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Optimal Prediction of Foreign Exchange Market Exploring the Effect of Water Cycle Algorithm Strategy on Data Segregation

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Abstract: ***The market of foreign exchange is very huge, complex, and volatile in nature. Prediction task for this market is highly challenging as the data is highly chaotic, volatile and noisy. In this work Artificial Neural Networks (ANN), Functional Link Artificial Neural Network (FLANN), Extreme Learning Machine (ELM) are the models used to predict the price. Simple Moving Average (SMA), Stochastic Oscillator, Exponential Moving Average (EMA), Momentum, Moving Average Convergence Divergence(MACD), Average True Range (ATR), Relative Strength Index (RSI), are different technical indicators used by economists to gain an insight into the market and predict the exchange rate of currency. Generally technical indicators are calculated from price, open price, low price, high price, change percentage. The proposed network is optimized by Genetic algorithm (GA), Differential Evolution (DE), Particle Swarm Optimization (PSO), Water Cycle Algorithm (WCA). The dataset collected for this experiment comprises of 4000 days of past currency exchange rates of the two currency pairs that is USA Dollar (USD) to Indian Rupees (INR) (USD\INR) and Soudi Arabia Riyal (SAR) to INR (SAR\INR). The proposed datasets are segregated into many parts and each part is trained individually. Optimization techniques such as GA, DE, PSO and WCA deployed in segregated datasets as well as the whole dataset. The experimental result shows that the segregated WCA is giving the better result when WCA applied on the whole dataset. The ELM and WCA with segregated dataset produces better result than other models what experimented in this work.***

Keywords : Forex; Water Cycle Algorithm(WCA); Differential Evolution(DE); particle Swarm Optimization(PSO); Genetic algorithm (GA); Extreme Learning Machine(ELM).

I. INTRODUCTION

The Foreign Exchange (Forex) rate is an important price indicator which gives an insight about the economic health of the country and it is defined as the price of one currency paid in terms of another country's currency. It has a great impact on the international trade relationship of the country which is a major decision making parameter of its citizen's standard of living. As a consequence economic policies are revisited and changed regularly on the basis of accurate prediction of Forex rate. These changes help in maintaining trade relationships properly which, in turn, lead its economy to be stronger.

In the era of globalization and liberalization, global market currency exchange policy and standard is an important factor. As a result the global business leader USA's currency USD is a common standard currency for international trade. Apart from this geopolitics and internal business policies, Forex rate has so many influential factors such as socio-economic scenarios, political condition, other country's currency, economic policies, investor's psychological factors, investor's expectations etc [1]-[2]. For the current business decision of a government of country need to forecast the foreign exchange rate of its own currency and targeting business partner's currency with respect to USD. Thus, the prediction of Forex rate is paramount, and it should never be underestimated. Generally, the data of stock market is highly dynamic, noisy, volatile, nonlinear and non-parametric in nature. Hence, the data is not of fixed pattern. Beforehand factual methodologies, for example, moving normal, weighted moving normal, autoregressive moving normal (ARMA), autoregressive coordinated moving normal (ARIMA) have been utilized to forecast trend [3]. But those techniques were not capable enough to grab the non linear and dynamic nature of forex rates for the prediction task as they were working on the assumption that data are co related and linear in nature. ARIMA had poor performance when applied on time series data due to the non stationary and non linearity nature of data. ARMA basing upon DE was proposed to overcome the drawbacks of statistical methods [4].The method was implemented on rupees, Pound and Yen Exchange and compared with USD. Features of statistical measures such as mean, variance, normalized exchange rate price are taken for the above said model. Using the above features an efficient non linear adaptive model with less complexity was proposed and its improved performance was proved for most of the cases [5]. It was proposed for conversion from USD to INR.

So machine learning algorithms have been developed to overcome the drawbacks of statistical techniques recently and it can be concluded that performances of these are better than that of statistical techniques in predicting Forex rate. Machine Learning is an emerging field of computer science and the machine learning approaches include genetic algorithm, decision tree learning, fuzzy system, neural network, association rule learning, deep learning, ANN, support vector machines (SVM) and hybrid methods[6].

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Out of these above approaches functionality of ANN is imitated from the working principle of biological neural network which helps to forecast the near future price of Forex rate by analyzing the past data.

In the literature many exciting works have been done on forecasting the Forex rate. Few are cited below. Parametric and nonparametric approach and hybridization of both the approaches have been proposed [7].Hybridization is done to get better result. As Forex data is highly non linear and volatile, the mean and variance of the series change regularly with the time passes. To alleviate non linearity and volatility problem in time series data many techniques have been proposed such as Autoregressive Conditional Heteroscedasticity[8], GARCH[9] etc. Previously linear models are easy to implement [10].

From the survey of literatures it can be concluded that back propagation algorithm is efficient as compared to other ANNs, but rate of convergence is less in back propagation algorithm. Many different optimization techniques such as Particle Swarm Optimization, Genetic Algorithm (GA) are used to overcome the problem of slow convergence [11].ANN hybridized with GA and PSO was proposed for share price prediction but failed to give superior performance [12].ARIMA time series model and neural networks models are explored for Turkish to USD exchange giving the result as ANNs are the better performers as compared to ARIMA in terms of accuracy [13]. ANN based models such as Standard Back Propagation (SBP), Scaled Conjugate Gradient (SCG) and Back propagation with Bayesian Regularization (BPR) methods were proposed by [14] to predict the currency exchange rate against Australian dollar where prediction accuracy is the evaluating parameter, Multilayer Perceptron (MLP) and Volterra are two techniques of ANN used for forecasting [15]. As there are many factors involved in forecasting, Hidden Markov Model is not a good choice for the time series forecasting [16]. Multi layer Perceptron (MLP) models are time consuming and failed to restore the past data though it is used widely for forecasting [17]. Optimized Elman Recurrent Neural Network (Elman NN) was proposed for prediction of Taiwan stock price trends which have tried to overcome the limitations of past models [18] . It performed better due to faster convergence, nonlinear prediction capabilities, and accurate mapping ability. A feed forward multilayer perceptron (MLP) was used for predicting company's stock value by taking past data and the performance was compared with Elman Recurrent Network and Regression Model[19].MSE,MAPE and MAE are having less values in Elman and linear regression ,but Elman NN was having better performance than MLP in prediction.

