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Bootstrap Methods for Foreign Currency Exchange Rates Prediction

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Abstract— **This paper presents the research of using bootstrap methods for time-series prediction. Unlike the traditional single model (neural network, support vector machine, or any other types of learning algorithms) based time-series prediction, we propose to use bootstrap methods to construct multiple learning models, and then use a combination function to combine the output of each model for the final predicted output. In this paper, we use the neural network model as the base learning algorithm and applied this approach to the foreign currency exchange rate predictions. Six major foreign currency exchange rates including Australia Dollars (AUD), British Pounds (GBP), Canadian Dollars (CAD), European Euros (EUR), Japanese Yen (JPY) and Swiss Francs (CHF) are used for prediction (base currency is US Dollar). Simulations on the most recently available exchange rate data (January 01, 2003 to December 27, 2006) on both daily prediction and weekly prediction indicate that the proposed method can significantly improve the forecasting performance compared to the traditional single neural network based approach.**

I. Introduction

Time series prediction is one of the most active research areas in the computational intelligence society. Over the past decade, many efforts have been reported in literature focusing on different aspects of time-series prediction. Financial forecasting is one of the most difficult ones. This is due to the inherent characteristics of such time series, including small sample size, huge amount of noise, non-stationary and non-linearity [1]. In this paper, we investigated foreign currency exchange rate prediction using bootstrap mechanism based on neural network approach.

The foreign currency exchange market is the largest and most liquid financial market with an estimated trading of $ 1.5 trillion a day [2]. Therefore, understanding the relationship and predicting the trend of the major currency exchange rates have attracted extensive efforts. However, predicting such time-series is extremely difficult as it is highly influenced by world economic situations, political issues and even psychological effects [3]. Computational intelligence methods are one of the major techniques used for foreign currency exchange rate prediction.

In [3], J. Yao and C. Tan presented a case study of using neural networks (NN) to predict the foreign currency exchange rate between US Dollar and five major currencies. Comparisons between neural network models and traditional auto-regressive integrated moving average (ARIMA) models show that neural networks are more effective. In [1], C. L. Giles et. al discussed the inherent difficulties and fundamental limitations for using neural network models to handle the noisy time series. Based on these analysis, a method based on a symbolic representation with self-organizing map and a grammatical inference with recurrent neural networks was proposed. Simulation results for 5 daily foreign exchange rate prediction shows the prediction error of direction of change is around 47.1%, and this error rate can be further reduced to 40% when rejecting examples with low confidence level. In [4], R. Ghazali et. al presented the application of Ridge polynomial neural networks for financial time-series prediction. Simulation results on 3 foreign currency exchange rates forecasting illustrated the effectiveness of the method. In [5][6], three neural network models based on standard backpropagation (SBP), scaled conjugate gradient (SCG) and backpropagation with Baysian regularization (BPR) were studied to predict six different currencies against the Australian Dollar. Simulation results also indicated that neural network models can outperform the ARIMA model based on five performance metrics. In [7], support vector machine (SVM) was investigated for forecasting currency exchange rates. Effects of different kernel functions which related to the prediction error were analyzed.

Recently, many research results have been reported on the use of ensembling techniques to improve the classification/regression performance. Among the popular ensembling mechanisms, bootstrap aggregating (bagging) and boosting are two of the most popular methods. Bagging was proposed by L. Breiman using a bootstrap ensembling method to get an aggregated predictor [8]. L. Breiman pointed out that for unstable learning mechanisms, bagging can significantly improve the prediction accuracy [8]. Boosting is another way to reduce the prediction error of any “weak” learning algorithms [9] [10]. In boosting, the training data points are given various distributions (more weight is given to the data points that are incorrectly predicted). Both bagging and boosting take advantage of ensembling multiple classification/regression models. In [11] and [12], different ensemble methods are presented. Some other interesting research results in this area including the stacked regressions [13], random forests [14], and decision tree and forests [15][16].

