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FOREX trend analysis using machine learning techniques: INR vs USD currency exchange rate using ANN-GA hybrid approach

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ABSTRACT

Time series is the analysis of historical data which is used to analyse the past trend and then to determine the future directions. This helps organizations to make a proper plan and develop the appropriate strategic decision in the right direction. One such example is the analysis of the currency exchange rate. Prior information on the currency exchange rate or currency conversion rate helps the organization to make a better decision while trading in the international market. This is also called FOREX trend analysis. This study attempts to analyse the applicability of machine learning techniques in predicting the currency exchange rate in a very short-term period particularly in the case of Indian Rupees (INR) Vs U.S Dollars (USD). Two approaches have been implemented 1) A simple Artificial Neural Network (ANN) model and 2) A hybrid model of ANN with a Genetic Algorithm (ANN-GA) where the ANN weight matrix is being optimized using Genetic Algorithm (GA). Finally, the results of both methods have been compared in terms of RMSE values obtained from their implementations.

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1. Introduction

The conversion of currency from one form to another is known as forex or foreign exchange. It is also known as FX trading. It deals with the conversion of currency of one country into the currency of another country. Forex trading is one of the most actively traded markets in the world, with an average daily trading volume of $5 trillion. There are many reasons for forex trading however, profit-making is one of the major reasons. This specific reason makes the traders know the trend in the exchange movements and advanced knowledge helps the investors in maximizing the profit. Though there are several factors like market sentiment, news reports, Govt. policies largely affect the exact prediction of future trends still based on historical data a standard prediction could be possible up to some extent. This type of prediction based on historical data is known as time series analysis.

Time series data is a sequence of data in a fixed interval over some time. The analysis that deals with these data are called time series analysis. The scope of the study of the time series is not only very broad but also very significant for business entities. Various researchers have completed their work in various fields using specific techniques. Nowadays, Neural Network (NN) is used mainly in time series forecasting. However, when trained with the backpropagation algorithm, NN suffers from certain limitations, such as getting stuck in local minima. This is a common problem in using ANN for time series data. Authors like Singh et. al. [1], Gupta et. al. [2], Chauhan et. al. [3], Sarangi et. al. [4], Singla et. al. [5], Sinha et.al. [6] have reported this problem in their papers and also have suggested the use of the hybrid model as a solution. This paper will investigate the applicability of the Genetic Algorithm (GA) and Backpropagation algorithm to forecast the conversion rate for the Indian Rupees vs. United States Dollar.

The paper consists of four major parts. i) Detailed review and analysis of existing works, ii) Implementation of ANN, iii) Implementation of GA-ANN and iv) Result analysis with conclusions.

2. Review of related works

According to Nanayakkara et. al. [7], the regular exchange rate of the US Dollar against Sri Lankan Rupee (USD vs LKR) has been predicted using GARCH and Back Propagation techniques. The

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results revealed that the neural network-based forecasting model is better suited and given 82% of predictive accuracy with learning levels of 0.005 and momentum of 0.8 while the GARCH model was found to be the best model in a time series approach with 69% predictive accuracy.

Kiplagat et al. [8] addressed the application of ANN in Kenyan currency modeling against the four major currencies of the world: US dollar (USD), Japanese Yen (JPY), European Euro (EUR) and Great Britain Pound (GBP). The main focus of this work was to establish neural networks and evaluate the model for the volatile exchange rates in Kenya. This model, however, showed a low NN model error value that can be taken for simulation and predictive indicators.

Daniya Tlegenova [9] applied the ARIMA model for annual exchange rate forecasting and used time series analysis to compare the actual data with the existing forecasts. Consequently, the overall increase for all currencies was more than 44 percent of the upward trend, and the MAPE values were the smallest and most powerful.

