

Using RBF neural networks to identify relationship between development of oil prices in world market and value of Chinese currency

Jakub Horák^{1}, Jaromír Vrbka¹, Tomáš Krulický¹*

¹Institute of Technology and Business, School of Expertness and Valuation, Okružní 517/10, 37001 České Budějovice, Czech Republic

Abstract. The objective of the contribution is to identify a possible relationship between the development of the price of Brent oil (Brent in USD/barrel) and the CNY / USD Exchange rate by means of artificial neural networks. Understanding future fluctuation characteristics and the trend in oil prices is the basis for a deep understanding of systemic mechanisms and trends in related research areas. However, given the complexities of oil prices, it is very difficult to obtain accurate forecasts. Within the experiment, a total of 50,000 artificial RBF neural networks were generated. Was found the CNY / USD price will play a significant role in creating China's real product. Given that it was already proven that the CNY / USD exchange depends on Brent in USD / barrel, it is important to focus the further research on finding out the time lag with which the price of Brent in USD / barrel is actually reflected in the price of CNY / USD.

Key words: RBF neural networks, value, oil prices, exchange rate

1 Introduction

Oil is a vitally important energy source. The fluctuation of international oil prices influences all aspects of economy. The exchange rate is one of the important channels which demonstrate how the international shock on oil prices is reflected on the actual economy and financial markets. The change in the exchange rate of the US dollar will inevitably influence international oil prices. Quiang et al. [1] explore impacts of the fluctuation of oil prices on the national exchange rate in oil-importing countries. As a result of the detailed exploration the authors argue that a future research may be conducted in exploring inherent laws on the reserve of oil price volatility in different modes of exchange rates and in studying the way in which and to which extent the fluctuation of oil prices influences the effects of exchange rates.

The understanding of fluctuation characteristics and trends in oil prices gives grounds for a deep understanding of system mechanisms and gradual trends in related researches. In a view of the characteristics of oil prices being rather complex, it is very difficult to make accurate predictions. In order to increase the accuracy of international predictions of oil

* Corresponding author: horak@mail.vstecb.cz

prices, Chai et al. [2] developed a new prediction hybrid model of which the results show that the accuracy of the prediction of the designed hybrid model, based on fuzzy clustering algorithm with dynamic time deformation, is fairly good. In case of China, the main world's importer of oil, the slightest fluctuation of the oil price or the exchange rate will have a dramatic impact on the oil import [3]. China's dependence rate on foreign oil continuously increases. The fluctuation of the international oil price has an overwhelming influence on Chinese oil import, which continuously shocks the economic development of China. This article proves Markov's properties of the international fluctuation of oil prices and the strong probability of a state's transfer to Markov's chain is calculated. This document estimates that the fluctuation of the international oil price may cause a loss about 47,078 billion yuan on GNP in a single month [4].

Baek and Kim [5] examine the influence of the fluctuation of oil prices on exchange rates in selected sub Saharan African countries (SSA). In order for this issue to be thoroughly explored, the authors are, in contrast to previous studies, delayed in specifically describing asymmetrical effects of changes in oil prices in their modelling process using the nonlinear autoregressive model. The results demonstrate strong evidence that changes in oil prices will have long-term asymmetrical effects on actual exchange rates. The fluctuation of actual exchange rates thereby reflects the increase in oil prices rather than their drops. Changes in oil prices have various impacts on financial ratios of global markets and economies [6]. The aim the study of Kayalar, Küçüközmen and Selcuk-Kestel [7] is to explore the structure of the dependence between oil prices and indexes of stock markets and exchange rates in various economies categorized in regard to their position in developing markets and countries which import or export oil. The authors of the research found out that exchange rates and stock market indexes of most of the countries exporting oil demonstrate a higher dependence on the oil price; on the other hand, developing markets where oil imported are less sensitive to price fluctuations.

