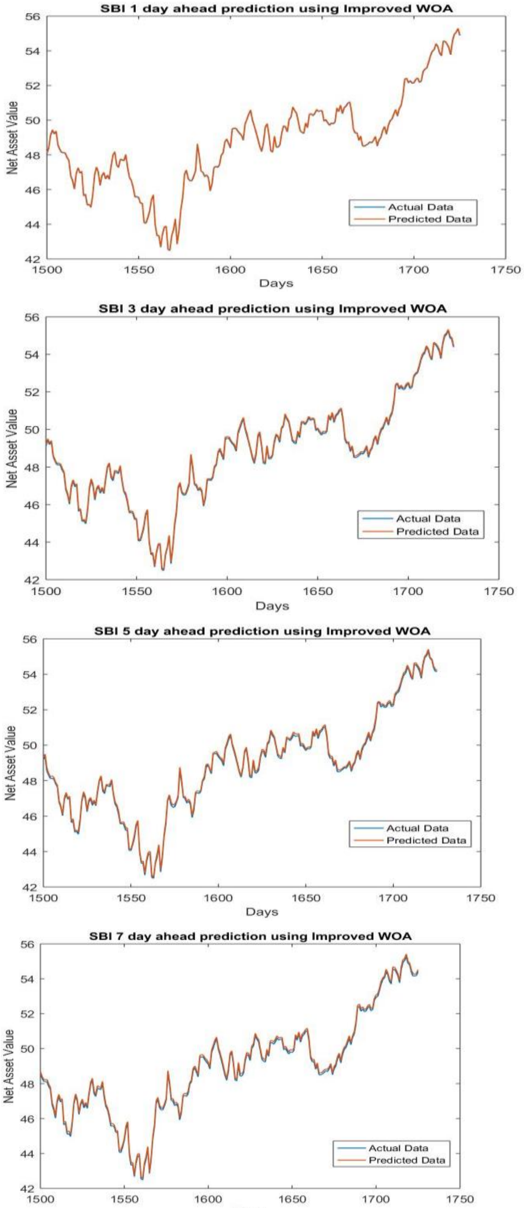

Fig. 4. Different day ahead Actual vs. Predicted NAV comparison of SBI Magnum Equity Mutual Fund using proposed modified WOA based ensemble model

The MAPE and RMSE values of the modified WOA based ensemble model are found to be minimum with respect to other ensemble and individual models for the two Indian mutual funds as shown in Table 1-4.

Table 1: Comparison of RMSE values for different day ahead prediction of SBI Magnum Equity Mutual Fund using different ensemble model.

Model	1-day	3-day	5-day	7-day
AMA	1.7089	1.9599	2.2124	2.3118
ANN	1.6185	1.7654	1.9341	2.1205
FLANN	1.5663	1.6783	1.8466	2.1318
GA-Ensemble	1.1560	1.3115	1.5861	1.9190
PSO-Ensemble	0.2503	0.3515	0.4048	0.5552
WOA-Ensemble	0.1041	0.1529	0.2074	0.3062
Modified WOA-Ensemble	**0.0253**	**0.0764**	**0.1050**	**0.1209**

Table 2: Comparison of MAPE values for different day ahead prediction of SBI Magnum Equity Mutual Fund using different ensemble model.

Model	1-day	3-day	5-day	7-day
AMA	3.9575	4.5495	5.1269	5.3519
ANN	3.7288	4.0564	4.4389	4.8601
FLANN	3.5943	3.8291	4.1896	4.8857
GA-Ensemble	2.6856	3.0272	3.6119	4.3188
PSO-Ensemble	0.5783	0.8141	0.9297	1.2736
WOA-Ensemble	0.2333	0.3500	0.4638	0.7019
Modified WOA-Ensemble	**0.0585**	**0.1746**	**0.2353**	**0.2778**

Table 3: Comparison of RMSE values for different day ahead prediction of TATA Dividend Yield Fund-Direct GrowthMutual Fund using different ensemble model.

Model	1-day	3-day	5-day	7-day
AMA	4.1249	4.7475	5.6129	5.9918
ANN	3.8165	4.2648	4.5126	4.7856
FLANN	3.6419	3.9958	4.4368	4.7855
GA-Ensemble	1.1017	1.3542	1.5474	1.7501
PSO-Ensemble	0.5999	0.7034	0.9030	1.1027
WOA-Ensemble	0.2524	0.5047	0.7544	0.9544
Modified WOA-Ensemble	**0.1530**	**0.3605**	**0.5019**	**0.8032**

Table 4: Comparison of MAPE values for different day ahead prediction of TATA Dividend Yield Fund-Direct GrowthMutual Fund using different ensemble model.

Model	1-day	3-day	5-day	7-day
AMA	7.8924	8.0215	11.0012	12.0681
ANN	6.5841	8.0259	9.0247	9.2105
FLANN	6.3218	7.8951	8.9103	9.1102
GA-Ensemble	2.1252	2.6089	2.9757	3.3653
PSO-Ensemble	1.1532	1.3530	1.7365	2.1180
WOA-Ensemble	0.4840	0.9670	1.4419	1.8291
Modified WOA-Ensemble	**0.2904**	**0.6730**	**0.9589**	**1.5279**

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So from this simulation study, it is concluded that the modified WOA based ensemble model performs better than WOA based, GA based, PSO based ensemble models and the three individual AMA, ANN and FLANN models.

VI. CONCLUSION

Our work in this paper is primarily focused on the design of the modified WOA based ensemble model for the prediction of NAV data. Initially, one linear model i.e. AMA model and two nonlinear models i.e. ANN and FLANN models are considered for NAV prediction. Then the output NAV of each individual models are combined using weighted linearensemble method to predict the NAV and the weights are optimized using GA, PSO, WOA and an modified WOA algorithm. The performance measures i.e. RMSE and MAPE values are evaluated for the comparison of the prediction performance of different models. It is concluded that the modified WOA based ensemble model performs better as compared to other bio inspired ensemble models and the individual models considered in our work.

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AUTHORS PROFILE

Sarbeswara Hota: He is an Assistant Professor and pursuing Ph.D. in Computer Science & Engineering Department ofSiksha O AnusandhanDeemed to be University. His research area includes financial data prediction and soft computing techniques. He has published 02 papers in this area also.

PranatiSatapathy: She is working as Lecturer in Integrated MCA Department, Utkal University and pursuing Ph.D. in Computer Science & Applications Department of Utkal University. Her research area includes image classification using soft computing techniques and use of bio inspired algorithms.

Debahuti Mishra: She is working as Professor and Head of the Computer Science & Engineering Department of Siksha O AnusandhanDeemed to be University. She has guided 32 number of M.Tech students and 9 number of PhD students. She has published 165 number of research papers in reputed journals and conferences. Her research area includes Data Mining and soft computing techniques.

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