Kamruzzaman and Sarker [10] built and examined various ANN forecasting models using Scaled Conjugate Gradient (SCG), Standard Backpropagation (SBP), and Backpropagation, using Australian Foreign Exchange Bayesian regularisation to estimate six different currencies opposite to the Australian dollar. Results calculated in terms of different performance parameters namely; NMSE, MAE, DS, CU, CD between 35 weeks and 65 weeks. The results showed that neural network models performed better than the linear ARIMA model.

Venugopal and Raghavender [11] proposed a model based on ARIMA and feed-forward networks to investigate the outcomes of INR / USD forecasts. The FFNN model has also outperformed better than the ARIMA Model. The results showed a decline in the exchange rate and a rise in the value of rupee in the future.

Baffour et. al. [12] have examined the growth of hybrid neural network model in currency exchange rate volatility forecasting. The currency being used is CAD / USD, AUD / USD, EUR / USD, CHF / USD, and GBP/USD respectively. An experimental proof indicated that all applicable test models were remarkably superior to the ANN-GJR hybrid model. A major increase in forecast accuracy was observed by using the MAD, MSE, and MAPE scales of the ANN hybrid model as opposed to regular models.

Mustafa and Ismail [13] proposed a novel approach based on SVM and genetic algorithm for data input and trade strategy. Input data comprises of technical indicators created as trend-deterministic from currency price data (i.e. open, good, low, and near prices) and representation of those technical indicators. The results of the experiments indicate that the use of trend heuristic technical indicator signals in conjunction with raw data usually enhances the productivity and leads to greater profits by dynamically changing the input data to each period of the trade. Outcomes also illustrate that the use of a strong trading strategy among currency pairs improves the average analytical accuracy and revenue of the model.

Moosa and Burns [14] employed traditional macroeconomic models to estimate long-term exchange rates. The purpose of the work was to beat out a spontaneous move in-of-sample forecast, in terms of the inertial symmetry of the analysis as well as to achieve the uniformity in prediction. The experiment is carried out using Canadian dollar / US dollar, Japanese yen / Canadian dollar (JPY / CAD), British pound / US dollar (GBP / US dollar), Japanese yen / British pound (JPY / GBP), British pound / Canadian dollar (GBP / CAD), respectively. For all currencies, monthly usage was spanning between 1997 and 2013. For the years 2007–2013, data from 1997 to 2007 was used for analysis and testing. The highest average accuracy is 72 percent, which is used for GBP / USD every 6 months and 12 data points. Quarterly predictions on the same data observed 56 percent correct and monthly predictions 48 percent accurate. The lowest recorded accuracy is 38 percent for every 6 months on JPY / USD data points.

Jae huei and Arun Kumar [15] explored how to assess long-term currency exchange rates and also to define prime factors for policy-makers in Forex markets. The research would assist decision-makers in taking positions on the competitive Forex market. Results indicated that the economic self-regressive moving average model use defined prime variables to predict exchange rates, not from a business or economic perspective as a whole. When making a purchase, it helps to aspire traditional, normative (and probably correct) a purchase decision.

Zheng and Xiao [16] introduced the DBN concept and its function and examined the DBN parameter's learning law. It surveyed the impact of input nodes, hidden nodes, and hidden layer numbers on DBN using the data of the INR / USD and CNY / USD exchange rates. The paper also reported that DBN can also be used by predicting foreign exchange data through DBN to forecast high-frequency trading.

A significant amount of research work has been done in this field. Apart from the works discussed above Gupta and Kashyap [19], Zhang [20], Rout et. al. [21], Davis et. al. [22], Perwej and Perwej [23], Kumar [24], Roudgar [25], Tudela [26], and Dell'Ariccia [27] had also proposed different solutions for forecasting exchange rates for different currencies. Table 1 shows a summary of the research works carried out with their outcomes.

The table above summarizes some of the related works with the focus on the techniques and the data set used. Some key findings from the above review that motivates to carry forward this work are:

a) Out of many techniques, ANN is one of the most popular techniques in forecasting currency exchange.
b) There is no fixed rule to decide the number of sample data.
c) As low as 25 days samples could also be used to forecast the future currency exchange rate.
d) Hybrid models such as SVM-GA produce better accurate results.

