This research work demonstrates an application of the Time Delay Neural Network (TDNN) technique for predicting currency exchange rates. The predictive power has been tested using the currency rates of China, India and Japan per US dollar. The model can be effectively used to predict other currency rates. A data sets of five years of Chinese Yuan Renminbi/US dollar (CNY/USD), Indian Rupees/US dollar (INR/USD) and Japanese Yen /US Dollar (JPY/USD) were used to test the model. The results show that the Mean Square Error (MSE), in case of daily CNY/USD currency exchange rates, is the lowest as compare to other two exchange rates. Thus the comparison indicates that the Chinese currency has been more stable as compared to other two currencies during the period of the study.

**KEYWORDS:** Artificial Neural Networks, Time Delay Neural Network, Foreign Currency, Exchange Rates, Forecasting

**INTRODUCTION**

The fluctuations in currency exchange rate require the continuous monitoring of economic, financial and political variables of the country. The exchange rate of a country’s currency compared with US dollar is primarily depend on the demand of the currency, which of course, is determined mainly by net export positions in a given period as well as the accumulated trade deficit and some other factors. The countries selected for the study are close competitors and have demonstrated the demand of their products in the US Market. Since the net export of China to the USA, has increased during the period of study, the currency exchange rate of China remained stronger in comparison to the US dollar. On the other hand, due to the global economic slowdown, the exchange rates of India and Japan did not perform well due to internal and external factors.

The forecast of foreign exchange (FX) rates is extremely important as the currency exchange rates are one of the most important economic indices in the international monetary markets. The FX market is the largest and equally lucrative market within the financial markets (Baillie & McMahon, 1989). Researchers have been supporting the market by developing sophisticated
models by capturing trends in economic and financial variables (Meese and Rogoff, 1983; Kilian and Taylor, 2003; Ni & Yin, 2009). FX rates are determined by various micro and macroeconomic variables as well as political and psychological variables. Since the dynamics of the global economic is ever evolving, there is a need for continuous research in designing and developing models using the latest tools and techniques to capture maximum factors and their impact on the FX rates. Thus, the modeling for the prediction of FX rates presents challenges and opportunities for researchers and mathematical modelers to support the global economy.

There are three different categories of Artificial Neural Networks (ANN): (1) Feed Forward Neural Network (FFNN), (2) Recurrent Neural Networks (RNN) and (3) other special type of neural networks. The FFNN is widely used for predicting trends of financial time series data by linking input data directly to the output. Similarly the RNN with feedback path is also used for predicting trends in financial data. Other special types of neural network are the hybrid forms of ANN. The Time Delay Neural Network (TDNN) falls under the third category where input memory is generated from the stored information over time. This technique has not been widely explored by researchers for predictions in the finance area, specifically in FX rate predictions. As mentioned earlier, the output generated by a TDNN model takes into account current input as well as historical inputs, which differentiates the technique from other neural networks. The technique has unique features, which can be helpful in designing and developing powerful and efficient models for making better predictions for financial time series data. This study designed and developed a model using TDNN to predict the exchange rates of three Asian countries (China, India and Japan) with respect to the US dollar because of the dynamics of the FX market. Based on our analysis, the study provided support for the model developed over traditional statistical modeling and other prevailing ANN techniques.

The rest of the study is organized as follows. Section 2 provides a brief review of the literature. Section 3 presents a description of data. Section 4 defines the Time Delay Neural Network. Section 5 provides insight on the experimental results. Finally, Section 6 concludes the findings of the study.

LITERATURE REVIEW

The literature reveals that ANN is superior to the conventional statistical models (Coats and Faut, 1993; Leonard et al., 1991; Fletcher and Goss, 1993; Salchengerger et al., 1992). Over the past two decades, several mathematical models in finance area have applied ANN to successfully predict trends of FX prices (Lapedes & Farber, 1987; Weigend et al., 1991; Refenes et al., 1993; Kodogiannis & Lolis, 2002; Lisi & Schiavo, 1999; Nag & Mitra, 2002; Vojinovic et al., 2001; Yao & Tan, 2000; Chen & Leung, 2004; Chun & Kim, 2003; Davis et al., 2001). Various research works in this area are listed in table 1.