In this paper, we investigate the use of the bootstrap method for foreign currency exchange rate prediction based on neural networks. While most of the existing time series prediction methods use a single regression model, for instance, neural networks, SVMs, or ARIMA, we studied the ensembling of multiple base regression models using

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bootstrap sampling for such noisy time series prediction. In addition, unlike most of the literature results that are based on large training data points to predict relatively short period of testing points, we focused on a more challenging and difficult aspect for such problem: training on one year foreign currency rate to predict three years in the future. Simulation results based on 6 major foreign currency exchange rates illustrated the effectiveness of the proposed method.

The rest of this paper is organized in the following way. Section II discusses the proposed bootstrap based multiple neural network approach for time series prediction. Section III presents the foreign currency data statistics and experimentation environment. In section IV, simulation results and its corresponding performance analysis are presented. Finally, a conclusion is given in Section V.

II. Bootstrap based multiple neural network approach

A. Foreign currency exchange rate prediction

The foreign currency exchange market is filled with uncertainty and a huge amount of noise. The well-known but still controversial statement is that “the market is unpredictable”. This is reflected by the Random Walk Hypothesis and Efficient Market Hypothesis [17]. Random walk hypothesis claims that the market price is purely random and unpredictable, while efficient market hypothesis states that the market fully reflects all known information immediately (efficient enough) and therefore it is impossible to consistently outperform the market.

On the other side, there are many research efforts trying to predict such market using many advanced mathematics, statistics and computational intelligence approaches. This can be categorized into two groups: fundamental analysis and technical analysis. Fundamental analysis uses in-depth financial information of each country, including the economic statistics, currency demand and supply etc. to predict the future currency exchange rate. Technical analysis studies the history trend of the currency exchange rate and tries to forecast its future behavior, for instance, the moving average approach.

Due to huge amount of noise, non-stationary and non-linearity characteristics of such time series, the traditional ARIMA method is not effective enough to predict its future trend. Recent research has mainly focused on using the computational intelligence methods, mainly neural networks to forecast its future exchange rate [1] [3-6]. All of these models are based on training a single neural network based model to predict the future exchange rate. In situations where there is very limited information available, single model may not be able to catch the trend in such change. Therefore, we proposed to use the bootstrap method to create multiple neural network models, and then combine their predicted results to improve the prediction accuracy. In addition, we use the most recent available data (January 02, 2003 to December 29, 2006) for analysis to reflect the global economic changes in the most recent 4 years.

B. Bootstrap based multiple neural network approach

Fig. 1 illustrats an example of the foreign currency exchange rate prediction. As we can see here, two issues make this problem difficult:

(1) Training period is much shorter (about 1/3) than the testing period. This makes the model difficult to learn the intrinsic tendency in such time series.

(2) Training range is smaller than the testing range. This makes the prediction very difficult since the model is not trained with inputs in the range of testing period.

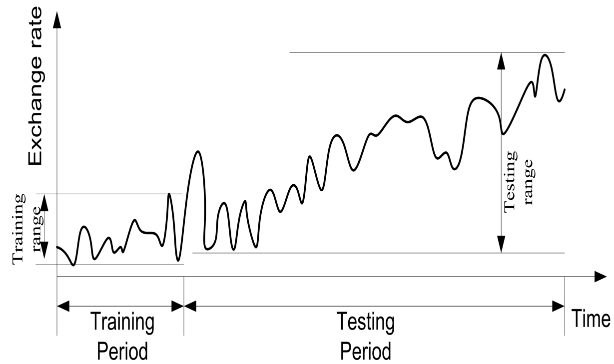

Fig. 1. An example of foreign currency exchange rate prediction

In this research, we propose the use of bootstrap-based multiple neural network models for analysis. This idea is illustrated in Fig. 2. For the time series prediction, in order to capture the dependence structure, we use the blocks bootstrap mechanism for re-sampling. In the blocks bootstrap, blocks of consecutive observations are sampled with replacement from the training period. There are two types of block bootstrap, nonoverlapping blocks bootstrap and overlapping blocks bootstrap.