This article focuses on the use of artificial neural structures, RBF in particular, which are suggested in the next part. Artificial neural networks (ANNs) are considered as a highly efficient method of data collection, their analysis and prognosis; therefore, they may be applied while resolving various complex issues and situations including the prognosis of the development of stock market prices [8; 9]. ANNs may be used for the classification, regression or, for example, cluster analysis. Their big advantage is the ability to process a large amount of data, a simple application of the acquired neural network or the accuracy of results [10]. On the other hand, their disadvantage is the way in which individual models of artificial neural networks are created [11].

ANNs are currently a very popular method for the prognosis of key ratios in a company [12]. ANNs have gradually become very significant in universal domains Adhikari and Agrawal [13] and Sayadi et al. [14] argues that they are highly accurate in the prognosis. One of the crucial issues, though, is that there is no consensus about how to use them the best [15]. Šnorek [16] argues that the biggest advantages of ANN methods for the prognosis of key ratios of the company are non-linear approximate functions and the ability to learn and generalize. Rowland, Šuleř and Vochozka [17] on the other hand argue that disadvantages of ANNs are that variables should be carefully selected and prioritized (it requires highly accurate data); furthermore, there is a risk of illogical behaviour of the network and their architecture requires an exact definition.

The time series can be referred to as a specific data monitoring; these data are recorded horizontally with respect to time – from the past to present [18]. The analysis of time series is mainly used for the future prognosis [19]. Vrbka and Rowland [20] declare that the analysis of time series provides for ANNs a wide application. Rodrigues, Markou and Pereira [21] state that through the time series prognosis it is possible to predict future values from previously monitored values. The accurate prediction of time series is very important

for a wide range of areas of competence [22]. The prediction requires a most accurate data on prognosis variables, data characteristics and data accessibility; moreover, the method of the prediction and its time horizon need to be devised [23].

Networks of radial basic functions (RBF) belong to ANNs called feedforward networks since the data in the network structure are processed in one direction – from input neurons to output neurons. These networks are different from other ANNs of this sort; they actually use radial basic functions as activation functions. This enables them learn faster while their sensitivity to the order of the presented data is reduced [24]. They usually consist of three layers: the input layer, the hidden layer with non-linear activation RBF function and the linear output layer. RBF can be applied in a lot of ways including approximation of a function, time series prediction and system classification and management. RBF are the best used to deal with problems of a smaller number of inputs [25].

2 Data and methods

Some researchers claim that exist relationship between the oil price in the world market and the value of Chinese Yuan. However, a question remains, whether the influence is somehow significant and clear from the comparison of the two-time series.

The data for analysis are available on the World Bank web pages [26]. For the purpose of the analysis, the information on (CNY/USD) exchange rate will be used. The second time series will be (Brent in USD/barrel). The use of the USD value for calculating the prices of CNY and Brent[†]oil enables to eliminate the delay that could occur due to the fluctuations of the USD value. These data are also available on the World Bank web pages [26]. The contribution will use the final value of both variables at the time interval of 1 September 2014-30 August 2019.

The descriptive characteristics of both time series are available in Table 1.

Table 1. Descriptive characteristics: Brent in USD/barrel and Brent in USD/barrel

Samples	Brent in USD/barrel Input variable	CNY/USD Output (target)
Minimum (Training)	27.8800	0.139600
Maximum (Training)	102.7900	0.163600
Average (Training)	58.5614	0.152175
Standard deviation (Training)	12.9949	0.006092
Minimum (Testing)	30.5000	0.139800
Maximum (Testing)	100.2000	0.163600
Average (Testing)	61.7022	0.152119
Standard deviation (Testing)	12.2878	0.006461
Minimum (Validation)	31.5500	0.139600
Maximum (Validation)	102.7700	0.163600
Average (Validation)	59.8710	0.152370
Standard deviation (Validation)	18.2674	0.009356
Minimum (Overall)	27.8800	0.139600
Maximum (Overall)	102.7900	0.163600
Average (Overall)	59.2272	0.152196
Standard deviation (Overall)	13.1782	0.006168

Source: Own processing.