<table>
<thead>
<tr>
<th>YEAR</th>
<th>REFERENCES</th>
<th>JOURNAL/BOOK</th>
<th>TECHNIQUE USED</th>
</tr>
</thead>
<tbody>
<tr>
<td>1996</td>
<td>Tenti</td>
<td>Journal</td>
<td>Recurrent NN</td>
</tr>
<tr>
<td>1999</td>
<td>Gencay</td>
<td>Journal</td>
<td>ANN, GARCH and Random walk</td>
</tr>
<tr>
<td>2000</td>
<td>Leung et al.</td>
<td>Journal</td>
<td>MLFN and General regression neural network (GRNN)</td>
</tr>
<tr>
<td>2001</td>
<td>Zhang &amp; Berardi</td>
<td>Journal</td>
<td>Ensemble NN with serial partitioning methods</td>
</tr>
<tr>
<td>2006</td>
<td>Fulcher et al.</td>
<td>Journal</td>
<td>Higher Order Neural Networks (HONN)</td>
</tr>
</tbody>
</table>
DATA DESCRIPTION

Time series data is a series of observations taken at regular interval of time such as hourly, daily, weekly, monthly, quarterly or yearly. This study focuses on the data of daily observations of the exchange rates of three Asian countries, India, China and Japan per US Dollar. The time period of the data set is from April 1, 2009 to March 31, 2014, which consists of 1252 daily observations. Since we are going to predict the next day’s exchange rate based on prior day’s exchange rate, the input data range is considered from April 1, 2009 to March 31, 2014 while for output (Next day’s exchange rate); data are shifted one day forward and considered for the range of April 2, 2009 to April 1, 2014. Data was downloaded from http://fx.sauder.ubc.ca which is maintained by the University of British Columbia, Sauder School of Business (Pacific exchange rate service) and provided by Professor Werner Antweiler. The site provides an interactive way to retrieve daily, monthly and weekly exchange rate data in various file formats like xls, pdf, plaintext and a combination of CSS and HTML.

Data is partitioned into three different parts for the purpose of training, validation and testing in a randomized manner. Training data is presented during training for the TDNN and the weights are adjusted as per the learning algorithm based on an error obtained at the outer layer. The validation data is used to measure the network generalization and to halt training when the generalization stops improving. This way of learning a neural network is very helpful since neural networks may stop improving their performance due to problems of local minima. On the other hand, the testing data is used to verify the performance of the network after (sometimes during training) training and provides independent measures of network performance. The latest data from April 1, 2014 to April 14, 2014 is used for N-days ahead prediction of exchange rates.

EXPERIMENTAL SETUP OF TIME DELAY NEURAL NETWORK

Theoretical Framework: The Artificial Neural Network (ANN) is inspired by the human brain in the form of artificial neurons, which are connected through synaptic weights and are widely accepted for financial time series data forecasting. Researchers have designed and developed models for FX rate prediction using several types of ANN including, Back Prorogation Neural Network (BPNN) (Ye, 2012; Panda & Narasimhan, 2007) and Radial Basis Function Network (RBFN) (Lean et al., 2008; Georgios et al., 2013). Recently, hybrid models are being widely used for exchange rate predictions. Researchers (Huseyin et al., 2006; Yan et al., 2007; Sharmishta et al., 2006) have suggested hybrid models for financial predictions in a combination of fuzzy logic with neural network and wavelet transform with a genetic algorithm. However, there is a limited literatures related to TDNN applications, especially for FX rate prediction. The literature supports that TDNN has better capabilities for time series data predictions. Therefore, TDNN technique can effectively be applied for exchange rate predictions.
The neural network (Shivanandam & Deepa, 2011) responds to a sequence of patterns where the network produces a particular output sequence corresponding to a particular sequence of inputs and a shift register can be defined a tapped delay line. A TDNN, with reference to a case of a multilayer perceptron, is defined as the tapped outputs of the delay line, and is applied to its inputs. Thus, the output consists of a finite temporal dependence on its inputs, given as:

$$y(t) = f(x(t), x(t-1), \ldots, x(t-d))$$  \hspace{1cm} (1)