The motivation behind this study is to improve the skill of time series model using the concept of data segregation. Very few work has done using the concept of data segregation, through which the complexity can be reduced, hence this is the noble idea to introduce data segregated methods. The next objective of this paper is to introduce ELM along with WCA, which is new to this area as not any one has tried for this, particularly in the field of Forex as this is totally application oriented based. ELM is a simple learning approach, where the input weights of the model and the biases in the hidden layer are chosen randomly, which analytically calculates the output weights. WCA is a nature inspired and based upon the observation of water cycle and how the streams and rivers only flow downwardly to meet the sea.

In this study technical indicators such as EMA, Stochastic Oscillator, Momentum, RSI, SMA, ATR, Willium%R or %R, MACD have been considered to observe the behavior of the hidden pattern of Forex rate [20]. Generally it is calculated from the basic data provided by Forex such as open price, high price, low price etc. In this study USD/ INR and SAR/ INR are taken into account. Forex rate is predicted using machine learning techniques such as ANN, FLANN and ELM which are the most recent machine learning algorithms [21]-[22].Above approaches are inspired by biological neural network which will help us to predict the near future price from the historical data of Forex [23]-[27].Inputs are given to these models and to optimize the performances of above used models GA, DE, PSO and WCA have been used. GA, DE, PSO are evolutionary optimization methods out of which GA is used for discrete optimization, DE are for continuous optimization and WCA is physics chemistry based optimization technique. As the dataset are too large they are segregated to many small parts and each particle is assigned with a fixed range of dataset. It is observed that performance of each particle is enhanced by using this segregation method.

II. METHODOLOGIES ADOPTED

ELM has only one hidden layer and many nodes. ELM is a model which randomly assigns weight for input and bias. Weights for the hidden layer are calculated methodically [28]-[29].

There are many physics chemistry based optimization techniques are proposed like big bang-big crunch, black hole optimization algorithm, electromagnetic field optimization, intelligent water drop, WCA and many more. Out of the many physics chemistry based optimization techniques WCA is experimented in this prediction model. The proposed WCA approach is nature based and has been derived from the concept of water cycle. It mimics the phenomenon of water flow towards the rivers followed by downhill towards the sea [30].

In the real world streams are made from rain drops, again which stream flows down most other streams are joining and become a river, and all rivers are flow downhill and become a sea and sea is the most downhill stream or river. Evaporation occurs from stream, river and sea when one stream evaporates then that stream, river or sea does not exist and by raining process another new stream will be created.

All the streams, river and sea are created by randomly assigning weights. Each stream is represented by equation (1). Where *x1, x2...xn* are the weights. Total numbers of population is represented by equation (2). Where *Nsr* is total numbers of sea and river in equation (4) randomly choose 1 of the stream as sea and randomly select some of the stream as river. All rivers are assigned to sea.

$$Stream = [x_1, x_2, x_3 \dots x_n] \tag{1}$$

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$$\text{Total population} \left\{ = \begin{matrix} Sea \\ River_1 \\ River_2 \\ River_3 \\ \vdots \\ Stream_{Nsr+1} \\ Stream_{Nsr+2} \\ Stream_{Nsr+3} \\ \vdots \\ Stream_{Npop} \end{matrix} \right\} = \begin{Bmatrix} x_1^1 & x_2^1 & x_3^1 & \cdots & x_N^1 \\ x_1^2 & x_2^2 & x_3^2 & \cdots & x_N^2 \\ x_1^3 & x_2^3 & x_3^3 & \cdots & x_N^3 \\ \vdots & \vdots & \vdots & & \vdots \\ x_1^{Npop} & x_2^{Npop} & x_3^{Npop} & \cdots & x_N^{Npop} \end{Bmatrix} \quad (2)$$

Using fitness function calculating the cost (Ci) of each stream, river and sea in equation (3).

$$C_i = Cost_i = f(x_1^i, x_2^i, \ldots x_{Nvar}^i), i = 1, 2, 3, \ldots, N_{pop} \quad (3)$$

$$N_{sr} = Number\ of\ Rivers + 1(sea) \quad (4)$$

At first iteration stochastically assign $Nstreams$ numbers of streams to rivers and sea in equation (5).

Based on the intensity of water flow, the streams are allocated to rivers or sea and the whole process is explained by equation (6) as follows. Where NSn is the number of streams assigned to the specific river and sea.

$$N_{stream} = N_{pop} - N_{sr} \quad (5)$$

$$NS_n = \text{round}\left\{ \frac{Cost_n t}{\sum_{i=1}^{Nsr} Cost_i} \times N_{Streams}, \right\} n = 1,2, \ldots N_{sr} \quad (6)$$

Raindrops are associated to formulate streams, which further aggregate to flow into a river and finally ends its journey in the sea. However some streams directly join the sea. A random distance value is used to represent the connecting line between the stream and the river mentioned as:

$$X \,\varepsilon\, (0, C \times d)\ C > 1 \quad (7)$$

Equation (7) represents a random number in the range $[0, C \times d]$, where d is the distance between the source and destination of water flow. The streams are allowed to flow in many directions towards the river and hence the value of C has been assumed as greater than 1. The same consideration is also applied while the river flows into the sea. The positions of streams and rivers can be updated as per the following equation:

$$X_{Stream}^{i+1} = X_{Stream}^{i} + rand \times C \times (X_{River}^{i} - X_{Stream}^{i+1}) \quad (8)$$

$$X_{River}^{i+1} = X_{River}^{i} + rand \times C \times (X_{Sea}^{i} - X_{River}^{i}) \quad (9)$$

Here *rand* is a random value ranges between [0,1]. When any solution generated for a stream becomes better than that of river then their positions gets exchanged. Such exchanges are also applicable for the rivers and the sea. After the exchange between stream with rivers and rivers with sea depending on their cost at the end of the current iteration sea is the best solution which is the optimal solution for current iteration.