[†] In this contribution, Brent oil price represents the price of oil in the world market, because it is used for valuation of two thirds of the world oil supply.

Course of Brent in USD/barrel time series is shown in Figure 1.

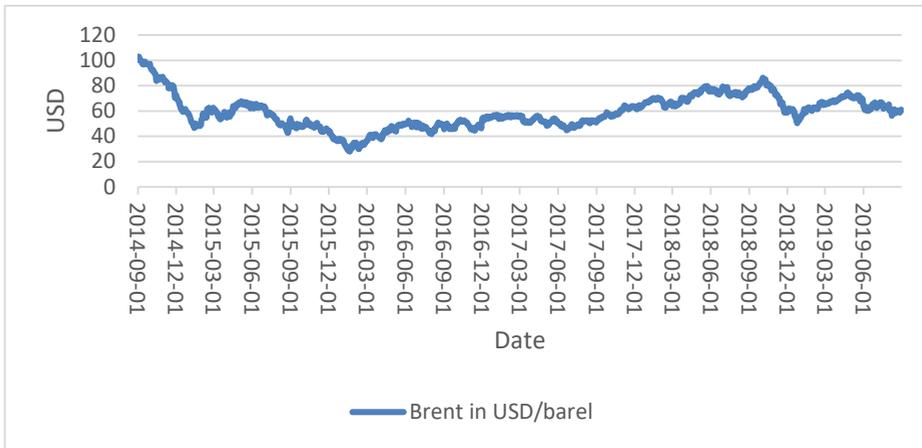


Fig. 1. Course of Brent in USD/barrel time series

Source: World Bank [26], own processing.

The course of the Brent in USD/barrel series can be seen in Figure 2.

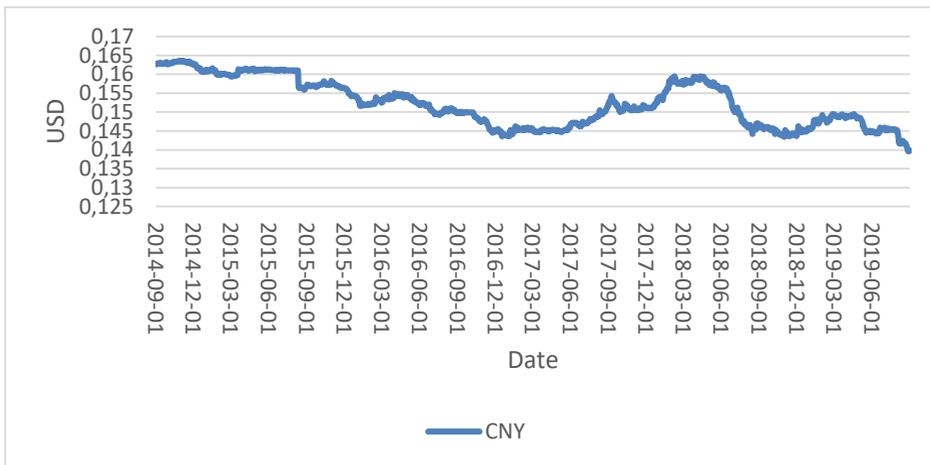


Fig. 2. Course of CNY/USD

Source: World Bank [26], own processing.

The influence of Brent in USD/barrel on the development of CNY/USD does not have to be immediate. It can be seen on the same day or with one-week or even one-month lag. Time lag cannot be calculated. It does not even have to be constant time lag throughout the monitored period of time. It is therefore necessary to carry out an experiment to find out whether there is a real dependence between the monitored time series and at which time lag this dependence is greatest. The following factors will be assumed:

1. Change in CNY/USD price shows on the same day. In such a case, CNY/USD would probably not react on Brent in USD/barrel, but the exchange rate would more likely reflect the cause resulting in the change of Brent in USD/barrel price. There can also be signs that the oil price will change.