Detailed descriptions of the extracts from the review in graphical form are given in the Figs. 1–3.

(i) Publications based on error calculation methods between the years 1991 and 2020 considered in this research work as shown in Fig. 1.
(ii) Frequency of publications considered in this work
(iii) Techniques-wise segregation of the publications used in the bibliometrics.

ANN mainly depends on the back-propagation algorithm for weight optimization and one critical drawback of the backpropagation method is the local minima problem. Hence, a hybrid approach such as ANN-GA could be a better choice to overcome the local minima problem and will also increase the efficiency of the ANN models.

3. Objective

The objectives of this work are:

a) To implement an ANN model in forecasting the currency exchange and in particular INR Vs USD.
b) To propose and implement a hybrid model using ANN and GA for the same data set.

Table 1
A summary of the research works and their outcomes.

S. No. [Reference Number]	Techniques	Data set	Duration	Findings
1 [7]	GARCH and Feed-forward neural network with Backpropagation	USD vs LKR	2007 to 2011	ANN performs better when compared with the GARCH model.
2 [8]	Multilayer Perceptron neural networks with backpropagation	KES vs USD, JPY, EUR, GBP	2005 to 2017	A high potential of ANN and Low error value.
3 [9]	ARIMA	USD/KZT, EUR/KZT, SGD/KZT	2006 to 2014	Effectiveness of the model was compared and MAPE values were the smallest among all
4 [10]	ANN-based forecasting model using Standard Backpropagation (SBP), Scaled Conjugate Gradient (SCG) and backpropagation with Bayesian Regularisation	USD, GBP, JPY, SGD, CHF, NZD	1991 to 2002	Performance of SCG based ANN model was better than ARIMA model and another model
5 [11]	Box-Jenkins Methodology and Neural Networks	INR/USD	2012 to 2013	The exchange rate is declining and the value of rupee is increasing soon. NN performs well.
6 [12]	Artificial neural network & GJR-GARCH models	AUD/USD, EUR/USD, CHF/USD, CAD/USD, and GBP/USD.	–	The hybrid ANN-GJR model reduces the error by 90%.
7 [13]	SVM and Genetic algorithms	EUR/USD, GBP/CHF	2010 to 2015	Raw data increases overall efficiency and contributes to increased profits by dynamically adjusting the input data
8 [14]	Linear Regression, monetary model	CAD/USD GBP/CAD GBP/USD JPY/CAD JPY/GBP JPY/USD	2003 to 2014	The highest reported accuracy is 72% GBP / USD while forecasting for every 6 months and 12 data points. quarterly forecasts are 56% accurate and monthly forecasts 48% accurate.
9 [15]	–	AUD/USD	1988 to 2010	To predict future exchange rates using specified prime factors revealed good results.
10 [16]	DBN (Deep belief network)	INR / USD and CNY / USD	2006 to 2016	The predictive accuracy decreases with the rise in the forecast duration. Thereafter the predictive value indicates some divergence.
11 [17]	LSTM	INR/USD	25 days	LSTM techniques produced better accuracy compared with neural networks
12 [18]	ANN, Autoregressive and random walk	INR/USD	–	A neural network has a superior in-sample forecast than linear autoregressive and random walk models.
13 [20]	ARIMA and ANN	British pound/US dollar and Wolf's sunspot data, the Canadian lynx data	Canadian lynx data series (1821 to 1934). Sunspot series (1700 to 1987). Weekly BP/USD exchange rate series (1980 to 1993).	An efficient way to improve forecasting.
14 [21]	ARIMA	Indian Rupees, Japanese Yen and British Pound	1973 to 2005	Provides the best values for forecasting rates.
15 [22]	ANN models	Canadian/US Dollar	1992 to 1994	To build a model for optimizing trading profits, the model should be trained using an objective function designed to maximize benefit rather than predict the accuracy of the classification of shifts in direction
16 [23]	ANN	INR/USD	1989 to 2009.	ANN gives better results
17 [24]	Local Whittle test, Autocorrelation function (ACF)	USD/INR	2009 to 2011	Shows good results on non-overlapping samples.
18 [27]	ANN and AI	INR-USD and GBP-USD	1999 to 2013.	ANN to forecast near-future exchange rates as it must look after the noisy data and the unpredictable behavior.