Where $f$ is a nonlinear function, $x(t)$ is time series data, and $d$ is time delay. The multilayer perceptron with delay line is shown in figure 1. The function $f(t)$ is a weighted sum and the TDNN is equivalent to a finite impulse response (FIR) filter. When the output is being fed back through a unit delay into the input layer then the net computed, is equivalent to an infinite impulse response (IIR) filter. Thus a neuron with a tapped delay line is called a TDNN unit, and a network which consists of TDNN units is called a TDNN. The TDNN is trained using a back-propagation-learning rule with a default momentum and learning factors.

**Figure 1: Time delay neural network (FIR filter)**

**MATLAB Implementation:** A program using MATLAB is written to implement TDNN for FX rate prediction. The explanation of important inputs and its corresponding outcomes of the program are explained as follows:

(a) Input and output variables are loaded into MATLAB workspace either from an excel file or a MAT file. A MATLAB function `tonndata` as written below converts the data in the neural network cell array form to feed it to the TDNN.

```matlab
inputSeries = tonndata(input,false,false)
targetSeries = tonndata(output,false,false)
```

(b) The parameters such as input delay and number of hidden neurons are set to construct a TDNN. However, there is no rule of thumb rule to determine the number of neurons in a hidden layer. Many authors have used the following formula to decide hidden layer neurons $n2$:

$$n2 = 2n1 + 1$$

where $n1$ is number of neurons in input layer.
MATLAB codes are generated to assign input delay and hidden layer neurons. Neurons in hidden layer are decided for experiment by using a trial and error method. The performance of TDNN is verified by increasing and decreasing the number of neurons in a hidden layer and ultimately stabilized with 10 neurons. Other parameters like momentum, learning rate and are others are set as the default.

\[
\text{inputDelays} = 1:2 \\
\text{hiddenLayerSize} = 10
\]

(c) A time delay neural network “net” is constructed based on the parameters set in sections (b) as follows:

\[
\text{net} = \text{timedelaynet}(	ext{inputDelays}, \text{hiddenLayerSize})
\]

(d) The data for training and simulation is then prepared following the MATLAB code. The function PREPARETS prepares time series data for a particular network:

\[
[\text{inputs}, \text{inputStates}, \text{layerStates}, \text{targets}] = \text{preparets}(\text{net}, \text{inputSeries}, \text{targetSeries})
\]

(e) Following the code, the data is divided into three different parts as training, validation and testing with 70%, 15% and 15% respectively as explained in the data description section.

\[
\text{net.divideParam.trainRatio} = 70/100 \\
\text{net.divideParam.valRatio} = 15/100 \\
\text{net.divideParam.testRatio} = 15/100
\]

(f) Training and testing of TDNN is done with the help of following codes. TDNN is trained using levenberg marquardt backpropogation learning algorithm.

\[
[\text{net.tr}] = \text{train}(\text{net}, \text{inputs}, \text{targets}, \text{inputStates}, \text{layerStates}) \\
\text{outputs} = \text{net}(\text{inputs}, \text{inputStates}, \text{layerStates}) \\
\text{errors} = \text{gsubtract}([\text{targets}, \text{outputs}]) \\
\text{performance} = \text{perform}(\text{net}, \text{targets}, \text{outputs})
\]

(g) TDNN constructed in section C can be viewed with the following code as shown in figure 2 with bias weight b.

\[
\text{view}(\text{net})
\]

Figure 2: MATLAB generated TDNN designed for exchange rate prediction
Finally, the results or outcome is plotted using various curves with the following codes:

- `figure, plotperform(tr)`
- `figure, plottrainstate(tr)`
- `figure, plotresponse(targets,outputs)`
- `figure, ploterrcorr(errors)`
- `figure, plotinerrcorr(inputs,errors)`

