Mining Foreign Exchange Rates using Bio-Inspired Neuralnets

Puspanjali Mohapatra, Soumya Das, Ashutosh Bhoi, Tapas Kumar Patra

***Abstract*— To *calculate the profit and risk associated with international transactions, currency exchange forecasting is highly desirable. If the forecasting is done accurately then the transaction can give maximum profit.To perform the above task several statistical and machine learning methods have already been proposed by the researchers in the literature. However this paper presents a comparative study between two predominantly used bio-inspired optimization techniques namely particle swarm optimization (PSO) and differential evolution (DE) to forecast the currency exchange rates for one day and one week ahead. For both the algorithms the functional link artificial neural network (FLANN) model is taken into consideration. In the proposed model DE and PSO are used as the evolutionary algorithms for supplementing the optimized value of unknown parameters of the FLANN model. Root mean square error (RMSE) and mean absolute percentage error (MAPE) are considered for performance evaluation of the proposed model. Here JAPANESE YEN(JPY), INDIAN RUPEE(INR), FRENCH FRANC(FRF) to US DOLLAR(USD) datasets are considered as the training and testing datasets.The results of FLANN-DE and FLANN-PSO are analyzed.The simulation results show that FLANN-DE outperforms the FLANN-PSO model regarding the accuracy , convergence speed over different time spans.*

Index Terms*— *FLANN, PSO, DE, Currency exchange rate prediction.

I. INTRODUCTION

The currency exchange rate is the purchasing power of a currency with respect to another. To evaluate the profit and risk associated to international transactions, accurate currency exchange prediction is highly desirable. The advantage of successful currency exchange rate prediction is to get financial benefits and to facilitate strategic financial planning. Prediction of various currency exchange rates is influenced by many economical, political and psychological factors and hence it is a complex task to predict these values. Prediction methods can be broadly classified into four types, such as fundamental analysis,statistical analysis,traditional time series analysis and the latest and most powerful machine learning techniques. To overcome the limitation of statistical based methods of predicting exchange rates, soft and evolutionary computing based techniques have been introduced in literature. In one of the referenced paper artificial neural networks has been used for forecasting currency rates and the effectiveness is compared with that of standard ARIMA model and partial adaptive estimation technique. The comparison shows that forecasting with ANN gives better results than the other methods [1].

For efficient exchange rate forecasting a cascaded functional link artificial neural network model has been designed which employs a less complex structure and performs superior to the LMS based ANN [2]. Fuzzy interval neural network can provide more robust prediction results [3]. GA can be used as a parameter optimization method to determine the near optimal architecture and parameters of a neural network with minimal effort and time [4]. Particle swarm optimization algorithm is applied in the probabilistic neural network to optimize the smoothing factors and gives better performance [5][12-15]**.** Another powerful and most widely used machine learning technique i,e Support vector machine (SVM) accurately forecast time series data when the underlying system processes are typically non-linear and non-stationary[6]. ARMA-DE is gives the best result in time series prediction when it is compared with other existing evolutionary based algorithms[7].WFLANN gives better result than WANN for time series value forecasting [8].RBF based neural network performs better than MLP[9]. Neural network hybridised with self-organizing modelling outperform the individual methods[10].

This paper presents a comparative study of particle swarm optimization and differential evolution hybridised with FLANN model.

Section 2 discusses about Functional link artificial neural network (FLANN), section 3 and section 4 discusses about Particle swarm optimization and differential evolution respectively. The different performance evaluation criteria and results are discussed in section 5 and 6. Finally conclusion is drawn in section 7.