To avoid convergence, evaporation is the most important factor to be taken care of. Water evaporates from streams, river and sea. The evaporated water condenses in the colder atmosphere to form cloud and the cloud returns back the water content again to the surface of earth in the form of rain and forms new streams. To avoid local optima, the following pseudo code determines whether the river flows into to the sea or merged with the sea.

```
if X_sea − X_river < d_max i = 1,2, … N_sr−1
Evaporation and raining process

End
```

Here, $dmax$ is a random number near to 0 that controls the intensity of search near the sea. When the distance between the river and sea becomes less than the value of $dmax$, it is concluded that the river has reached the optimal point, the sea. A greater value $dmax$, decreases the search process while a smaller value increases the search intensity near to sea area. The $dmax$ value adaptively decreases as:

$$d_{max}^{i+1} = d_{max}^{i} - \frac{d_{max}^{i}}{max\ iteration} \quad (10)$$

The process of evaporation is always followed by the process of rain. Through the process of rain, new streams are formed on different points of earth. The following equation is used to represent these streams:

$$X_{stream}^{new} = LB + rand \times (UB - LB) \quad (11)$$

Here, LB = lower bound and UB= upper bound.

The best of the above newly formed streams are united to flow as a river. The remaining of the streams may form a new river or directly join to the sea. To enhance the performance of the algorithm and convergence for constrained problems, we apply equation 12 only for those streams that directly join the sea.

$$X_{Stream}^{new} = X_{Sea} + \sqrt{\mu}\ x\ rand(1, N_{var}) \quad (12)$$

Where,

μ= the coefficient of search range near sea area (suitably se to 0.1).

rand= a distributed random number.

III. EXPERIMENTAL ANALYSIS

A. Experimental setup

The model has developed using MatLab ver. R-2014B with Intel I3 Processor in Windows 8.1 Pro.

B. Dataset Description

Forex rate of two currencies can be stated as the rate at which one currency will be exchanged against another. The trade between two countries determines the exchange rate .suppose a country imports more products from another country and exports less valued products then currency rate of this country decreases compare with other country. How much valued goods one country exports are the sale price and how much valued products purchases from that country are the buying price. Saleing price and buying price ratio decides the exchange rate of both at the country. If a country buys less valued products and sales more valued products this country's currency has more purchase power. For the simulation of the experiment in this work USD/INR [31] and SAR/INR [32] exchange dataset are being used for experiment. In the **Table 1** it is described the range of the dataset, total number of samples, number of training samples and number of test samples.

Using these two dataset different technical indicators are calculated with the window size 12, which are commonly used for understanding the trend of the Forex. Before training and testing the model, the dataset must be processed, at first designed the dataset by calculating the technical indicators, and then normalize the dataset. Dataset normalization is a very important step before process the data by normalizing the dataset the values of all the input to the machine lies between 0 and 1 so machine can predict properly otherwise the machine cannot work correctly. The actual value which would be comparing with predicted value by the machine must be normalized. The difference between actual price and predicted price is known as error. The objective of this study is to reduce the training error which should be able to predict the future value effectively. Therefore, here an attempt has been made to normalize the data based on data segregation.

C. Description about Technical Indicators

The technical indicators are proposed by the economist to understand the trend of change in exchange rate of two currency the below in **Table 2** describes about the technical indicators used in this work.

D.Schematic Layout of Proposed Work

The proposed model for Forex rate is shown in the **Figure 1.** This model works step wise. At first the currency exchange rate dataset is taken and regenerated using some technical indicators with the window size 12. After regeneration of the dataset, it is divided into training part and testing part in the ratio of 7:3. The model is trained using ELM, FLANN and ANN models and each of them is optimized with GA, DE, PSO and WCA with segregated as well as un-segregated dataset..

Table 1. Description of data samples and data range

Datasets	Data Range	Total samples	Training Sample	Test Sample
USD to INR	Nov 04,2003- Dec 03,2018	4000	2800	1200
SAR to INR	Nov 04,2003- Dec 03,2018	4000	2800	1200

Table 2. List of selected technical indicators with statistical measures and their formulas

Technical Indicators	Formula
SMA (Simple Moving Average)	$\frac{Summationoftdaysopenprice}{t}$
Momentum	$\frac{Openprice(p)}{Openprice(p-n)\times 100}$ $Openprice(p)$is the opening price of the current bar and $Openprice(p-n)$ is the opening bar price n periods ago.
EMA (Exponential Moving Average)	$\left(Price_{[today]} \times SF\right) + \left(EMA_{[Yesterday]} \times (1-SF)\right)$ SF (Smoothing Factor) =$\frac{2}{k+1}$, k = the length of the EMA
ATR (Average True Range)	$\frac{ATR_{t-1}X(n-1)+TR_t}{n}$ TR= $Max((Today'shigh - Today'slow), (Today'shigh - Today'sopen), (Today'sopen - Today'sl$
RSI (Relative Strength Index)	$RSI = 100 - \frac{100}{(1+RS^*)}$ Where, RS=$\frac{Averageof\ t\ daysup\ opens}{Averageof\ t\ daysdown\ opens}$ RSI = If$\left(Averageloss = 0{,}100{,}100 - \left(\frac{100}{(1+RS)}\right)\right)$
%R (Willium %R)	$\frac{(Highesthigh - Open)}{(Highesthigh - Lowestlow)} \times -100$
MACD (Moving Average Convergence Divergence)	EMA (t days EMA for the open price) is = $(12+1)^{th} dayopenprice \times \left(\frac{2}{12+1}\right) + Average(1\ totdaysofopenprice) \times \left(1 - \frac{2}{(12+1)}\right)$ EMA (26 days EMA for the open price) is = $26^{th} dayopenprice \times \left(\frac{2}{26+1}\right) + Average(1\ to\ 26\ daysofopenprice) \times \left(1 - \frac{2}{26+1}\right)$ Calculation of MACD = $12\ daysEMA - 26\ daysEMA$
%k (Stochastic Oscillator)	$100 \times \frac{(O - L_{12})}{(H_{12} - L_{12})}$ Where, O= most recently opening price, L_{12} is the lowest price of the t previous trading session and $H_{12}$is the highest price of the t previous trading session.

