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Foreign Currency Exchange Rates Prediction using CGP and Recurrent Neural Network

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Abstract

Feedback in Neuro-Evolution is explored and evaluated for its application in devising prediction models for foreign currency exchange rates. A novel approach to foreign currency exchange rates forecasting based on Recurrent Neuro-Evolution is introduced. Cartesian Genetic Programming (CGP) is the algorithm deployed for the forecasting model. Recurrent Cartesian Genetic Programming evolved Artificial Neural Network (RCGPANN) is demonstrated to produce computationally efficient and accurate model for forex prediction with an accuracy of as high as **98.872 %** for a period of 1000 days. The approach utilizes the trends that are being followed in historical data to predict five currency rates against Australian dollar. The model is evaluated using statistical metrics and compared. The computational method outperforms the other methods particularly due to its capability to select the best possible feature in real time and the flexibility that the system provides in feature selection, connectivity pattern and network.

Keywords: Foreign exchange rate forecasting; Neural Networks; Cartesian Genetic Programming; Neuro-evolution; Recurrent Networks; Time Series Prediction

1. Introduction

The data associated with financial time series is noisy, unstable and fluctuating. The non-linear and

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volatile nature of foreign exchange data cannot be efficiently predicted by current statistical models used for forecasting of stock exchange rates (Philip et al., 2011). Artificial neural networks (ANNs) are used to solve countless real-world problems, with financial time series forecasting being one of the most challenging amongst them. The performance of time series forecasting model however is limited by its low accuracy for forecasting longer periods of time. This work presents a Neuro-evolutionary algorithm based on Cartesian Genetic Programming evolved Artificial Neural Network (CGPANN).

This paper depicts a novel computational method of input selection for stock market forecasting using neural networks. Such an approach, where the algorithm selects the desired number of nodes that gives the best possible output and an optimal network, has not been proposed up till now. The method involves extracting the best possible feature of input variables of neural networks and that of stock market time series. The system provides flexibility in real-time feature selection, network architecture and connectivity pattern for prediction. Feature selection results in the removal of irrelevant features. Selection of the connectivity pattern involves deciding whether to use a recurrent connection or a feed-forward connection. Hence the system could be used as a recurrent neural network as well as a feed-forward network.

2. Literature review

Forecasting research literature is rich in terms of the published work in recent times owing to the development of information technology. The experimental results show that as opposed to the statistical models such as ARIMA (Autoregressive integrated moving average), neural network models produce better results, demonstrating their suitability for forecasting the foreign exchange rates. (Kadilar & Adla, 2009) explored both ARIMA time series model neural networks for Turkish TL/US dollar exchange rate series. The results show that the ANN method has a far better accuracy compared to the ARIMA time series model, proving the superiority of ANNs over statistical model. (Kamruzzaman et al., 2010) explored three different Artificial Neural Network (ANN) based forecasting models: Standard Back propagation (SBP), Scaled Conjugate Gradient (SCG) and Back propagation with Bayesian Regularization (BPR) to predict six different currencies against Australian dollar and evaluated their performance in terms of prediction accuracy. (Naeini et al., 2010) focused on the use of a feed forward multilayer Perceptron (MLP) to use the historic records regarding the stock share in order to predict a company's stock value and compared it with Elman Recurrent Network and Regression Model. Results indicate that MLP has lower MSE, MAPE, and MAE values in comparison with Elman and linear regression whereas the Elman recurrent neural network outperforms the multilayer Perceptron in predicting the direction of changes. Time series forecasting carried out by (Kryuchin et al., 2011) uses two ANN techniques, Multilayer Perceptron (MLP) and Volterra. According to (Philip et al., 2011), Hidden Markov Models are unstable for trading tool on foreign exchange data, the reason being that the results are dependent on too many factors. Although the Multilayer Perceptron (MLP) neural network is used widely in forecasting systems, it has the drawback of being time consuming and not being able to restore the memory of past events (Wei & Cheng, 2012). To improve the past forecasting models, (Wei & Cheng, 2012) suggests a hybrid forecasting model that refines past models and optimizes the Elman Recurrent Neural Network (Elman NN) for predicting the Taiwan stock price trends. The proposed model outperforms the other listed models due to nonlinear prediction capabilities, faster convergence, and accurate mapping ability.

3. Recurrent Cartesian Genetic Programming evolved Artificial Neural Network (RCGPANN)

The research solution discussed here for the purpose of foreign currency exchange forecasting has been implemented for recurrent CGPANN or RCGPANN, which is different from other classes of CGPANN due to the existence of a feedback mechanism in the network that feeds one or more outputs back to the system. In RCGPANN however, the network produced has partially linked neurons rather than the fully linked ones. This eliminates redundant connections and results in efficiency in terms of time and implementation feasibility. Unlike other networks, RCGPANN represents and encodes hidden states, in which a network's output is dependent on a random number of previous inputs. A recurrent CGPANN node consists of input connections, weights and node functions. An input that enters the network from the outer environment is referred to as the input node. A node that receives input from the preceding node(s) and from the system inputs is the intermediate node. The inputs supplied to the network can either be program inputs or feedback. The weighted output patterns are supplied to the sigmoid activation function and fed back to the input layer to obtain new output patterns. In our study, we monitor the behaviour of the network for single, five and ten number of feedback paths.

