# Exchange Rate Forecasting Using Classifier Ensemble

Zhi-Bin Wang[1], Hong-Wei Hao[1], Xu-Cheng Yin[1], Qian Liu[1], Kai-zhu Huang[2]

[1] Department of Computer Science, School of Information Engineering,
University of Science and Technology Beijing, Beijing 100083, China
[2] Institute of Automation, Chinese Academy of Sciences, Beijing 100080, China
wzb1818@yahoo.cn; hhw@ies.ustb.edu.cn; xuchengyin@ies.ustb.edu.cn; lq6000lq@163.com; kzhuang@nlpr.ia.ac.cn

**Abstract:** In this paper, we investigate the impact of the non-numerical information on exchange rate changes and that of ensemble multiple classifiers on forecasting exchange rate between U.S. dollar and Japanese yen. We first engage the fuzzy comprehensive evaluation model to quantify the non-numerical fundamental information. We then design a single classifier, addressing the impact of exchange rate changes associated with this information. In addition, we also propose other different classifiers in order to deal with the numerical information. Finally, we integrate all these classifiers using a support vector machine (SVM). Experimental results showed that our ensemble method has a higher degree of forecasting accuracy after adding the non-numerical information.

**Keywords:** exchange rate, forecasting, non-numerical information, support vector machine, classifier ensemble

## 1 Introduction

With the development of economic globalization, exchange rate, as an important link of the international economic relations, is becoming more and more important. As a consequence, analyzing and forecasting the exchange rate accurately is of great significance, especially for making policies and investment decisions.

However, predicting exchange rate has always been a very difficult task. It involves a large number of economic, political, military and other factors. Currently, the neural network has been widely used to forecast exchange rate and become the main method for forecasting. In the literature, different structures of neural networks have been adopted and they can usually achieve remarkable results [1-5]. De Matos compared the performance of the multilayer feedforward network (MLFN) and the recurrent neural network (RNN) with the Japanese Yen Futures forecasting. Hsu and others developed a clustering neural network (CNN) to forecast the direction of movement of U.S. Dollar against German Mark. Similarly, combining the genetic algorithm and the neural networks, Shazly designed a hybrid neural network to predict the three-month forward rate of the Pound, German Mark, Japanese Yen and Swiss Franc.

From the study above, the predicting accuracy obtained with a certain neural network is usually higher than that of the traditional statistical prediction models and the random walk model. However, there are still many limitations to this family of methods. First, these neural network based methods usually adopt a single classifier model, which may not be able to deal with a large number of input features adequately and appropriately. More importantly, due to the limited capacity of a single neural network and its inherit nature, these methods can merely utilize the quantified information. As a result, the non-numerical information, proven to be critical for the prediction accuracy, is usually discarded.

In order to deal with these problems, we adopt an integration method so as to combine multiple classifiers. We investigate the impact of non-numerical information for the exchange rate changes and engage a classifier ensemble method to forecast exchange rate between U.S. dollar and Japanese yen. First, we exploit the fuzzy comprehensive evaluation model to quantify the non-numerical fundamental information. Second, the corresponding single classifier is designed to present the impact of exchange rate changes with this information. In addition, other different classifiers are also proposed to deal with the numerical information. Finally, all these classifiers are integrated with a support vector machine (SVM).

The rest of the paper is organized as follows. Section 2 describes the non-numerical information quantification. And multiple classifiers ensemble is shown in Section 3. Section 4 describes experiments of forecasting exchange rate between U.S. dollar and Japanese yen. Finally, some conclusions and final remarks are set out in Section 5.

## 2 The Non-numerical Information Quantification

Exchange rate forecasting is a complex problem and involves many factors. Previous approaches merely adopt the numerical information. The non-numerical information which is difficult to be quantified is always discarded. However the impact of exchange rates changes with this information is also important and hence cannot be ignored.

### 2.1 The Non-numerical Information Selection

With analyzing the theories of exchange rate determination and considering the significant impacts on exchange rate changes, we select several important non-numerical information items which mainly include the following six aspects: government and banking policy, market psychology, news media, oil price, political situation and unexpected factors.