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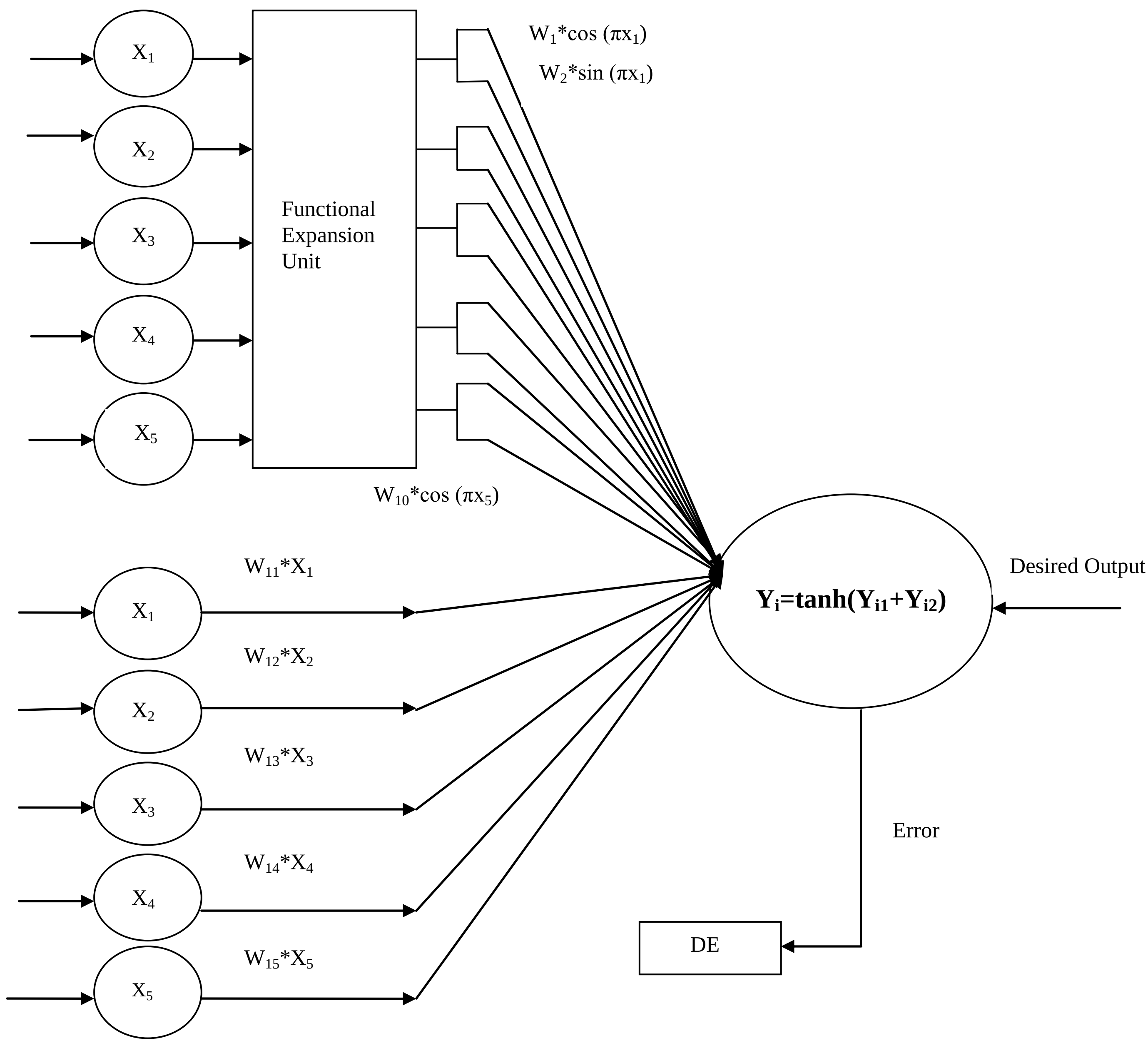