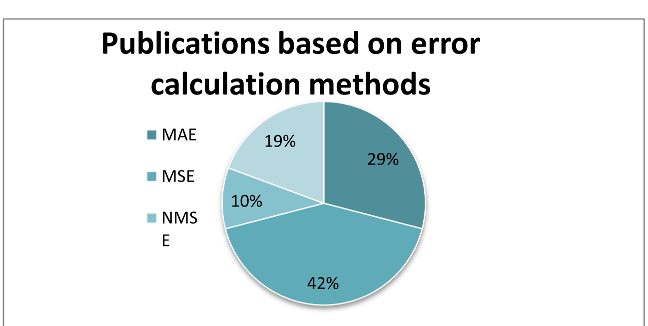

Fig. 1. Publications based on error calculation methods.

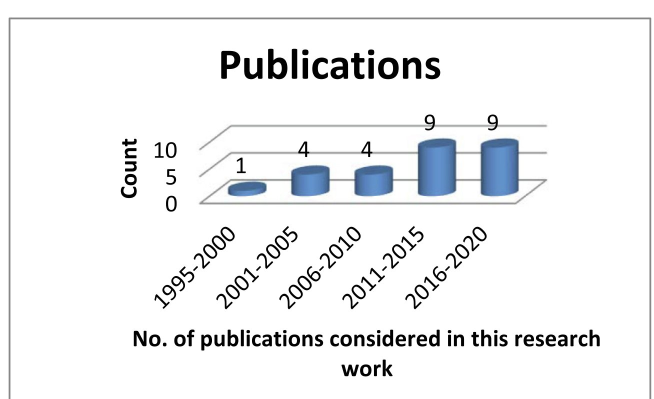

Fig. 2. No. of publications considered in this research work.

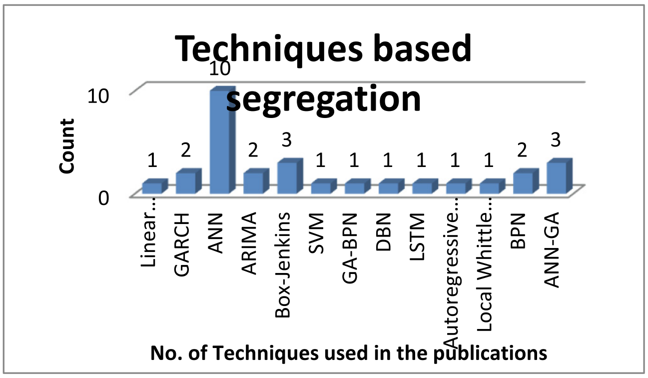

Fig. 3. No. of Techniques used in the publications.

c) To compare the effectiveness of both the models using INR Vs USD currency exchange values.

3.1. Data

The data included in this work is the data of currency conversion 36 days between August and September 2019.

4. Methodology and implementation strategy

The methodology consists of two different approaches: Implementation of ANN with backpropagation algorithm and Implementation of ANN-GA approach.

4.1. ANN implementation

ANN is very popular in regression and classification problems. It is very capable to conform to the real world. However, while using ANN, it is very difficult to decide a stable network structure for a particular problem. This can only be decided by implementing various architectures with varying parameters such as network structure, learning rate, and momentum. Hence, in this work, several experiments were carried out to find the best suitable architecture. Finally, three architectures 6-6-1, 4-4-1, and 3-3-1 were considered.

As the above diagram shows, a three-layered network is used to carry out all experiments related to ANN. The implementation strategy with model details of one of these architectures is given in Fig. 4 below.