(a) Nonoverlapping blocks bootstrap. Given a time series of $S = \{X_i, i = 1, 2, ...n\}$, this series can be divided into a set of nonoverlapping blocks of fixed length l : $B_1 = \{X_j, j = 1, 2, ...l\}$, $B_2 = \{X_{l+j}, j = 1, 2, ...l\}$ and $B_k = \left\{X_{(k-1)l+j}, j = 1, 2, ...l\right\}$, where $k = n/l$. Then the blocks bootstrap is created by sampling (with replacement) of k blocks from $\{B_1, B_2, ...B_k\}$.

(b) Overlapping blocks bootstrap. The overlapping blocks bootstrap is similar to the non-overlapping block bootstrap except that the block consists of data points of $B_k = \{X_{k-1+j}, j = 1, 2, ...l\}$. In this way, the blocks are created in a way similar to the moving block (moving block bootstrap). Detailed discussions about the block size choice and related issues can be found in [18].

For each blocks bootstrap samples, a neural network model is trained with random initial weights. The testing data sets are sent to all these neural networks, and their outputs will be combined through a combination function to get the final predicted output.

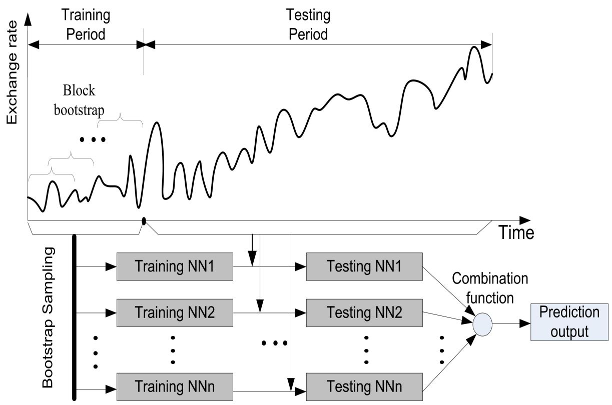

Fig. 2. Bootstrap multiple classifier method

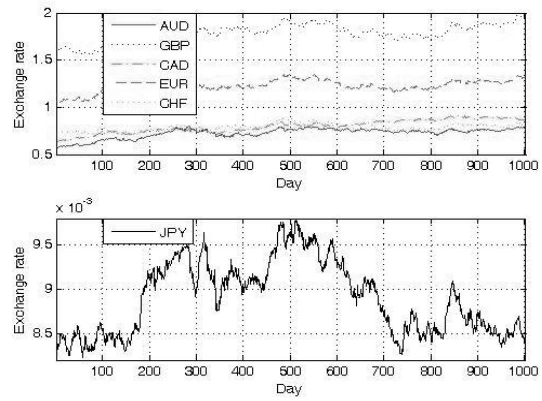

Fig. 3. Foreign exchange rate from 01/02/2003 to 12/29/2006

III. Simulation analysis

A. Dataset analysis

In this research, we use the most recently available foreign currency exchange rate (from January 02, 2003 to December 29, 2006) for analysis. Since most of the existing foreign currency prediction analysis in literature is based on the period of 1973-1987 [1], 1984 to 1995 [3] and 1991 to 2002 [5]-[7], we hope the analysis performed in this research can provide further understanding for the foreign currency market in the most recent 4 years.

We use the data set of six major foreign currency exchange rates, named Australia Dollars (AUD), British Pounds (GBP), Canadian Dollars (CAD), European Euros (EUR), Japanese Yen (JPY) and Swiss Francs (CHF) for analysis [19]. US Dollar (USD) is selected as the base currency.

Both daily analysis and weekly analysis are performed in this research. For daily analysis (trading day), we use the data from January 02, 2003 (Thursday) to December 31, 2003 (Wednesday) for training, and use the data from January 2, 2004 (Friday) to December 29, 2006 (Friday) for testing. Therefore the training period contains the trading closing price of 251 data points and the testing period contains the trading closing price of 752 data points. In weekly analysis, we use every Wednesday's closing price as the target price. Similar to the daily analysis, training period is from January 01, 2003 (Wednesday) to December 31, 2003 (Wednesday), and testing period is from January 7, 2004 (Wednesday) to December 27, 2006 (Wednesday). This corresponds to 53 points for training period and 156 points for the testing period. In both cases, the training period is about 1/3 of the testing period. Fig. 3 shows the daily currency exchange rate for these 4 years and Table 1 is their statistics.