Inputs are chosen from the input array I:

$$I = \{i1, i2, i3 \ldots in\} \tag{1}$$

It can either be the program input or the feedback. The weight Matrix W,

$$W = \{W1, W2 \ldots Wn\} \tag{2}$$

has random figures between -1 and +1. A summing junction in ANN is signified by:

$$y' = \sum_{i=1}^{N} x_i \tag{3}$$

Where x_i is the junction input. If this input is multiplied with a randomly assigned weight w_i, then

$$y' = \sum_{i=1}^{N} x_i \tag{4}$$

for N inputs entering a node, y_j output is obtained such that

$$y_j = f^j\left(y'_j\right) = f^j\left(\sum_{i=1}^{N} x_i\, w_i\right) \tag{5}$$

Here f is an activation function, linked to node. N_T, being the total numbers of nodes in the network is defined by

$$\{j | j \in N \wedge 1 \le j \le N_T\} \tag{6}$$

Let I be the input associated to a unique genotype network Gk, considering each i has a unique value such that, for all inputs

$$i \in R \wedge 0 \le i \le 1 \tag{7}$$

in I = {i1, i2, i3….in, r1, r2……rm}

Where 'i' is the system input and 'r' the feedback from output:

$$ri = f(\sum(O_j W_j + O_{j-1} W_{j-1} + \cdots + O_1 W_1)) \tag{8}$$

network Gk is a set of input values selected randomly from inputs I, outputs of nodes y_j, for a single output Op such that

$$O_p = \frac{1}{n} \sum_{i=1}^{N} O \tag{9}$$

Where

$$Oi = f(\sum(y_j W_j + y_{j-1} W_{j-1} + \cdots + y_1 W_j + I W_k)) \tag{10}$$

Here, W_j, W_{j-1}, … W1 are Random subsets of W such that Wk is a subset Wj and

Wj={Wk|Wk R Λ -1≤ Wk ≤ 1}

4. Application of RCGPANN to Foreign Currency Exchange Rates Prediction

4.1. Experimental Setup

The suggested prediction model is trained on the historical data extracted from Australian Reserved Bank. Starting from the 500 days' data of US currency used to train ten different Recurrent Neural Networks. Five seeds are used for each network to make sure that the specificity of the seed selection does not affect the solution. Sigmoid is used as the activation function. Each node consists of five nodes. Because a mutation rate of 10% is thought to produce more satisfactory results in comparison to other rates, it has been used in our experiment (Kadilar & Alada, 2009; Chen et al., 2008). The inputs to the network are the 10 consecutive currency values. The network choses the optimal number of inputs from these 10 inputs in the final evolved network. There are 5 inputs per neuron so these inputs can be connected either to input of the system or the other preceding neurons. The mutation of initial genotype generated randomly results in further nine networks. This is done using the 1+λ evolutionary strategy where λ corresponds to 9. The resulting offspring is assessed for its performance using the Mean Absolute Percentage Error (MAPE) value and compared to select the fittest network for up gradation to the next generation. The same network is used to produce nine more networks through mutation. The process goes on until the desired fitness is achieved or the maximum number of generations is completed. We run all our experiments for one million generations when the network is being trained. MAPE and fitness is given by:

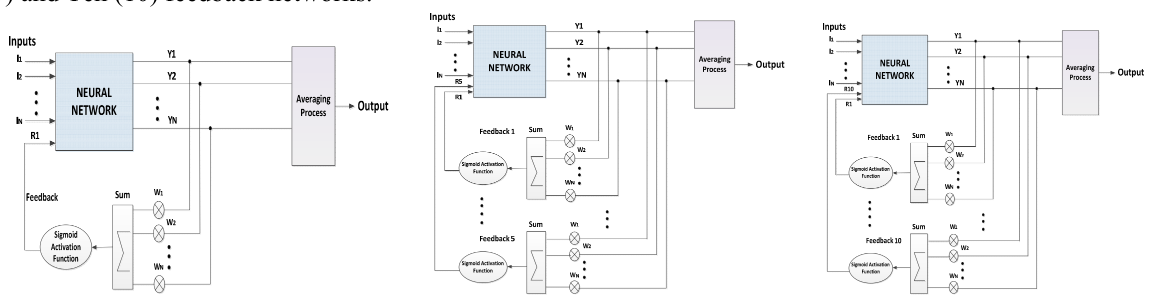
$$MAPE = \frac{1}{N}\sum i = 1toN\left(\frac{|L_F - L_A|}{L_A}\right) \times 100 \tag{11}$$

$$\text{Fitness} = 100\text{- MAPE} \tag{12}$$

L_F is the forecasted value, L_A the actual value and n indicates the number of days. Fig 1(a) shows an RCGPANN phenotype with weights, connection and functions and a single feedback path, with Fig 1(b, c) representing the corresponding 5 and 10 feedback paths respectively.