Figure 1: FLANN-DE model

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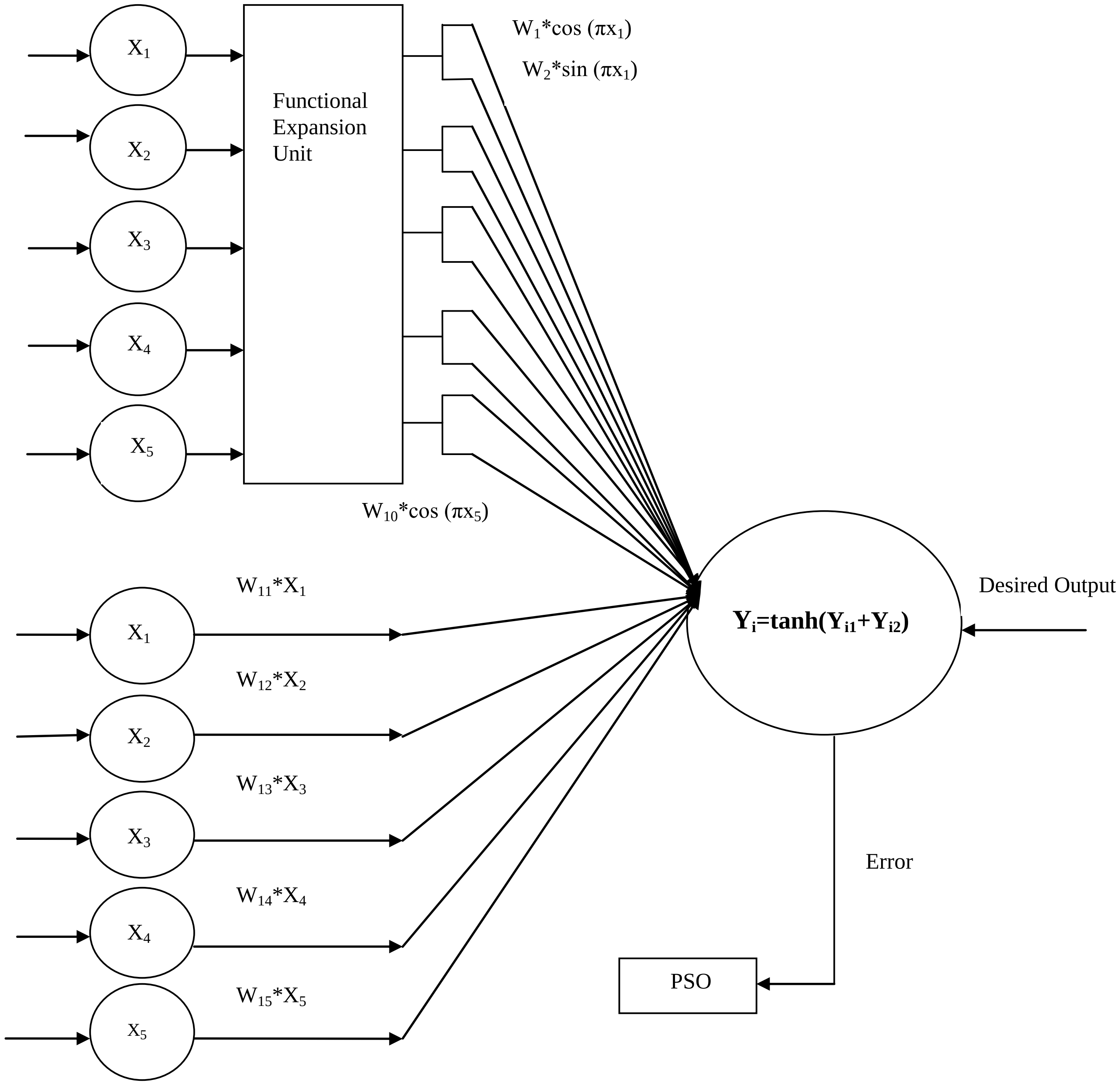

Figure 2: FLANN-PSO model

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II. INTRODUCTION TO FLANN:

Neural network (NN) represents an important paradigm for classifying patterns or approximating complex nonlinear process dynamics.Advanced NN based model such as multilayer perceptron (MLP), radial basis function network (RBFN), support vector machine (SVM) gives better results than simple ANN at the cost of higher complexity in the structure and computation of the network due to the presence of hidden layer. So to minimize the complexity and computational cost, an efficient but least complex NN model has been introduced called functional link ANN(FLANN).This single layer ANN provides high convergence rate and low computational cost.