The implementation details and results are given in Fig. 5.

4.2. Model summary

As discussed above, several different architectures were implemented to select the best suitable architecture. Finally, the architecture 3-3-1was found to be most suitable. The model summary for the same is given in the Table 2 below.

Forecasting results are given in Table 3.

4.3. Limitations of ANN

Besides the advantages, ANN also brings some limitations along with it. Some of these are:

- It does not provide any information about the relative significance of the various parameters
- It requires a large diversity of training for operation.
- It is very difficult to interpret the overall structure of the network.
- May stuck at local minima and also having over-fitting problems.

4.4. Solution

From the review of the existing works, it was found that hybridization of ANN with other techniques may increase the efficiency of ANN hence, in this work a hybrid model of ANN-GA has been implemented. In this model, the weight matrix of the ANN model has been optimized by using the Genetic algorithm. The detailed implementation plan is given in the following section.

4.5. Implementation of the proposed model (ANN-GA)

It has been observed from Table 2, that the 3-3-1 architecture provided the lowest RMSE for ANN implementation. Thus, the architecture 3-3-1 was considered for optimization using a genetic algorithm. The implementation plan is illustrated below in Fig. 6.

The random population is responsible for creating initial weights for the Genetic Algorithm. GA operations are then applied to find the matrix with the fittest weight. This matrix of weight is then used as an initial matrix of weight for neuron networks. When

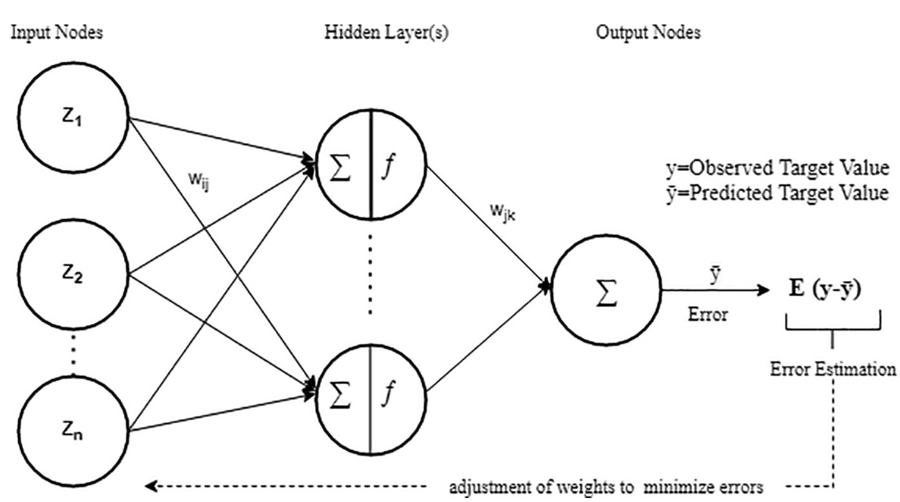

Fig. 4. ANN Architecture.