The training of TDNN requires several attempts until the minimum Mean Square Error (MSE) is reached. Performance curve in case of three different exchange rates are shown in figure 3. As depicted by the figure, the best performances of TDNN have been achieved at 30, 54 and 55 epochs respectively for CNY/USD, INR/USD and JPY/USD exchange rates. There is a smooth convergence of TDNN in all three cases. The predictions have been found more reliable in the case of the CNY/USD exchange rate. This implies that the CNY/USD exchange rate has been
less volatile in comparison to the INR/USD and JPY/USD exchange rates used during the period of study.

**RESULTS AND DISCUSSION**

The study used MATLAB to run the program designed and developed for simulating TDNN for exchange rate predictions of three Asian countries with repeated iterations. Since training, validation and testing data are selected randomly; hence different runs of the program produced different results. An average of 10 runs is considered as appropriate outcome of TDNN for each currency exchange rate. The performance of TDNN is verified in terms of Mean Square Error (MSE) and R value. MSE, which is the average squared difference between TDNN output and target output. MSE value must tend towards zero for better performance of the neural network. R value measures the correlation between TDNN output and target output. An R-value of 1 means there is perfect correlation between TDNN output and target output. The results of the study in terms of the above two statistical measures for all three exchange rate data are presented in table 2. This results explicitly reveal that the MSE for CNY/USD exchange rate is much lower as compare to the INR/USD and JPY/USD exchange rates, which implies that the FX rate has been very stable for CNY/USD. However, the higher value of R reveals that there has been strong correlation of these currencies with US dollar during training, validation and
testing stages while N-day ahead predictive values as shown in table 3 reveal that the highest R value has been for JYP/USD followed by CNY/USD and IND/USD.

<table>
<thead>
<tr>
<th>Currency Exchange Rate</th>
<th>MSE Training</th>
<th>MSE Validation</th>
<th>MSE Testing</th>
<th>R-Value Training</th>
<th>R-Value Validation</th>
<th>R-Value Testing</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNY/USD</td>
<td>0.00003</td>
<td>0.00004</td>
<td>0.00005</td>
<td>0.997</td>
<td>0.996</td>
<td>0.996</td>
</tr>
<tr>
<td>INR/USD</td>
<td>0.1762</td>
<td>0.2460</td>
<td>0.2974</td>
<td>0.997</td>
<td>0.996</td>
<td>0.995</td>
</tr>
<tr>
<td>JPY/USD</td>
<td>0.5849</td>
<td>0.8596</td>
<td>0.5973</td>
<td>0.995</td>
<td>0.994</td>
<td>0.995</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Exchange Rate</th>
<th>MSE</th>
<th>R-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNY/USD</td>
<td>0.00007</td>
<td>0.3540</td>
</tr>
<tr>
<td>INR/USD</td>
<td>0.0183</td>
<td>0.1964</td>
</tr>
<tr>
<td>JPY/USD</td>
<td>0.2290</td>
<td>0.8922</td>
</tr>
</tbody>
</table>

CONCLUSIONS

Predicting exchange rate has been beneficial for foreign investment, foreign currency trading, currency comparison and overall financial decision-making process for both investors and government. There are several methods like ARIMA and artificial neural networks (ANN), which have been used by the researchers for foreign exchange rate predictions. ANN are successfully applied by the researchers not only for exchange rate predictions but also in other applications due to its capabilities of mapping high dimensional nonlinear data in a better way. This study has been conducted using a special type of ANN, called TDNN for predicting the exchange rate of three Asian countries (China, India and Japan) during the period of global recession with respect to the US dollar. The results of the study reveal that the N-days prediction was close to the real exchange rate for CNY/USD as compared to the INR/USD and JPY/USD exchange rates, which further implies that the rate of CNY/USD has been less volatile in comparison to IND/USD and JPY/USD, during the period of study.

REFERENCES


(A complete list of references is available upon request)