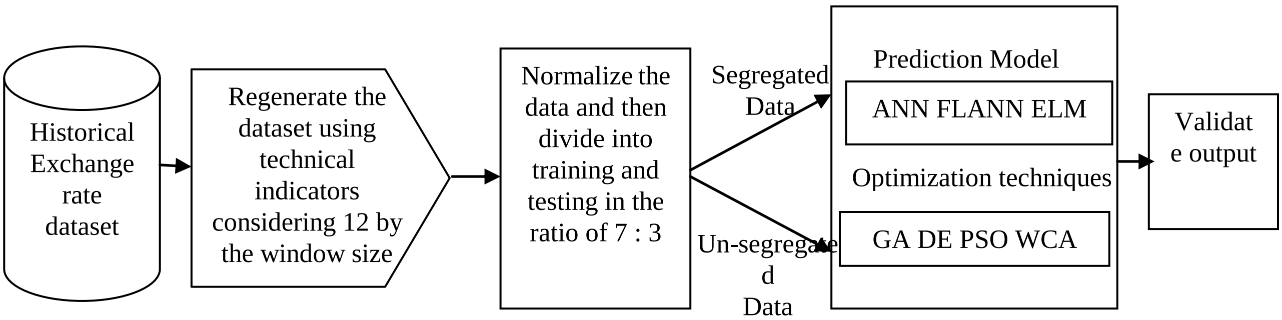

Figure 1. Abstract view of Proposed Model

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E. Parameter discussion

Table 3: Parameter Description

ANN	FLANN	ELM	GA	DE	PSO	WCA
Number of hidden layers-3 Number of nodes in the hidden layers-5 Alfa-0.1 Number of Iteration-100	Size of expansion-9	No of nodes in the hidden layer-15	Population size-100 Iteration-100 Selection operator-Roulette wheel Crossover rate-0.25 Mutation rate-0.1	Population size-100 Iteration-100 Crossover rate-0.8 Mutation constant/Scale factor-0.5	Population size-100 Iteration-100 w-1 Acceleration Coefficient1-2 Acceleration Coefficient2-2	Population size-100 Iteration-100 No. of River-19 No. of sea-1 dmax-0.01 μ=0.1

F. Performance Evaluation

Table 4 describes various performance evaluation measures.

Table 4: Performance evaluation measures

Methods	
MAE	$=\frac{1}{N}\sum_{i=1}^{N}\left\lvert A_i - \overline{P}_i\right\rvert$
MedAE	Median Absolute Error
MSE	$=\frac{1}{N}\sum_{i=1}^{N}(A_i - P_i)^2$
MSLE	$=\frac{1}{N}\sum_{i=1}^{N}\log(A_i - P_i)^2$
RMSE	$=\sqrt{\frac{\sum_{i=1}^{N}(P_i - A_i)^2}{N}}$
MAPE	$=\frac{\sum_{i=1}^{N}\left\lvert\frac{A_i - P_i}{A_i}\right\rvert}{N}\times 100$
Theil'sU	$=\frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(A_i - P_i)^2}}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}A_i^2}+\sqrt{\frac{1}{N}\sum_{i=1}^{N}P_i^2}}$
ARV	$=\frac{\sum_{i=1}^{N}(P_i - A_i)^2}{\sum_{i=1}^{N}(P_i - \bar{A})}$
EVS	$=1-\frac{\sum_{1}^{N}(error - mean\_error)^2}{\sum_{1}^{N}(Ai - Aaverage)^2}$
RSuare	$=1-\frac{\sum_{1}^{N}(P_i - A_{average})^2}{\sum_{1}^{N}(A_i - A_{average})^2}$

IV. Result Analysis

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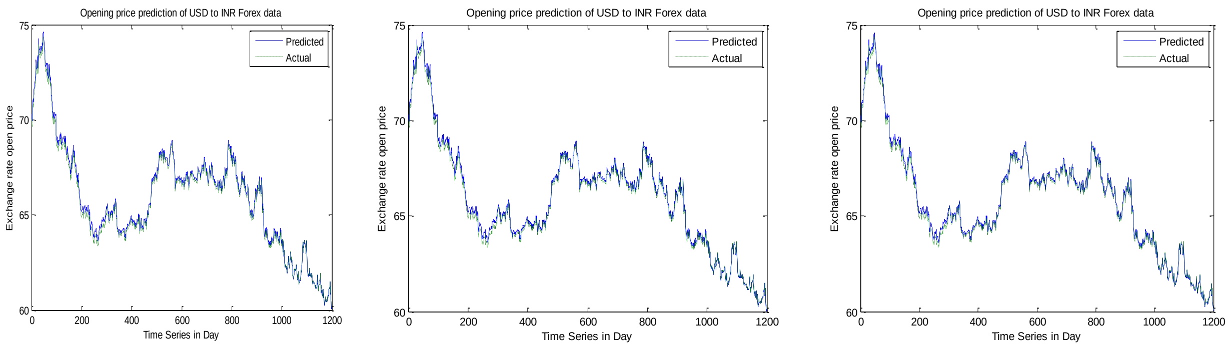
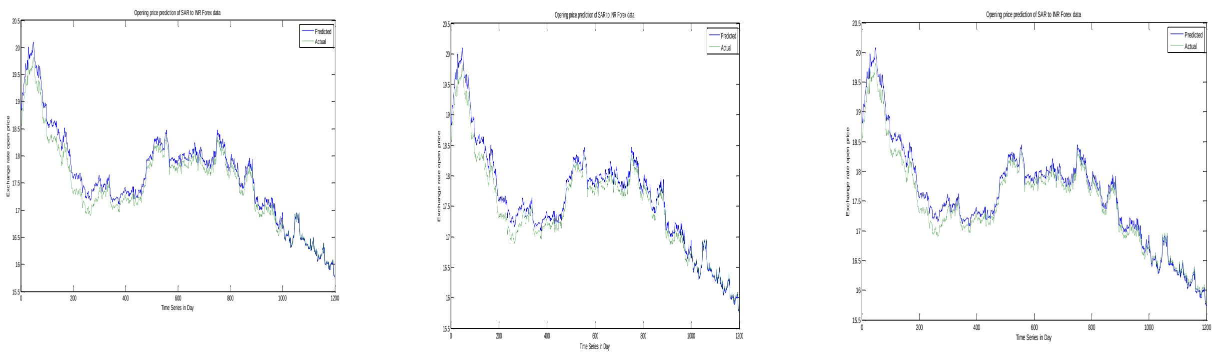