The above information is mainly from the following websites:
http://edu.xinhuaonline.com; http://www.reuters.com/; http://www.fx185.com/.

We collected a total of 85 trading days of the relevant information from January 1 to May 2, 2008 about the United States and Japan, and study the non-numerical information for the impact of exchange rate changes between the two currencies.

## 2.2 The Non-numerical Information Quantification

The non-numerical information is quantified by the fuzzy comprehensive evaluation model [6]. The process is described as follows.

First, calculate the weight of the non-numerical information with the binary comparison method. Then, evaluate the degree of membership according to the size of the affection to exchange rate changes. At last, quantify the non-numerical based on the weight and the degree of membership.

After calculation and analysis, the degree of impact is described as follows: Government and banking policy > market psychology > news media > oil price > political situation > unexpected factors. According to this relationship, the weight of the non-numerical information is calculated. The results are shown in Table 1.

**Table 1.** The matrix table and weight.

| Indicators | Government and banking policy | Market psychology | News media | Oil price | Political Situation | Unexpected factors | Σ | Weight |
|---|---|---|---|---|---|---|---|---|
| Government and banking policy | 1 | 1 | 1 | 1 | 1 | 1 | 6 | 0.286 |
| Market psychology | 0 | 1 | 1 | 1 | 1 | 1 | 5 | 0.238 |
| News media | 0 | 0 | 1 | 1 | 1 | 1 | 4 | 0.190 |
| Oil price | 0 | 0 | 0 | 1 | 1 | 1 | 3 | 0.143 |
| Political situation | 0 | 0 | 0 | 0 | 1 | 1 | 2 | 0.095 |
| Unexpected factors | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0.048 |
| Σ | 1 | 2 | 3 | 4 | 5 | 6 | 21 | 1 |

While computing the degree of membership, we mainly consider the impact of exchange rate changes. If the information is favorable to the exchange rate rising, its degree of membership is close to 1. Contrarily, it is close to 0. If the change of exchange rate is not obvious, it is 0.5. Because the exchange rate involves two countries, the membership degree of the two countries is contrary in the table.

At last, we obtain the quantified value of this information with the weight and the degree of membership. Partial results are shown in Table 2.

# 3 Classifier Ensemble for Exchange Rate Forecasting

The exchange rate forecasting with multiple classifiers is proposed to deal with exchange rate changes with many economic indicators. First, we use different classifiers to deal with the economic indicator. Then we integrate these results from each single classifier. The classifier ensemble structure is shown in Fig. 1.