III. PARTICLE SWARM OPTIMIZATION (PSO):

Particle swarm optimization is one of the leading optimization methods which is inspired by birds and fishes to exhibit co-ordinated, collective behaviour. It was originally proposed by Eberhart and Kennedy in 1995. This method can be generalised as a behavioural model in which each agent follows three rules:

Separation: Each agent tries to move away from its neighbours if they are too close

Alignment: Each agent tries to move towards the average heading place of its neighbours.

Cohesion: Each agent tries to move towards the average heading place of the swarm.

Each particle in pso has a position vector as well as a velocity vector represented by $X_i=[x_1, x_2, \ldots, x_i]^T$ and $V_i=[v_1,v_2,\ldots v_i]$ spread over a D-dimensional search space. For each particle there is a personal best position (pBest) represented as $Pb=[pb_i,pb_i,\ldots,pb_i]^T$. the global best position(gBest) of all particles, is determined by taking all pbest into consideration. Given for each particle a position vector, velocity vector, personal best vector as well as global best vector, the velocity vector for the next itearation is calculated. From the recent velocity vector and previous position vector the position vector for the next itearation is calculated.

The pseudocode for pso can be written as follows:

1. For each particle
   initialize particle
 END.
2. Do
   For each particle
     Calculate fitness value
     If the fitness value is better than the best fitness value (pBest) in history
       set current value as the new pBest
   End
3.Choose the particle with the best fitness value of all the particles as the gBest
4. For each particle
   Calculate particle velocity according to the equation

$$\mathbf{V_i^{t+1}=V_i^t+\psi_1 U_1^t(Pb_i^t-X_i^t)+\psi_2 U_2^t(Gb_i^t-X_i^t)} \qquad (1)$$

Pb-particle best (pBest)
Gb-global best (gBest)
U_1, U_2 –random values
V_i^{t+1} - velocity of particle 'i 'at 't+1' iteration
X_i^t - position of particle 'i' at 't' iteration

Update particle position according to the following equation

$$\mathbf{X_i^{t+1}=x_i^t+V_i^{t+1}} \qquad (2)$$

End

While maximum iterations or minimum error criteria is not attained.

It can be noted here that $\boldsymbol{\psi_1 U_1}$ as well as $\boldsymbol{\psi_2 U_2}$ corresponds to the randomness of the loop. So these parameters must be carefully chosen to land in a semi-optimal solution. $\boldsymbol{\psi_1}$ and $\boldsymbol{\psi_2}$ are the acceleration constants determing the importance of personal best and global best.Lower values allow particles to roam far from target regions while high values result in abrupt movements. Each acceleration constant is usually taken to be 2.0 for almost all applications. $\mathbf{U_1}$ and $\mathbf{U_2}$ are two random functions in the range [0, 1].

IV. INTRODUCTION TO DIFFERENTIAL EVOLUTION (DE) ALGORITHM:

Differential evolution algorithm scheme was proposed by Storn and Price in 1995 as a population based global optimization algorithm[11].DE is used for many real life practical problems in the area of time series analysis ,image segmentation, pattern recognition ,web page classification etc ,whose objective functions are non-differentiable, non-linear, non-continuous ,multidimensional and many local minima constraints.The DE algorithm after initialization has three main operations i,e mutation, crossover and selection before finishing due to a termination condition.DE gives more priority to mutation as compared to crossover unlike other evolutionary algorithm. The fundamental idea behind DE is a specific way of generation of trial parameter vectors. This is achieved using mutation and crossover to generate new trial parameter vectors. Selection then determines which of the vectors will survive to be used in the next generation. Through repeated cycles of mutation, crossover and selection, DE is able to guide the search towards the vicinity of the global optimum