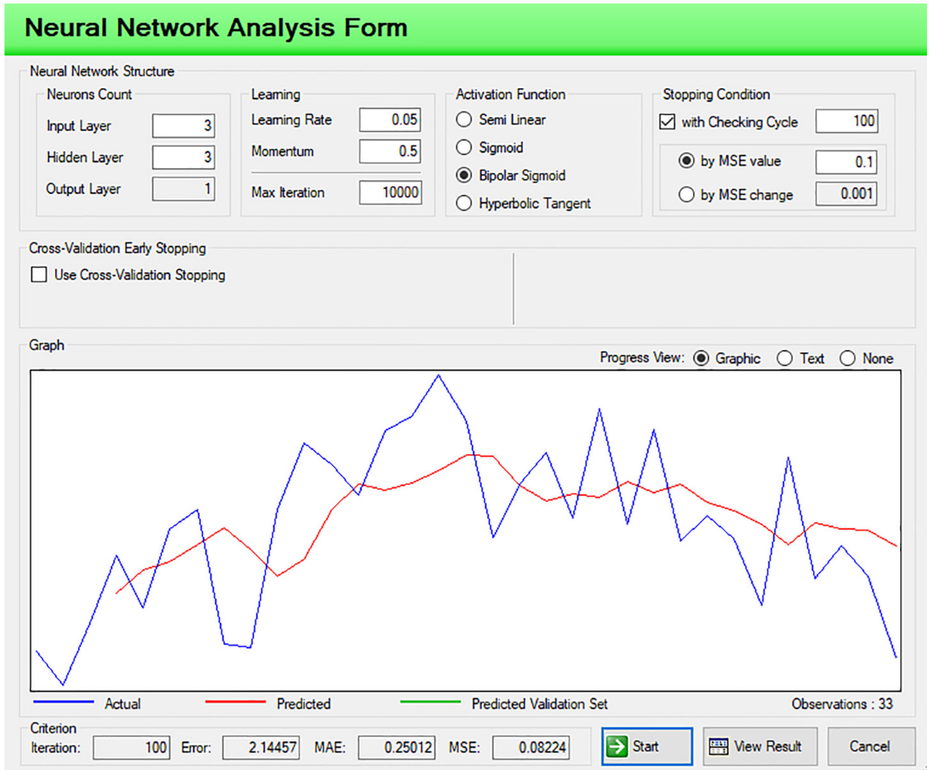

Fig. 5. ANN architecture and model summary of 3-3-1.

Table 2
ANN Model Summary.

Architecture	Learning Rate	Momentum	Iterations	Network Error	MAE	MSE	No. of Observations
3-3-3	0.05	0.5	100	2.14457	0.25012	0.08224	33

Table 3
ANN Architectures Vs Prediction RMSE.

Architecture	Prediction RMSE
6-6-1	1.09
4-4-1	0.64
3-3-1	0.39

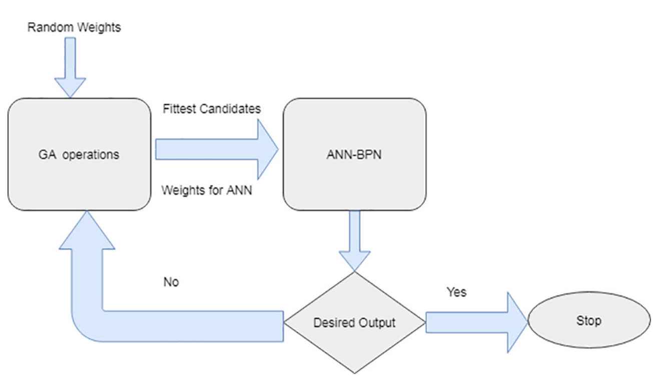

Fig. 6. Implementation Strategy of the Genetic Algorithm and Back-propagation.

applying back-propagation learning, the network is trained and the error is measured for each iteration, and the process is repeated until the desired result is obtained (as shown in the above Figure).

After the network has been equipped, the optimized network can then be used to predict future values i.e. forecasted values (Fig. 7).

The data were encoded into the 0 to 1 range and then divided into training patterns and test patterns respectively as shown in Tables 4 and 5.

The pattern formation rule used in this model is as below:

Once the patterns were formed, the patterns were divided into training patterns and test patterns. Training patters were used to train and validate the network and test patterns were used to calculate the forecasted values.

The test patterns are given in Table 5.

Every row in the above table represents one pattern. The input values are the first three columns, and the last column represents the desired value.

4.6. Survival of the fittest

The genetic algorithm works on the principle of "Survival of the fittest". It starts with the initial population size and after that various operations such as cross over, mutation, and reproduction takes place, and finally, a set of the fittest population is produced. These are used as the weight matrix to the ANN model. However, there is no defined rule to decide the population size. It depends on the nature of the problem under discussion. Hence, in this work different population sizes have been experimented to finally select one best population size. The results of different population sizes are given in Table 6 below.