TABLE I

Daily foreign exchange rate statistics

Exchange Currency	Mean	Standard Deviation	Variance	Max	Min
AUD	0.7262	0.0535	0.0029	0.7981	0.5634
GBP	1.7824	0.1032	0.0106	1.9795	1.5502
CAD	0.7982	0.0683	0.0047	0.9099	0.6350
EUR	1.2189	0.0681	0.0046	1.3622	1.0363
JPY	0.0089	0.0004	1.700e-7	0.0098	0.0082
CHF	0.7880	0.0370	0.0014	0.8815	0.7053

B. Bootstrap neural network model

Similar to [3] [5] - [7], we use moving-averages as inputs to the neural networks. This is illustrated in Fig. 4. Take daily analysis as an example, we take the input feature vector $F = \{F1, F2, F3, F4, F5\} = \{X(T), MA5, MA10, MA20, MA60\}$, where $X(t)$ is the current day foreign exchange rate, $MA5, MA10, MA20$and $MA60$ is the moving average for one week, two weeks, one month and one quarter, respectively. The prediction target is the next trading day exchange rate, $X(t+1)$. J. Yao and C. L. Tan presented an analysis of the selection of such feature vectors for neural network prediction in [3]. Since the training samples are only about 1/3 of the testing samples, we use the blocks bootstrap method (overlapping blocks bootstrap with block length equal to 60) as presented in Section II to construct multiple neural network models [20]. At each simulation run, we used 10 NNs similar to the bagging approach. Each NN is a multilayer perceptron (MLP) network with backpropagations (5 input neurons, 2 hidden neurons and 1 output neuron). We use the conjugate-gradient method for optimization, and the simulations are performed using an Intel CPU with 3.0GHz and 2GB RAM memory under the MATLAB version 7.2.0.232(R2006a) environment. Once trained, all these neural networks (10 NNs in this paper) will predict the next-day exchange rate for a particular time instance, and their predicted results are combined by a simple combination function (average) to get the final predicted results. It should be noted that with careful selection of the NN parameters, number of NNs, and combination voting function, the prediction performance may be further improved. Interested readers can refer to [11] [12] [20] for a detailed discussion regarding these parameters.

Fig. 5 shows the predicted results for AUD daily exchange rates. Three lines are shown in Fig. 5, the solid line is the actual daily exchange rates, the dotted line is the predicted exchange rate by the traditional single NN model, and the

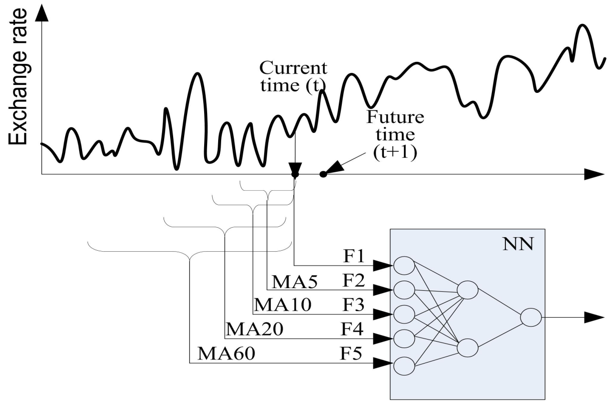

Fig. 4. Feature constructions for NN model

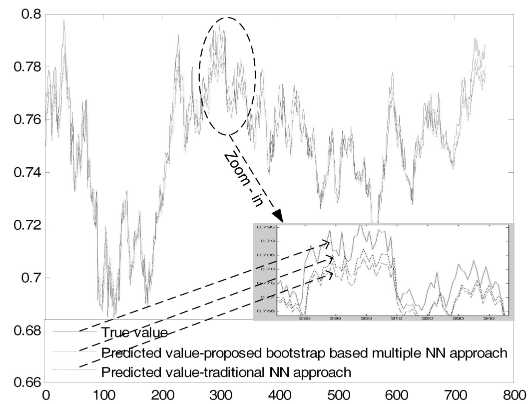

Fig. 5. Comparison of the single NN approach and the proposed bootstrap based multiple NN approach

dashed line is the predicted exchange rate by the proposed bootstrap multiple neural network approach. From the zoom-in part of the period, we can see that the predicted results by the proposed method are more accurate compared to those predicted by the traditional single NN approach. Fig. 6 (a)-(e) shows the predicted results of the other five foreign currency exchange rates.