(a) (b) (c)

Figure 2. One day ahead opening price prediction of USD to INR Forex dataset using (a)ANN-WCA-Segregated, (b)FLANN-WCA-Segregated, (c)ELM-WCA-Segregated using USD to INR

After training three models ANN, FLANN and ELM and optimized by four optimized techniques GA, DE, PSO and WCA with and without data segregation getting twelve solutions for the forex dataset USD to INR. Then applying all using testing dataset with segregated dataset and without data segregation. Due to the lack of space here only segregated dataset and WCA with ANN, FLANN and ELM models are shown in **Figure 2**. for dataset SAR to INR the graph has been shown in **Figure 3**.



(a) (b) (c)

Figure 3. One day ahead opening price prediction of SAR to INR Forex dataset using (a)ANN-WCA-Segregated, (b)FANN-WCA-Segregated, (c)ELM-WCA-Segregated using USD to INR

the solutions predicted price and actual price graph are ploted

Table 5. Comparison of different performance evaluation measure for dataset USD to INR using ANN 1day ahead

Methods	MAE	MedAE	MSE	MSLE	RMSE	MAPE	Theil'sU	ARV	EVS	RSquare
GA	0.198031	0.156364	0.041647	0.000009	0.204075	0.300590	0.000023	0.210304	0.999691	0.994702
GA With segregation	0.20386	0.199700	0.042586	0.000020	0.206364	0.451530	0.000050	0.208891	0.999509	0.979598
DE	0.17967	0.138011	0.034715	0.000008	0.186319	0.272652	0.000021	0.193205	0.999691	0.995583
DE With segregation	0.18526	0.181100	0.035348	0.000017	0.188011	0.410381	0.000046	0.190795	0.999507	0.982992
PSO	0.16346	0.159300	0.027746	0.000013	0.166570	0.362233	0.000040	0.169733	0.999507	0.986650
PSO With segregation	0.15823	0.116570	0.027469	0.000006	0.165739	0.240012	0.000019	0.173597	0.999691	0.996505
WCA	0.13116	0.127000	0.018229	0.000009	0.135015	0.290894	0.000033	0.138976	0.999507	0.991229
WCA With segregation	**0.12568**	**0.084015**	**0.018226**	**0.000004**	**0.135005**	**0.190454**	**0.000016**	**0.145021**	**0.999691**	**0.997681**

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In **Table 5**, **Table 6**, **Table 7** and **Table 8**, shows how segregated WCA gives better result than all other techniques, where as segregated GA and segregated DE have less performance than without GA and DE respectively. Segregated PSO gives better result than PSO but PSO and segregated PSO less performing than WCA and segregated WCA respectively.

Table 6. Comparison of different performance evaluation measure for dataset SAR to INR using ANN 1day ahead

Methods	MAE	MedAE	MSE	MSLE	RMSE	MAPE	Theil'sU	ARV	EVS	RSquare
GA	0.199833	0.179000	0.040541	0.000117	0.201348	1.142935	0.000325	0.202874	0.999028	0.935170
GA With segregation	0.200133	0.179300	0.040661	0.000117	0.201646	1.144654	0.000325	0.203170	0.999028	0.934978
DE	0.192233	0.171400	0.037561	0.000109	0.193807	1.099389	0.000313	0.195394	0.999028	0.939935
DE With segregation	0.194233	0.173400	0.038334	0.000111	0.195791	1.110848	0.000316	0.197362	0.999028	0.938699
PSO	0.165133	0.144300	0.027877	0.000081	0.166963	0.944113	0.000270	0.168813	0.999028	0.955422
PSO With segregation	0.161533	0.140700	0.026701	0.000077	0.163403	0.923486	0.000264	0.165295	0.999028	0.957302
WCA	0.132833	0.112000	0.018252	0.000053	0.135101	0.759042	0.000219	0.137408	0.999028	0.970812
WCA With segregation	**0.131533**	**0.110700**	**0.017909**	**0.000052**	**0.133823**	**0.751593**	**0.000217**	**0.136153**	**0.999028**	**0.971362**

Table 7. Comparison of different performance evaluation measure for dataset USD to INR using FLANN 1day ahead

Methods	MAE	MedAE	MSE	MSLE	RMSE	MAPE	Theil'sU	ARV	EVS	RSquare
GA	0.185667	0.144000	0.036903	0.000008	0.192101	0.281769	0.000022	0.198758	0.999691	0.995305
GA With segregation	0.185967	0.144300	0.037014	0.000008	0.192391	0.282225	0.000022	0.199037	0.999691	0.995291
DE	0.177967	0.136300	0.034103	0.000008	0.184669	0.270047	0.000021	0.191624	0.999691	0.995661
DE With segregation	0.180067	0.138400	0.034855	0.000008	0.186694	0.273244	0.000021	0.193565	0.999691	0.995566
PSO	0.150967	0.109300	0.025221	0.000006	0.158813	0.228945	0.000018	0.167067	0.999691	0.996791
PSO With segregation	0.147367	0.105700	0.024147	0.000005	0.155395	0.223465	0.000018	0.163860	0.999691	0.996928
WCA	0.118667	0.077000	0.016512	0.000004	0.128500	0.179775	0.000015	0.139149	0.999691	0.997899
WCA With segregation	**0.117367**	**0.075700**	**0.016205**	**0.000004**	**0.127301**	**0.177796**	**0.000015**	**0.138076**	**0.999691**	**0.997938**