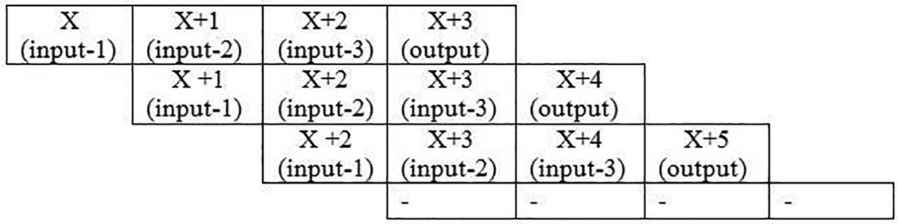

Fig. 7. Pattern Formation Rule.

Table 4
Training Pattern.

0.888542	0.883577	0.892652	0.902515
0.883577	0.892652	0.902515	0.894953
0.892652	0.902515	0.894953	0.906296
0.902515	0.894953	0.906296	0.909255
0.894953	0.906296	0.909255	0.889693
0.906296	0.909255	0.889693	0.889101
0.909255	0.889693	0.889101	0.909157
0.889693	0.889101	0.909157	0.918954
0.889101	0.909157	0.918954	0.915765
0.909157	0.918954	0.915765	0.911392
0.918954	0.915765	0.911392	0.920697
0.915765	0.911392	0.920697	0.922703
0.911392	0.920697	0.922703	0.928654

Table 5
Test Pattern.

0.902515	0.892652	0.883577	0.888542
0.892652	0.883577	0.888542	0.883577
0.883577	0.888542	0.883577	0.892652

The ANN-GA architecture has been introduced with varying population size, and the RMSE values have been measured. From the above Table 5, it is easy to observe that population size 40 has produced the network's lowest error. The value has been considered for comparison with the implementation of ANN. Table 7 provides a comparison of outcomes from each of the implementation.

5. Result analysis and conclusion

A common technique for analysing time series is an artificial neural network with backpropagation algorithm. A lot of computational work has been performed using algorithms for neural networks and backpropagation. This algorithm, however, suffers from a major drawback, called a local minima problem. In local minima, the network is trapped in a surface of error which is not, in fact, the minimal error. This creates an unstable network. After the exercise, the main factor behind this is the ANN weights. The genetic algorithm now helps the ANN solve the issue of local minima. A genetic algorithm is an optimization algorithm that helps to optimize the weights of the ANN. It is a population-based approach that helps improve network accuracy.

Table 7
Comparison of RMSE values.

Architecture	RMSE
ANN	0.39
ANN-GA	0.018930

From Table 6, it can be easily observed that when the experiments were performed with simple ANN with back-propagation learning, the network developed a higher RMSE, and at the same time, the error decreased significantly from 0.39 to 0.018930 when the ANN-GA network was introduced. This occurred because the weight matrix was optimized in the case of ANN-GA. Therefore, there was no question about local minima. One challenge in the case of ANN-GA, however, is to decide on the appropriate population size. To find the value of population size as shown in Table 3, this was achieved by trial and error process.

It can be assumed that ANN is a suitable technique for forecasting currency exchange rates, but ANN efficiency can be greatly enhanced by hybridizing ANN with an easily observable Genetic algorithm. The main goal of this work is to introduce a hybrid model to optimize ANN's weight matrix and the results show that the model has been efficient and gives accurate results.

Table 6
Results of different population sizes.

Experiment No.	Population Size	Desired	Obtained	RMSE
1	20	0.888542	0.908979	0.021231
		0.883577	0.909110	
		0.892652	0.909463	
2	40	0.888542	0.906405	0.018930
		0.883577	0.907177	
		0.892652	0.906760	
3	60	0.888542	0.911034	0.021091
		0.883577	0.908094	
		0.892652	0.907734	
4	80	0.888542	0.908693	0.020477
		0.883577	0.908475	
		0.892652	0.907881	

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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