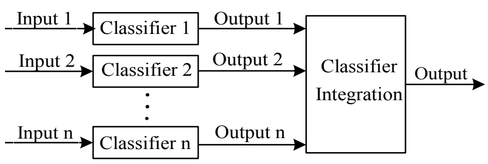


**Fig. 1.** The structure of the multiple classifiers system.

**Table 2.** The non-numerical information quantification results.

| Information | America | | | | | | Quantify value |
|---|---|---|---|---|---|---|---|
| | Government and banking policy | Market psychology | News media | Oil price | Political situation | Unexpected factors | |
| Weight | 0.286 | 0.238 | 0.190 | 0.143 | 0.095 | 0.048 | |
| 1/2/2008 | 0.5 | 0.4 | 0.5 | 0.3 | 0.5 | 0.5 | 0.4719 |
| 1/3/2008 | 0.5 | 0.6 | 0.5 | 0.6 | 0.5 | 0.5 | 0.5224 |
| 1/4/2008 | 0.6 | 0.5 | 0.6 | 0.6 | 0.5 | 0.4 | 0.5243 |
| 1/7/2008 | 0.5 | 0.5 | 0.5 | 0.7 | 0.5 | 0.4 | 0.5152 |
| 1/8/2008 | 0.5 | 0.5 | 0.6 | 0.3 | 0.4 | 0.5 | 0.5081 |
| 1/9/2008 | 0.5 | 0.5 | 0.6 | 0.4 | 0.6 | 0.4 | 0.5180 |
| 1/10/2008 | 0.5 | 0.4 | 0.4 | 0.6 | 0.5 | 0.5 | 0.4886 |
| 1/11/2008 | 0.5 | 0.3 | 0.4 | 0.6 | 0.5 | 0.5 | 0.4691 |
| 1/14/2008 | 0.5 | 0.6 | 0.5 | 0.4 | 0.6 | 0.5 | 0.5176 |
| 1/15/2008 | 0.5 | 0.4 | 0.4 | 0.7 | 0.5 | 0.5 | 0.5100 |
| 1/16/2008 | 0.5 | 0.4 | 0.4 | 0.6 | 0.4 | 0.5 | 0.4605 |
| 1/17/2008 | 0.5 | 0.4 | 0.4 | 0.6 | 0.5 | 0.5 | 0.4786 |
| 1/18/2008 | 0.7 | 0.3 | 0.4 | 0.4 | 0.5 | 0.5 | 0.4806 |
| 1/22/2008 | 0.7 | 0.4 | 0.4 | 0.4 | 0.5 | 0.5 | 0.4701 |
| 1/23/2008 | 0.5 | 0.6 | 0.5 | 0.6 | 0.5 | 0.5 | 0.5095 |
| 1/24/2008 | 0.7 | 0.6 | 0.4 | 0.3 | 0.5 | 0.5 | 0.5262 |
| 1/25/2008 | 0.5 | 0.4 | 0.5 | 0.4 | 0.5 | 0.5 | 0.4848 |
| … | … | … | … | … | … | … | … |

### 3.1 Integrated Forecast

The integrated forecast is based on the intuitive idea that by combining several separate prediction models, the forecasting effect may be better than a single one [7].

In the experiments, denote there are $n$ separate classifiers to predict, and for any input $x$ , the output is $f_i(x)$ , associated with the $i$ classifier. The integrated prediction model is displayed as follows.

$$\tilde{f}(x) = \sum_{i=1}^{n} w_i f(x) . \quad (1)$$

where, the $\tilde{f}_i(x)$ is the results of integrated forecasting, the weight of each individual classifier in integrated forecast is $w_i\,(i = 1, 2, \cdots n)$ , $0 \le w_i \le 1$ , $\sum_{i=1}^{n} w_i = 1$ .

The method of integrated forecast has advantages in reducing the variance of the forecasting error. However, how to calculate the weight and which integrated approach to be adopted are difficult problems. At present, there are two categories of methods, the linear integration and the non-linear integration. We use the integration of support vector regression prediction model to forecast the exchange rate.

### 3.2 Ensemble Forecast with Support Vector Machine

In order to overcome the problems caused by the neural networks, the SVM based method is designed [8-9]. It uses the support vector regression (SVR) to solve the problem of weight in Eq. (1). The basic idea is using the structural risk minimization to obtain the weight vector of the integrated forecast.

In fact, the support vector regression ensemble can be seen as a non-linear processing system [10]. It is displayed as following.

$$\tilde{y} = f(\tilde{x}_1, \tilde{x}_2 \cdots, \tilde{x}_n) \quad (2)$$

where, $(\tilde{x}_1, \tilde{x}_2 \cdots, \tilde{x}_n)$ is the forecast result of separate prediction model, $\tilde{y}$ is the integrated forecast result, $f(\bullet)$ is a non-linear function which is confirmed by the SVR. The solving steps are described as follows.

First, regress the forecast result of separate prediction model. Then, turn the results to the support vector using the kernel function. At last, study and output the optimal solution. The structure is shown in Fig. 2.

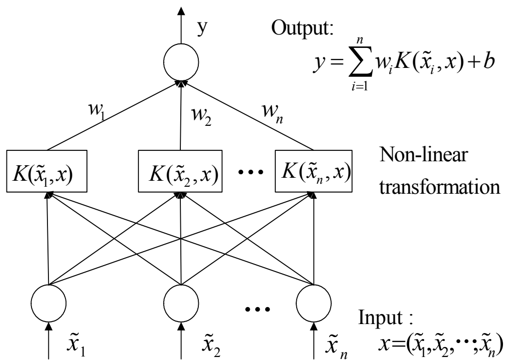


**Fig. 2.** The integration of support vector regression prediction model.

## 4 Experiments and Analysis

### 4.1 Data Sources

In this paper, we select U.S. Dollar / Japanese Yen to forecast the exchange rate. The experimental data are from the website: http://www.federalreserve.gov/release/.