C. Performance measurement

To measure the performance of the proposed method, we use the normalized mean square error (NMSE) as used frequently for time-series prediction. NMSE is defined as:

$$NMSE = \frac{\sum_k (x_k - \hat{x}_k)^2}{\sum_k (x_k - \bar{x})^2} = \frac{1}{\sigma^2}\frac{1}{N}\sum_k (x_k - \hat{x}_k)^2 \quad (1)$$

Where x_k and $\hat{x}_k$ are the actual and predicted values, respectively,$\bar{x}$ is the mean value, N is the size of the series set, and σ^2 is the estimated variance of the data set.

To reflect the performance statistics information, each method (both single NN approach and the proposed bootstrap

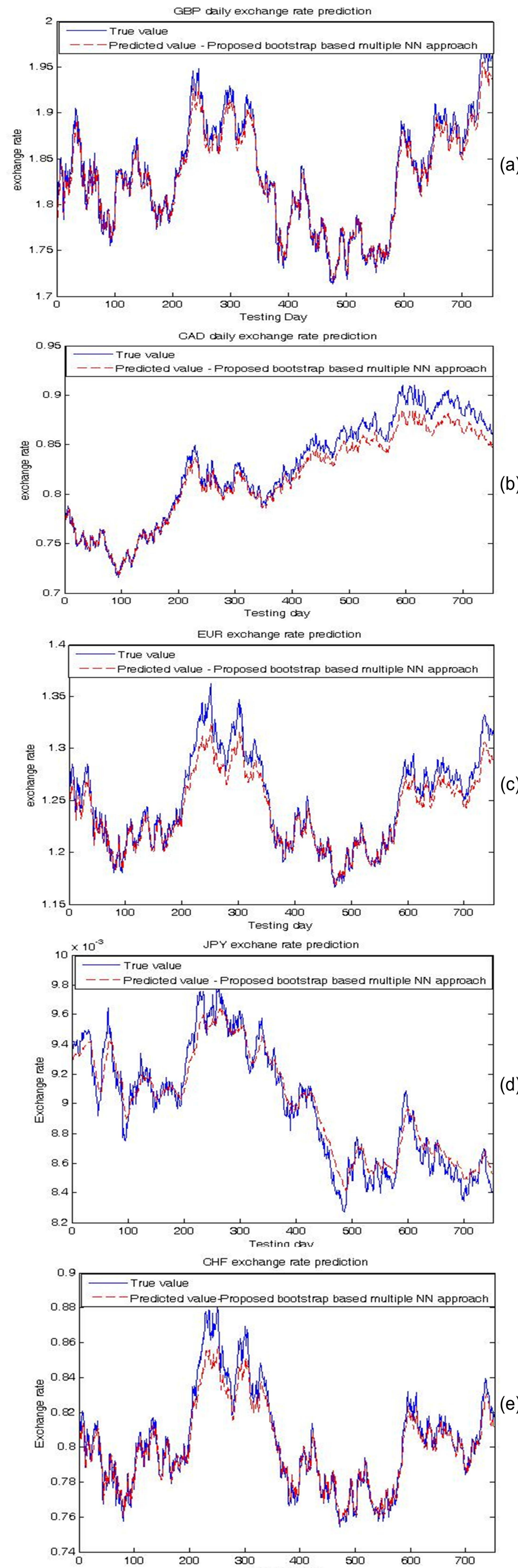

Fig. 6. Prediction value for different foreign currency exchange rate for the testing period (01/02/2004-12/29/2006)

based multiple neural network approach) is run 100 times with random initial weights. We take the average of the NMSE over 100 runs to show the performance of the two methods. Fig. 7 and Fig. 8 show the performance metrics information. As we can see from Fig. 7, the proposed method can consistently reduce the NMSE for all these six currency exchange rate predictions. From Fig. 8 we can see that the NMSE error reduction rate is from 21.7% (for AUD) to 44.1% (for JPY).