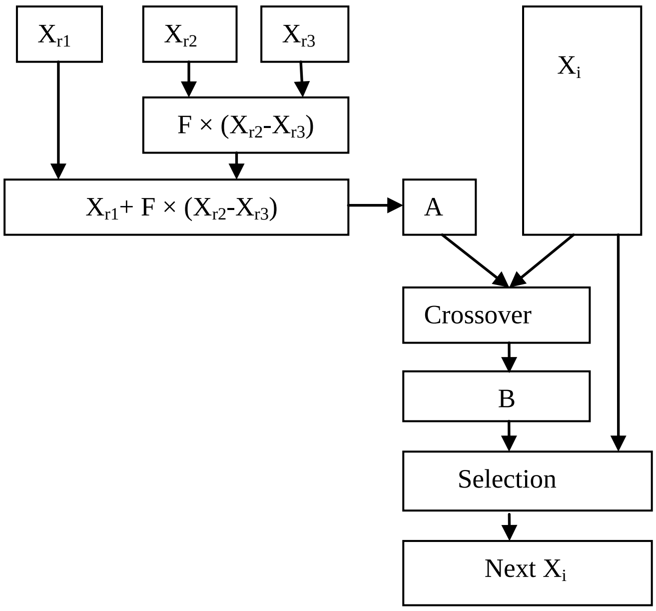

Figure 3: Flow diagram for Differential Evolution Algorithm

4.1. Initialization

DE generates an initial population size of N_P at G^{th} generation,D-dimensional parameter vectors called individual which encode the candidate solution.

$X_{i,G} = [X_{1,i,G}, X_{2,i,G} \ldots\ldots\ldots\ldots\ldots X_{D,i,G}]$

Where $i=1,2,\ldots..N_P$ s,t $N_P \geq 4$

4.2. Mutation operation

For each target vector $X_{i,G}$ one mutant vector $A_{i,G}$ has to be produced by using the mutation operation, where it first select three random vectors $X_{r1,G}$, $X_{r2,G}$, $X_{r3,G}$ such that the indices $i \neq r1 \neq r2 \neq r3$ which belongs to N_P.

So the associated mutant vector is $A_{i,G} = X_{r1,G} + F \times (X_{r2,G} - X_{r3,G})$ (3)

Where the mutation factor F is a constant which lies in between [0,2].

$$A_{i,G} = X_{r1,G} + F^* [X_{r2,G} - X_{r3,G}] \quad (4)$$

4.3. Crossover/Recombination operation

To complement the differential mutation search strategy, DE then uses a crossover operation, in which the mutated individual is mated with the principal parent and generates the offspring or "trial individual". This crossover operation for classic DE as reviewed here is known as binomial crossover.

$$\text{The trial vector } B_{i,j,G} = \begin{cases} A_{i,j,G} & \text{if } rand_j \leq CR \text{ or } j = rn(j) \\ X_{i,j,G}, & \text{otherwise} \end{cases} \quad (5)$$

J=1, 2,........,D

$rand_j$=[0,1]

rn(j)= a randomly chosen index from 1, 2,......., D

CR=Crossover ratio is constant in the range[0,1].

4.4.selection operation

Here in this phase the selection is made between the target and trial vector for the next generation.

$$X_{i,G+1} = \begin{cases} B_{i,G+1}, & \text{if } F(B_{i,G+1}) \leq F(X_{i,G}) \\ X_{i,G} & \text{Otherwise} \end{cases} \quad (6)$$

$i = 1, 2\ldots\ldots..,N_P$

The above steps are repeated until some stopping criteria are met.

V.SIMULATION STUDY

5.1 Dataset for training and testing:

The daily exchange rate of various currency exchange i.e. Us Dollar (USD) to Indian Rupee (INR) , France Franc (FRC) and Japanese Yen (JPY) are considered here as the experimental data. All these data are obtained from www.finance.yahoo.com and all the models are predicting for 1-day and 1-week ahead. All the inputs are normalized within a range of [0, 1] using the following formula.

$$X_{norm} = \frac{X_{orig} - X_{min}}{X_{max} - X_{min}} \quad (7)$$

Where X_{norm} is the normalised value, X_{orig} is the actual currency value, X_{max} is the maximum value and X_{min} is the minimum value.