We use the data of 61 days from January 2 to March 31, 2008 except for Weekends and holidays as the training set to establish the multi-classifier system. Similarly, we adopt the 24 days from April 1 to May 2, 2008 as the testing set. Specific data can be retrieved from the related websites.

### 4.2 Data Preprocessing and Evaluation Criteria

We first normalize the raw data of the exchange rate and transfer them into the special form which is suitable for the neural network processing. The data are mapped to [0.1, 0.9] according to repeatedly tested and compared in the experiments. The mapping function is described as follows.

$$y = \frac{(x - \min)(h - l)}{\max - \min} + l \, . \tag{3}$$

where, $y$ is the standardized data, $x$ denotes the raw data, $\max$ is the largest data of the raw data, $\min$ is the smallest one and $h$ is the upper bound of a specific interval as well as $l$ is the lower bound, $0.1 \le l \le h \le 0.9$.

In order to evaluate the forecast performance, we use the Mean Absolute Error (MAE) and the Direction Accuracy (DA) as the evaluation criteria. The formula for calculating MAE is as follows.

$$MAE = \frac{1}{N}\sum_{i=1}^{N} | x_i - \tilde{x}_i | \, . \tag{4}$$

where, $\tilde{x}_i$ is the forecast result, $x_i$ is the actual value, $N$ is the forecast period.

However, from the perspective of investors, the MAE can not bring direct suggestions to their investment. Due to the direction of exchange rate changes is more important for them to make decisions. So, we use the DA to evaluate the effect of forecasting.

$$DA = \sum_{i=1}^{N} \frac{A_i}{N} \, . \tag{5}$$

Here, if $(x_{i+1} - x_i)(\tilde{x}_{i+1} - x_i) \ge 0$, $A_i = 1$. Else, $A_i = 0$.

### 4.3 Experimental Results and Analysis

#### 4.3.1 The Effectiveness of Non-numerical Information

The quantified non-numerical information (in Table. 2) can be directly integrated with the exchange rate value and numerical index. In order to verify the effective of the quantitative methods and the selected information, we use the SVM and the RBF (Radial Basis Function) to carry out the experiment. Results are shown in Table 3 and Table 4 respectively.

Observed from the tables, the effect of forecast is better if we add the economic indicators. Moreover, with the non-numerical information, not only the MAE indicator is significantly lower, but also the DA is improved greatly. It fully demonstrates that the six types of information, as well as quantitative methods are effective.

**Table 3.** The forecast results of SVM.

| Input variables | Not the non-numerical information | | The non-numerical information | |
|---|---|---|---|---|
| | MAE | DA | MAE | DA |
| Exchange value | 0.0574 | 52.17% | 0.0467 | 66.96% |
| Exchange value and the large deposit rates | 0.0462 | 53.12% | 0.0369 | 86.96% |
| Exchange value and the bond yields | 0.0480 | 43.48% | 0.0370 | 78.27% |
| Exchange value and the lending rate | 0.0472 | 50.05% | 0.0373 | 70.83% |
| Exchange value and the treasury rates | 0.0509 | 53.41% | 0.0403 | 65.22% |
| Exchange value and the federal funds rate | 0.0465 | 50.15% | 0.0372 | 75.12% |

**Table 4.** The forecast results of RBF.

| Input variables | Not the non-numerical information | | The non-numerical information | |
|---|---|---|---|---|
| | MAE | DA | MAE | DA |
| Exchange value | 0.0674 | 52.17% | 0.0572 | 66.96% |
| Exchange value and the large deposit rates | 0.0467 | 52.36% | 0.0368 | 82.61% |
| Exchange value and the bond yields | 0.0543 | 47.83% | 0.0405 | 73.91% |
| Exchange value and the lending rate | 0.0431 | 51.18% | 0.0432 | 65.22% |
| Exchange value and the treasury rates | 0.0508 | 53.62% | 0.0382 | 83.58% |
| Exchange value and the federal funds rate | 0.0438 | 54.17% | 0.0384 | 66.67% |

### 4.3.2 The Integrated Forecast Results

We use the above method to forecast the exchange rate. The output of single classifiers forms a feature vector and the integration is seen as a secondary forecast.