Table 8. Comparison of different performance evaluation measure for dataset SAR to INR using FLANN 1day ahead

Methods	MAE	MedAE	MSE	MSLE	RMSE	MAPE	Theil'sU	ARV	EVS	RSquare
GA	0.189833	0.169000	0.036644	0.000106	0.191427	1.085638	0.000309	0.193034	0.999028	0.941401
GA With segregation	0.190133	0.169300	0.036758	0.000106	0.191725	1.087356	0.000309	0.193329	0.999028	0.941219
DE	0.182133	0.161300	0.033780	0.000098	0.183794	1.041518	0.000297	0.185470	0.999028	0.945981
DE With segregation	0.184233	0.163400	0.034550	0.000100	0.185875	1.053551	0.000300	0.187532	0.999028	0.944751
PSO	0.155133	0.134300	0.024674	0.000071	0.157080	0.886815	0.000254	0.159050	0.999028	0.960543
PSO With segregation	0.151533	0.130700	0.023570	0.000068	0.153525	0.866188	0.000248	0.155543	0.999028	0.962309
WCA	0.122833	0.102000	0.015696	0.000045	0.125282	0.701744	0.000203	0.127780	0.999028	0.974901
WCA With segregation	**0.121733**	**0.100900**	**0.015427**	**0.000045**	**0.124204**	**0.695441**	**0.000201**	**0.126725**	**0.999028**	**0.97533**

Table 9. Comparison of different performance evaluation measure for dataset USD to INR using ELM 1day ahead

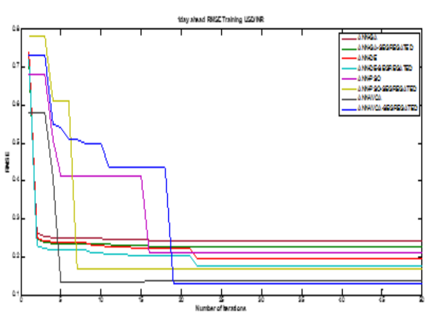
Methods	MAE	MedAE	MSE	MSLE	RMSE	MAPE	Theil'sU	ARV	EVS	RSquare	MAE
GA	0.16596	0.1243	0.029975	0.000007	0.173134	0.251779	0.000020	0.180612	0.999691	0.996186	0.165967
GA With segregation	0.16566	0.1240	0.029876	0.000007	0.172847	0.251323	0.000020	0.180338	0.999691	0.996199	0.165667
DE	0.16006	0.1184	0.028052	0.000006	0.167487	0.242798	0.000019	0.175251	0.999691	0.996431	0.160067
DE With segregation	0.15796	0.1163	0.027384	0.000006	0.165481	0.239601	0.000019	0.173353	0.999691	0.996516	0.157967
PSO	0.13096	0.0893	0.019583	0.000004	0.139939	0.198499	0.000016	0.149525	0.999691	0.997509	0.130967
PSO With segregation	0.12736	0.0857	0.018653	0.000004	0.136575	0.193019	0.000016	0.146450	0.999691	0.997627	0.127367
WCA	0.09866	0.0570	0.012166	0.000003	0.110298	0.149329	0.000013	0.123301	0.999691	0.998452	0.098667
WCA With segregation	**0.09756**	**0.0559**	**0.011950**	**0.000003**	**0.109315**	**0.147654**	**0.000013**	**0.122478**	**0.999691**	**0.998480**	**0.097567**

In **Table 9** and **Table 10**analysis shows how the segregated version of each optimization gives better performance.

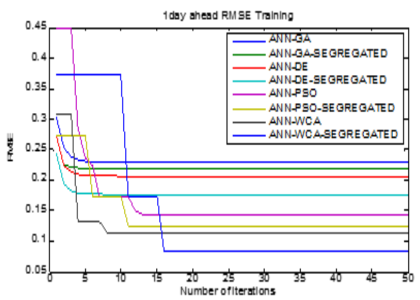
Methods	MAE	MedAE	MSE	MSLE	RMSE	MAPE	Theil'sU	ARV	EVS	RSquare	MAE
GA	0.17013	0.149300	0.029553	0.000085	0.171910	0.972761	0.000278	0.173705	0.999028	0.952741	0.170133
GA With segregation	0.16983	0.149000	0.029451	0.000085	0.171613	0.971042	0.000277	0.173411	0.999028	0.952904	0.169833
DE	0.16423	0.143400	0.027580	0.000080	0.166073	0.938956	0.000268	0.167933	0.999028	0.955896	0.164233
DE With segregation	0.16213	0.141300	0.026895	0.000078	0.163997	0.926923	0.000265	0.165881	0.999028	0.956992	0.162133
PSO	0.13513	0.114300	0.018869	0.000055	0.137363	0.772220	0.000222	0.139630	0.999028	0.969827	0.135133
PSO With segregation	0.13153	0.110700	0.017909	0.000052	0.133823	0.751593	0.000217	0.136153	0.999028	0.971362	0.131533
WCA	0.10283	0.082000	0.011182	0.000032	0.105747	0.587149	0.000172	0.108742	0.999028	0.982118	0.102833
WCA With segregation	**0.10173**	**0.080900**	**0.010957**	**0.000032**	**0.104677**	**0.580846**	**0.000170**	**0.107706**	**0.999028**	**0.982478**	**0.101733**

Table 10. Comparison of different performance evaluation measure for dataset SAR to INR using ELM 1day ahead

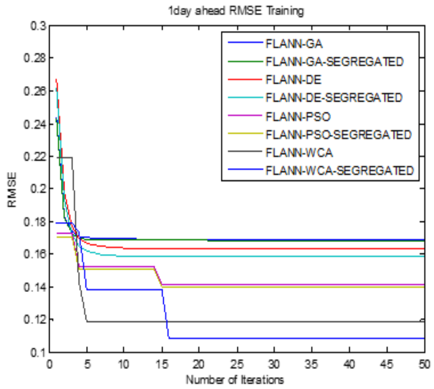
These **Table 5** to **Table 10** analysis shows how the segregated version of each optimization gives better performance.