4.2. Results and Analysis

The performance of the network has been evaluated on historical data sets of 1000 days for five different currencies, starting from the 1st of February, 2003. These currencies include Japanese Yen, New Zealand Dollars, Canadian Dollars, Korean Won and Indonesian Rupiah. The training phase was followed by testing. Tables 1, 2, and 3 give the accuracy achieved during the testing phase for the three scenarios with single, five (5) and Ten (10) feedback networks.



(a) (b) (c)

Fig. 1. RCGPANN phenotype with: (a) single feedback path; (b) five feedback paths, and; (c) ten feedback paths.

The final results have been obtained after averaging the 5 individual results, each from an independent evolutionary run carried out for various network sizes and feedback scenarios. The tables show the dominance of the algorithm in terms of accuracy, producing models having 98.5% accuracy on average, with more feedback based network achieving the highest accuracy of 98.872 % (400 nodes, 10 feedback network, highlighted in Table 3). The results validate the efficiency of the networks generated for currency forecasting. It is clearly evident from the comparison table (Table 4) that the best results are achieved by RCGPANN with an accuracy of **98.872 %** and MAPE value as low as **1.1280 %** for a period of 1000 days.

5. Conclusion

This work explores a recently introduced Neuro-evolutionary technique termed as Recurrent Cartesian Genetic Programming evolved Artificial Neural Network (RCGPANN) for implementation of forex prediction. The reason for the efficient performance of the system is the ability of the system to select the best possible feature, network architecture and connectivity pattern for prediction and to decide whether to use a recurrent connection or a feed-forward connection. The results also demonstrate that the network accuracy increases with increase in number of feedback paths, thus improving the capabilities of the network to predict the future data. A neural network model that implements feature selection is thus a promising candidate for forex prediction.

Table I. The testing results for various currencies in terms of accuracy of RCGPANN predicting the eleventh day on the basis of 10 days' data history with a single feedback for a period of 1000 days, starting from Feb, 2003.

Nodes	50	100	150	200	250	300	400	450	500
Yen	98.427	98.278	98.389	98.466	98.391	98.653	98.486	98.414	**98.692**
NZD	98.207	98.156	98.197	98.226	98.200	98.192	98.232	98.227	**98.257**
CAD	98.249	98.183	98.234	98.269	98.235	98.279	98.278	98.260	**98.309**
KRW	98.423	98.339	98.405	98.448	98.408	98.520	98.457	98.433	**98.543**
IDR	98.674	98.514	98.632	98.713	98.634	98.852	98.734	98.668	**98.866**

Table II The testing results for various currencies in terms of accuracy of RCGPANN predicting the eleventh day on the basis of 10 days' data history with a 5 feedback scenario for a period of 1000 days, starting from Feb, 2003.

Nodes	50	100	150	200	250	300	400	450	500
Yen	**98.705**	98.694	98.693	98.694	98.692	98.691	98.694	98.702	98.688
NZD	98.245	98.258	98.265	98.264	98.265	98.263	98.259	98.246	**98.266**
CAD	98.305	98.311	98.315	98.314	98.314	98.314	98.311	98.306	**98.315**
KRW	**98.544**	98.544	98.543	98.543	98.543	98.544	98.544	98.544	98.542
IDR	98.855	98.868	98.869	98.867	98.869	98.871	98.868	98.861	**98.872**

Table III. The testing results for various currencies in terms of accuracy of RCGPANN predicting the eleventh day on the basis of 10 days' data history with a 10 feedback scenario for a period of 1000 days, starting from Feb, 2003.

Nodes	50	100	150	200	250	300	400	450	500
Yen	98.692	**98.700**	98.691	98.690	98.689	97.541	98.683	98.639	98.689
NZD	98.262	98.235	98.255	**98.265**	98.249	97.128	98.265	98.172	98.263
CAD	98.313	98.299	98.310	98.315	98.305	97.281	**98.314**	98.270	98.314
KRW	98.544	98.539	98.542	**98.543**	98.540	97.456	98.541	98.500	98.542
IDR	98.871	98.855	98.868	98.872	98.864	97.469	**98.872**	98.843	98.871

Table IV. Comparison between the accuracy distribution rates and MAPE of RCGPANN and other models

Network	Accuracy (%)	MAPE(%)
Markov model (Khan et al., 2010)	-	1.928
Naïve (Khan et al., 2013)	-	7.2868
ARMA (Khan et al., 2013)	-	3.4649
MultiLayer Perceptron (Kryuchin et al., 2011)	72	-
HFERFM (Philip et al., 2011)	69.9	-
AFERFM (Philip et al., 2011)	81.2	-

Backpropagation with Bayesian Regularization (Kamruzzaman et al., 2010)	93.93	
RCGPANN (implemented)	**98.872**	**1.1280**

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