The details of dataset are described in table-1.

Table 1: Details of datasets used:-

Currency datasets	Duration	Range	Training sample	Testing sample
US Dollar(USD) to Indian Rupee(INR)	01/01/2008 to 31/12/2013	1827	1300	520
US Dollar(USD) to France Franc(FRF)	01/01/2008 to 31/12/2013	1827	1300	520
US Dollar(USD) to Japanese Yen(JPY)	01/01/2008 to 31/12/2013	1827	1300	520

5.2 Training and testing of the forecasting model

Training of the FLANN model is carried out using the DE and PSO algorithm given in Section 3 and 4 and the optimum weights are obtained. Then using the trained model, the forecasting performance is tested using test patterns for one-day, one-week ahead. MAPE and RMSE (as defined in table 2) is computed to compare the performance of various models.

Table 2: Performance evaluation criteria

Evaluation criteria	Formula used
Root mean square error(RMSE)	$RMSE = \sqrt{\frac{\sum_{m=1}^{M}(y(m) - d(m))^2}{M}}$
Mean absolute percentage error(MAPE)	$MAPE = \frac{1}{M}\sum_{m=1}^{M}\frac{\lvert y(m) - d(m)\rvert}{y(m)} \times 100$

VI. RESULTS AND DISCUSSION:

6.1 Results of FLANN-PSO model

Table 3: Performance evaluation of PSO based FLANN:

Currency Datasets	Duration of prediction	Details during training		Details during testing	
		RMSE	MAPE(%)	RMSE	MAPE(%)
USD to INR	1-day	0.0023	1.0024	0.0042	1.4819
	1-week	0.0062	1.2941	0.0040	1.4465
USD to FRF	1-day	0.0069	1.7218	0.0130	1.1962
	1-week	0.0056	1.5287	0.0042	1.4568
USD to JPY	1-day	0.0079	1.1943	0.0049	1.1971
	1-week	0.0026	1.2021	0.0039	1.2105

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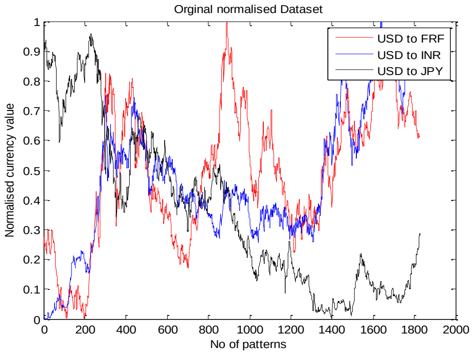

Figure 4: original normalised datasets within range[0,1]

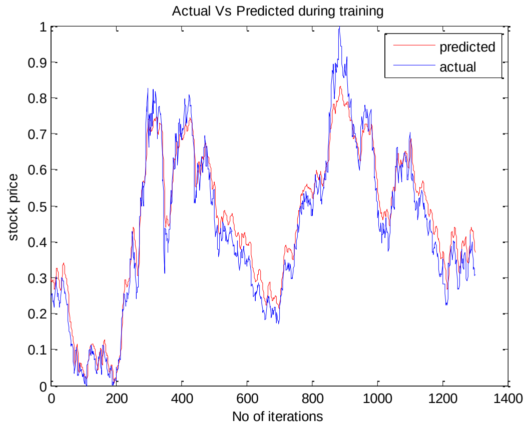

Figure 5: actual versus predicted of USD to JPY for 1day ahead currency rate prediction during training.