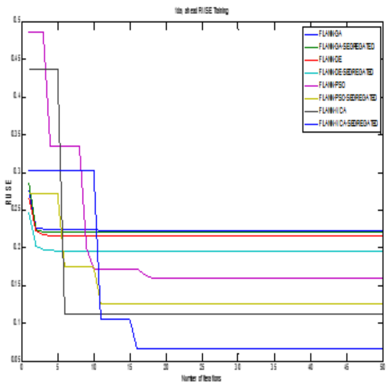
(a)



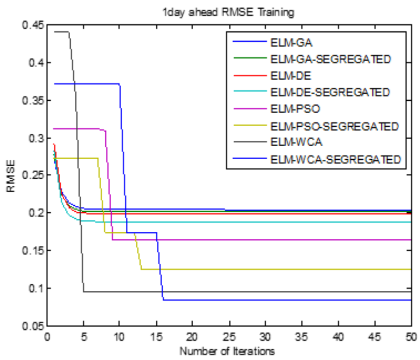
(a)



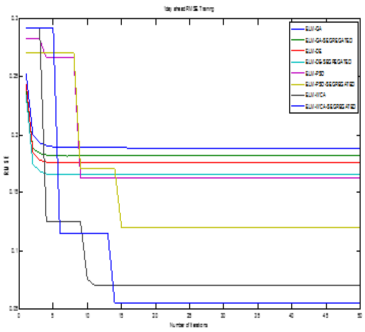
(b)



(b)



(c)



(c)

Fig 3: 1day ahead RMSE training using USD/INR **(a)** ANN **(b)** FLANN **(c)** ELM

Fig 4: 1day ahead RMSE training using SAR/INR **(a)** ANN **(b)** FLANN **(c)** ELM

Training time rmse plot for all the models and optimization techniques segregated dataset converges later but shows better result where as ELM-WCA with segregated dataset converge with optimal result. **Figure 4** is for with and without dataset USD to INR and **Figure 4 (a)** is the convergence graph for the model ANN, **Figure 4 (b)** is for the FLANN model and **Figure 4 (c)** is the plot of ELM model. Segregated and un-segregated dataset of SAR to INR the convergence graph is plotted in **Figure 5**, where **Figure 5 (a)** is for the ANN model, **Figure 5 (b)** is plotted for the FLANN, and **Figure 5 (c)** is the convergence graph of ELM model with different optimization techniques like GA, DE, PSO and WCA.

V. OVERALL FINDINGS

In this experiment datasets are used USD/INR and SAR/ INR. Currency exchange rate prediction is a required for trade between two countries. In this study emphasized on predicting the exchange rate between two counties. The proposed ELM based WCA with dataset segregation and without dataset segregation model and other traditional models with dataset segregation and without dataset segregation can be discussed as follows:

(1) In this work USD to INR and SAR to INR currency exchange has been considered. These datasets have been used for prediction techniques such as; ANN, FLANN, and ELM.

(2) ANN is a model which can train itself which can be improved by some optimized techniques like GA, DE, PSO and WCA but by applying the data segregation method the training and testing time can be minimized. There is another model FLANN which is a variation of ANN requires no hidden layer but more numbers of input layers for different functional values of actual input parameter and this model can be optimised by GA,DE, PSO and WCA. Another variation of ANN model is ELM which calculates the weights of hidden layer nodes and the numbers of hidden layer nodes are more in this ELM model. It also uses other optimized techniques to improve the model, GA, DE, PSO and WCA are the optimization techniques. It is observed that for minimizing the training time and testing time as well as minimizing the error the data segregation is the very nice techniques.

(3) In this work apart from the open price, close price, maximum, minimum and change some technical indicators are used and to calculate the indicator the window size is 12 which is commonly used by many economist. Technical indicators help for predicting the price and trend of price change which are proposed by many economists.

(4) There are many optimization techniques used by researchers to improve the model and to get the more accurate result out of many techniques GA, DE and PSO are commonly used techniques experimented by researchers. The WCA is a techniques inspired by nature like other three techniques and observed as physics chemistry based optimization technique. In this work it is observed that the result of WCA is similar with PSO but many times WCA shows better result than PSO. All the optimization techniques implemented in this experiment are population based and iteration based techniques

(5) Out of all the hybrid model the ELM-WCA combination is better than other hybrid models and it is also observed by segregating the data the performance of all the hybrid model shows better result than without data segregation which is observed from **Table 5** to **Table 10**.

VI. CONCLUSION AND FUTURE DIRECTION

The hybrid model comprising ELM with GA, DE, PSO and WCA with segregated and un-segregated dataset have been proposed to predict exchange rate prediction of USD to INR and SAR to INR data for 1 day ahead exchange rate prediction has done in this work. The model is compared with ANN and FLANN optimized with GA, DE, PSO and WCA with dataset segregation and without dataset segregation, which clearly establish that the model not only predict the open price but also able to guide the investor to invest in Forex market. The simulation result and performance of ELM trained by the above optimization technique perform better compared to ANN and FLANN. The machine trained with segregated shows better the better performance than without segregating the dataset. Many times WCA performs better than other optimization techniques. Hence, as a future work we have the intention to add the influencing factor to the data for better prediction result for high horizon.