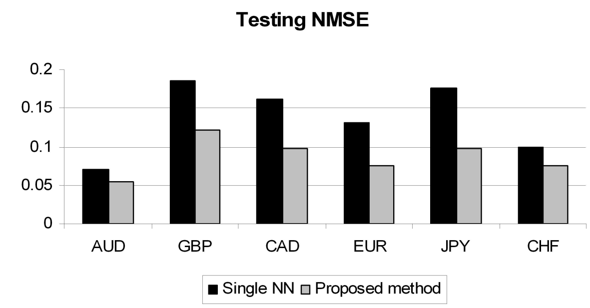

Fig. 7. Daily testing NMSE performance for traditional single NN approach and the proposed bootstrap based multiple NN approach

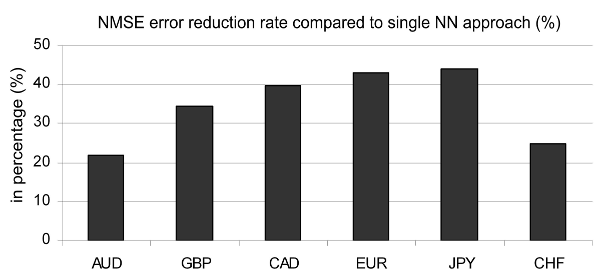

Fig. 8. Daily NMSE error reduction (in percentage) of the proposed method compared to the single NN approach

Although NMSE measurement in Fig. 7 and Fig. 8 shows the proposed method can improve the prediction accuracy compared to the traditional single NN approach, NMSE by itself may not be a conclusive criterion for comparing different prediction models. To this end, we use the most recently developed regression error characteristic (REC) for further analysis [21] [22] [23].

Similar to the receiver operating characteristic (ROC) curves [24], the REC curve provides a powerful method in visualizing and evaluating different regression models. The REC curve plots the error tolerance versus the percentage of points predicted within the tolerance [21]. Therefore, the REC curve provides an estimation of the cumulative distribution function (CDF) of the error. Generally speaking, two types of error signal are commonly used in REC analysis, absolute deviation $|x-\hat{x}|$ or squared residual $(x-\hat{x})^2$, where x and $\hat{x}$ are the actual and predicted value, respectively. In this way, the area-over-curve (AOC) is a biased estimation of the expected error for a prediction model. Detailed discussion regarding the REC analysis can be found in [21].

Fig. 9 and Fig. 10 show the REC analysis for the AUD prediction based on the absolute deviation error and squared residual error, respectively. From these two figures we can see, the REC curve of the proposed method is always above that for the traditional single NN method. That is to say, the proposed prediction method outperforms the traditional NN approach based on both error calculations. The corresponding AOC value is also presented in Fig. 9 and Fig. 10.

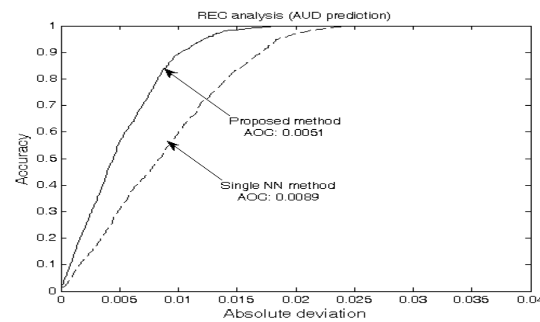

Fig. 9. REC analysis (absolute deviation)

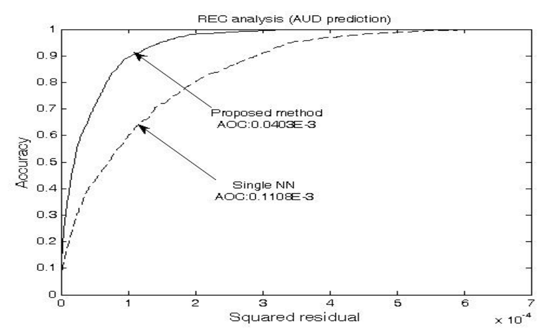

Fig. 10. REC analysis (squared residual)