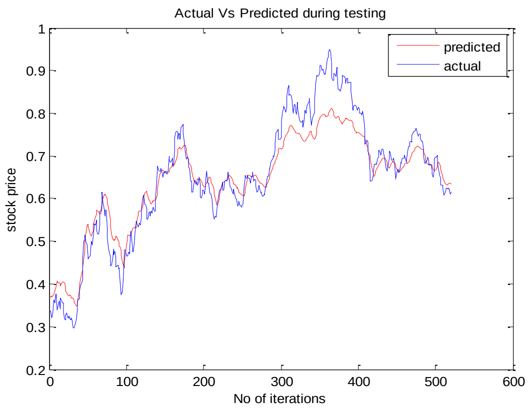

Figure 6: actual versus predicted of USD to JPY for 1day ahead currency rate prediction during testing

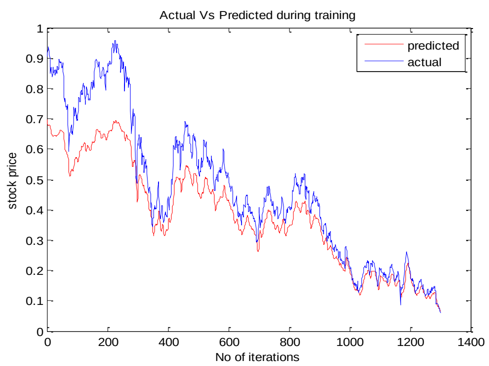

Figure 7: actual versus predicted of USD to FRF for 1day ahead currency rate prediction during training

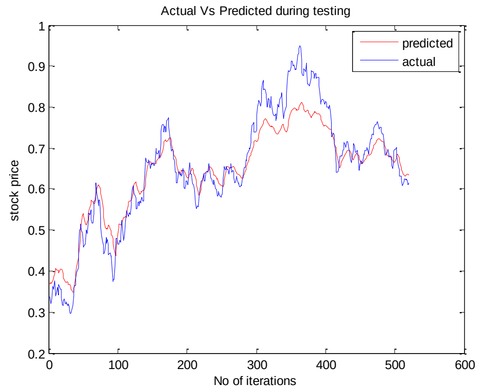

Figure 8: actual versus predicted of USD to FRF for 1day ahead currency rate prediction during testing

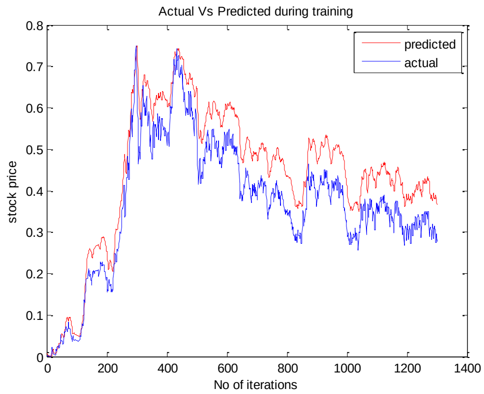

Figure 9: actual versus predicted of USD to INR for 1 week ahead currency rate prediction during training

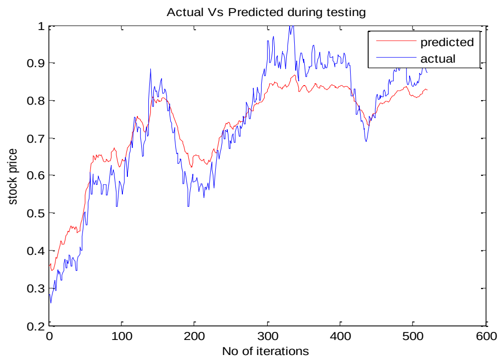

Figure 10: actual versus predicted of USD to INR for 1 week ahead currency rate prediction during testing

6.2 Results of FLANN-DE model

Table 4: Performance evaluation of DE based FLANN:

Currency Datasets	Duration of prediction	Details during training		Details during testing	
		RMSE	MAPE(%)	RMSE	MAPE(%)
USD to INR	1-day	0.0021	1.1708	0.0019	1.0812
	1-week	0.0043	1.2743	0.0035	1.2321
USD to FRF	1-day	0.0027	1.1372	0.0023	1.0096
	1-week	0.0039	1.2967	0.0032	1.2198