REFERENCES

1. Yao, J. and Tan, C.L., 2000. A case study on using neural networks to perform technical forecasting of forex. *Neurocomputing*, *34*(1-4), pp.79-98.
2. Majhi, B., Rout, M., &Baghel, V. (2014). On the development and performance evaluation of a multiobjective GA-based RBF adaptive model for the prediction of stock indices. *Journal of King Saud University-Computer and Information Sciences*, *26*(3), 319-331.
3. Chen, Y., and Hao, Y. (2018). Integrating principle component analysis and weighted support vector machine for stock trading signals prediction. *Neurocomputing*, *321*, 381-402.
4. Rout, M., Majhi, B., Majhi, R., and Panda, G. (2014). Forecasting of currency exchange rates using an adaptive ARMA model with differential evolution based training. *Journal of King Saud University-Computer and Information Sciences*, *26*(1), 7-18.
5. Majhi, R., Panda, G., Majhi, B. and Sahoo, G., 2009. Efficient prediction of stock market indices using adaptive bacterial foraging optimization (ABFO) and BFO based techniques. *Expert Systems with Applications*, *36*(6), pp.10097-10104.
6. Nayak, R. K., Mishra, D., and Rath, A. K. (2015). A Naïve SVM-KNN based stock market trend reversal analysis for Indian benchmark indices. *Applied Soft Computing*, *35*, 670-680.
7. Das, S.R., Mishra, D. and Rout, M., 2017. A hybridized ELM-Jaya forecasting model for currency exchange prediction. *Journal of King Saud University-Computer and Information Sciences*.
8. Engle, R.F., 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society*, pp.987-1007.
9. AmirAskari, M. and Menhaj, M.B., 2016, January. A modified fuzzy relational model approach to prediction of Foreign Exchange rates. In *2016 4th International Conference on Control, Instrumentation, and Automation (ICCIA)* (pp. 457-461). IEEE.
10. Box, G. E., Jenkins, G. M., Reinsel, G. C., and Ljung, G. M. (2015). *Time series analysis: forecasting and control*. John Wiley & Sons.
11. Majhi, B., Rout, M., &Baghel, V. (2014). On the development and performance evaluation of a multiobjective GA-based RBF adaptive model for the prediction of stock indices. *Journal of King Saud University-Computer and Information Sciences*, *26*(3), 319-331.
12. Dash, R., Dash, P. K., &Bisoi, R. (2014). A self adaptive differential harmony search based optimized extreme learning machine for financial time series prediction. *Swarm and Evolutionary Computation*, *19*, 25-42.

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13. Ranjit, S., Shrestha, S., Subedi, S. and Shakya, S., 2018, October. Comparison of algorithms in Foreign Exchange Rate Prediction. In *2018 IEEE 3rd International Conference on Computing, Communication and Security (ICCCS)* (pp. 9-13). IEEE.
14. Abdual-Salam, M. E., Abdul-Kader, H. M., & Abdel-Wahed, W. F. (2010, March). Comparative study between Differential Evolution and Particle Swarm Optimization algorithms in training of feed-forward neural network for stock price prediction. In *2010 The 7th International Conference on Informatics and Systems (INFOS)* (pp. 1-8). IEEE.
15. Rehman, M., Khan, G.M. and Mahmud, S.A., 2014. Foreign currency exchange rates prediction using cgp and recurrent neural network. *IERI Procedia*, *10*, pp.239-244.
16. Das, S. R., Panigrahi, P. K., Das, K., and Mishra, D. (2012). Improving rbf kernel function of support vector machine using particle swarm optimization. *International Journal*, *2*.
17. Dymova, L., Sevastjanov, P., and Kaczmarek, K. (2016). A Forex trading expert system based on a new approach to the rule-base evidential reasoning. *Expert Systems with Applications*, *51*, 1-13.
18. Lahmiri, S. (2017). Modeling and predicting historical volatility in exchange rate markets. *Physica A: Statistical Mechanics and its Applications*, *471*, 387-395.
19. Naeini, M.P., Taremian, H. and Hashemi, H.B., 2010, October. Stock market value prediction using neural networks. In *2010 international conference on computer information systems and industrial management applications (CISIM)* (pp. 132-136). IEEE.
20. Briza, A. C., & Naval Jr, P. C. (2011). Stock trading system based on the multi-objective particle swarm optimization of technical indicators on end-of-day market data. *Applied Soft Computing*, *11*(1), 1191-1201
21. Dehuri, S., Roy, R., Cho, S. B., & Ghosh, A. (2012). An improved swarm optimized functional link artificial neural network (ISO-FLANN) for classification. *Journal of Systems and Software*, *85*(6), 1333-1345.
22. Chakravarty, S., & Dash, P. K. (2012). A PSO based integrated functional link net and interval type-2 fuzzy logic system for predicting stock market indices. *Applied Soft Computing*, *12*(2), 931-941.
23. Das, S., &Suganthan, P. N. (2011). Differential evolution: A survey of the state-of-the-art. *IEEE transactions on evolutionary computation*, *15*(1), 4-31.
24. Hachicha, N., Jarboui, B., &Siarry, P. (2011). A fuzzy logic control using a differential evolution algorithm aimed at modelling the financial market dynamics. *Information Sciences*, *181*(1), 79-91.
25. AlRashidi, M. R., & El-Hawary, M. E. (2009). A survey of particle swarm optimization applications in electric power systems. *IEEE transactions on evolutionary computation*, *13*(4), 913-918.
26. Paterlini, S., &Krink, T. (2006). Differential evolution and particle swarm optimisation in partitional clustering. *Computational statistics & data analysis*, *50*(5), 1220-1247.
27. Das, S. R., Mishra, D., & Rout, M. (2017). A Survey on Impact of Bio-inspired Computation on Stock Market Prediction. *Journal of Engineering Science & Technology Review*, *10*(3).
28. Das, S. R., Mishra, D., & Rout, M. (2018). A hybridized ELM using self-adaptive multi-population-based Jaya algorithm for currency exchange prediction: an empirical assessment. *Neural Computing and Applications*, 1-24.
29. Huang, G. B., Zhu, Q. Y., &Siew, C. K. (2004). Extreme learning machine: a new learning scheme of feedforward neural networks. *Neural networks*, *2*, 985-990.
30. Eskandar, H., Sadollah, A., Bahreininejad, A., &Hamdi, M. (2012). Water cycle algorithm–A novel metaheuristic optimization method for solving constrained engineering optimization problems. *Computers & Structures*, *110*, 151-166.
31. http://in.investing.com/currencies/usd-inr-historical-data
32. http://in.investing.com/currencies/sar-inr-converterthese

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