D. Weekly data analysis

We now conduct simulation experiments for the weekly data. As the data set in [19], weekly data is the closing price for every Wednesday. As discussed in Section III A, the training period is from 01/01/2003 to 12/31/2003, while the testing period is from 01/07/2004 to 12/27/2006. For the weekly data, we use the current Wednesday closing price, plus the moving averages of one week (MA5), two weeks (MA10), one month (MA20) and one quarter (MA60) as feature vectors, to predict the next Wednesday's exchange rate. Again, 100 runs with random initial weights are simulated for the single NN approach and the proposed bootstrap based multiple NN approach. Fig. 11 and Fig. 12 illustrate the performance metrics. As we can see here, the simulation results on weekly prediction also confirmed that the proposed method can reduce the NMSE error compared to the traditional single NN approach.

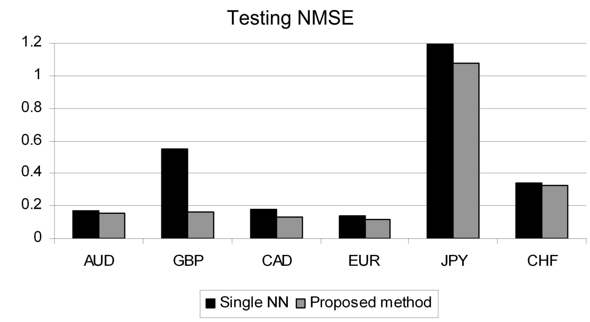

Fig. 11. Weekly testing NMSE performance for traditional single NN approach and the proposed bootstrap based multiple NN approach

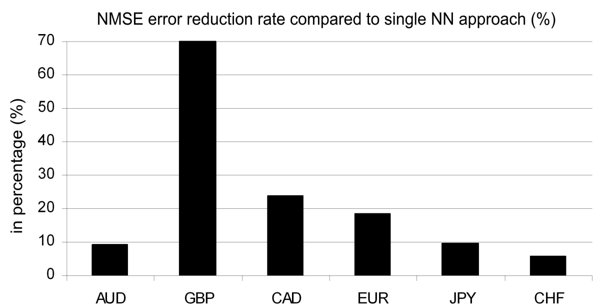

Fig. 12. Weekly NMSE error reduction (in percentage) of the proposed method compared to the single NN approach

Similar to the analysis we did for the daily prediction, Fig. 13 shows one of the REC analysis for the AUD weekly prediction. As we can see here, for the weekly foreign currency exchange rate prediction, the proposed method also outperforms the single NN approach.

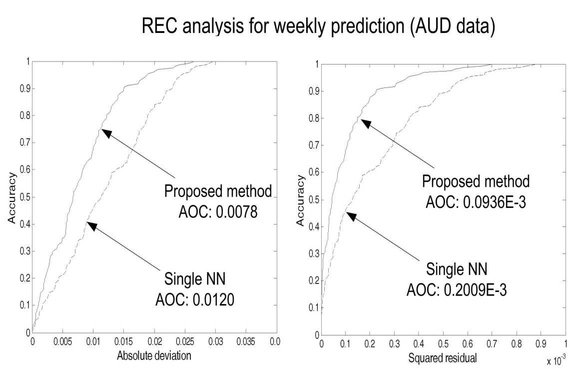

Fig. 13. REC analysis for weekly prediction

IV. Conclusion

In this paper, we investigated the bootstrap based multiple neural network models for foreign currency exchange rate prediction. This approach uses a bootstrap mechanism to train multiple neural networks, and after training, testing points are sent to every NN model and a combination function is used to combine the outputs from individual neural networks. Simulation results on six major foreign currency exchange rate predictions (both daily and weekly forecasting) indicated that this method can significantly reduce the prediction NMSE error.

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