In the experiment, we adopt one single classifier to process every different economic indicator. The process is showed as follows: (1) study the implicit principles with single classifier, (2) integrate these forecast results from every single classifier, and (3) finally obtain the forecast results. The experimental results are shown in Table 5.

**Table 5.** The integrated forecast results.

| Input variables | Not the non-numerical information | | The non-numerical information | |
|---|---|---|---|---|
| | MAE | DA | MAE | DA |
| Integrate all the indicators | 0.0393 | 78.26% | 0.0367 | 86.96% |

If we compare Table 5 with Table 3 and Table 4, the forecasting accuracy in terms of both MAE and DA is observed to be greatly improved and is much better than that of the single classifier. Additionally, the non-numerical information can also benefit the exchange rate forecasting. The results show that the integrated network can utilize different type of neural network architectures and information so as to make a better forecasting. It can overcome the defects of the single classifier and consequently achieves better performance.

## 5 Conclusion

In this paper, we adopt the integration method of multiple classifiers to forecast the exchange rate. We have investigated the impact of the non-numerical information on the exchange rate changes between the dollar and Japanese yen. Experimental results showed that our integrated method effectively improved the performance of exchange rate forecast. Specially, the DA is improved greatly. However, how many economic indicators to be integrated for reaching the best effect of forecasting is still an open problem. We are aware of that, with the global financial crisis intensifying, the exchange rate forecasting is a big challenge, which needs more theories, methods, and technologies from all related fields, such as economics, mathematics, and computer science. We will investigate these issues in the future.

## ACKNOWLEDGEMENTS

This work is supported by the National Natural Science Foundation of China under Grant No.60675006 and thanks Liang Jia for his contributions to this paper.

## References

1. Tenti, P.: Forecasting foreign exchange rates using recurrent neural networks. Applied Artificial Intelligence. 10, 567--581 (1996)
2. El Shazly, M.R., El Shazly, H.E.: Forecasting currency prices using a genetically evolved neural network architecture. International Review of Financial Analysis. 8, 62--82 (1999)
3. Leung, M.T., Chen A.-S, Daouk, H.: Forecasting exchange rates using general regression neural networks. Computers & Operations Research. 27, 1093--1109 (2000)
4. Reddy, M.K., Kumar, B.N.: Forecasting foreign exchange rates using time delay neural networks. In: the 2008 International Conference on Data Mining, pp. 181--194. IEEE Press, Las Vegas (2008)
5. Kasuga, H.: Exchange rates and ownership structure of Japanese multinational firms. Japan and the World Economy. 10, 661--678 (2008)
6. Xu Y.-T, Wang L.-S.: Fuzzy comprehensive evaluation model based on rough set theory. In: 5th International Conference on Cognitive Informatics, pp. 877--880. IEEE Press, Beijing (2006)
7. Krogh, A., Vedelsby, J.: Neural network ensembles, cross validation, and active learning. In: Advances in Neural Information Processing Systems, pp. 231--238. MIT Press, Cambridge, Massachusetts (1995)
8. Kamruzzaman, J., Sarker, R.A., Ahmad, I.: SVM based models for predicting foreign currency exchange rates. In: Third International Conference on Data Mining, pp. 557--560. IEEE Press, Los Alamitos (2003)
9. Duda, R.O., Hart, P.E., Stork, D.G.: Patten Classification, Second Edition. John Wiley & Sons, San Francisco (2001)
10. Wang S.-Y, Yu L.-A, Lai, K.-K.: TEI@I Methodology and Its Application to Exchange Rates Prediction. Chinese Journal of Management. 4, 21--27 (2007)