USD to JPY	1-day	0.0024	1.1084	0.0016	1.0907
	1-week	0.0052	1.2829	0.0046	1.2451

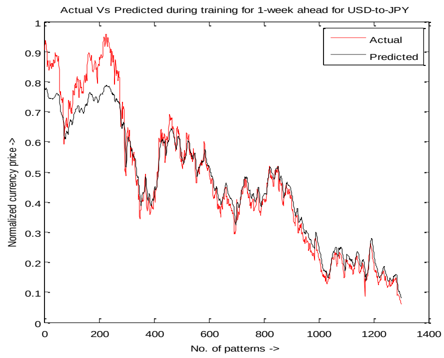

Figure 11: actual versus predicted during training USD to JPY for 1week ahead currency rate prediction

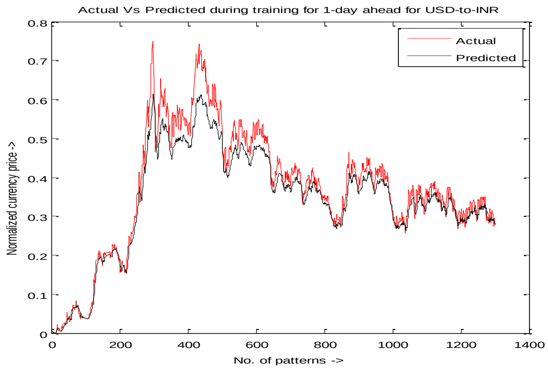

Figure 12: actual versus predicted during testing of USD to INR for 1day ahead currency rate for 1week ahead currency rate prediction

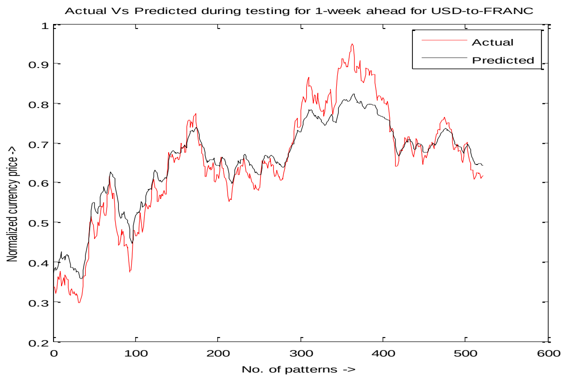

Figure 13: actual versus predicted during testing of USD to FRF for 1week ahead currency rate for 1week ahead currency rate prediction

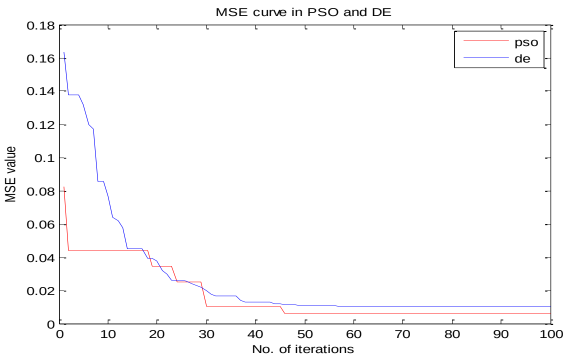

Figure 14: MSE curve comparison of FLANN-PSO and FLANN-DE models.

VI. CONCLUSION

In this paper, a FLANN model is proposed. A set of inputs are functionally expanded through the FLANN upper part where as the same set of inputs are passed to the lower part of the same FLANN model.Fast and hybrid training algorithm like PSO and DE are introduced to optimize all the unknown weight parameters. Simulation results showed that FLANN-DE model performed better in comparison to FLANN-PSO model.From the results of RMSE and MAPE during different duration, it can be concluded that the proposed FLANN-DE model is best forecasting 1 day ahead USD to INR.

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