2. Change in CNY/USD price shows with a one-day lag after the change of Brent in USD/barrel price. It would be a really small lag, which would indicate high sensitivity of CNY/USD to Brent in USD/barrel.
3. Change in CNY/USD price shows with a five-day lag after the change in the Brent in USD/barrel price.
4. Change in CNY/USD price shows with a 10-day lag after the change in Brent in USD/barrel price.
5. Change in CNY/USD price shows with a 30-day lag after the change in Brent in USD/barrel price.

Given that due to the complexity of the calculation we do not work with only one-day lag, there is a risk that if there is a real dependence between the two-time series, time lag will not be identified. Despite this potential risk, the objective of the contribution can be achieved.

Regression using neural structures will be carried out in DELL's Statistica software, version 12. Radial basis function (RBF) neural networks will be generated. The independent variable will be Brent in USD/barrel. The dependent variable will be CNY/USD. The time series will be divided into three data sets – training, testing and validation. The first set will contain 70% of the input data. Based on the training data set, neural structures will be generated. The remaining data sets will contain 15% of the input data. Both sets will be used for the verification of the neural structure reliability. There will be generated 10,000 neural networks for each time lag. 5 calculations will thus be carried out. 5 artificial neural networks with the best characteristics[‡] will be calculated for each calculation. We will thus compare 25 artificial neural structures; and their performance expressed by the correlation coefficients of the training, testing, and validation data sets will be investigated. In ideal case, the correlation coefficient values will be significant (over 0.7). Statistical dependence is at the interval of 0.5-0.7. Nevertheless, the dependence can be identified if the correlation coefficient values are at the interval of 0.3-0.5. In such a case, however, the dependence is not strong. At the same time, it is important that the correlation coefficient value is approximately the same in all data sets. The error will also be assessed. The sensitivity analysis will also be interesting.

In the hidden layer of RBF there will be always 21-30 neurons. The activation function of the hidden layer will always be the Gaussian function. For the activation of the output layer, the Identity function will be used. As an error function, the sum of the least squares will be used. For the networks training, the RBFT algorithm integrated in the Statistica software will be used.

Other settings will remain default according to the ANN (Automated Neural Networks) tool. If needed, the corrections of the individual neurons weight will be corrected and tested using the VNN tool. It must be stated that improving artificial neural network using this tools is rather accidental than an exact process with a predictable outcome.

3 Results

3.1 Result without lag

First, regression analysis using RBF without a time lag was carried out (Table 2).

[‡] The least squares method will be used. Generating of networks will be finished when there is no improvement, that is, no reduction in the sum of squares. The retained networks will be those whose sum of residual squares to the development of CNY / USD will be as low as possible (zero in ideal case).

Table 2. Retained neural networks for time series without lag

Index	Network	Training performance	Testing performance	Valid. performance	Training error	Testing error	Validation error
1	RBF 1-24-1	0.412751	0.372668	0.511868	0.000015	0.000018	0.000014
2	RBF 1-29-1	0.402858	0.411735	0.501684	0.000016	0.000017	0.000015
3	RBF 1-27-1	0.421069	0.363556	0.501947	0.000015	0.000018	0.000015
4	RBF 1-29-1	0.416481	0.331440	0.505133	0.000015	0.000019	0.000015
5	RBF 1-25-1	0.403294	0.314854	0.501389	0.000016	0.000019	0.000015

Source: Own processing.

The table clearly indicates that the retained networks contain 24-29 neurons in the hidden layer. The performance of all retained neural structures is above 0.3. The validation data sets always show the highest values; in their case, correlation coefficient value is always above 0.5, while the lowest values are in the case of the testing data set, namely between 0.31 (the 5. RBF 1-25-1) and 0.41 (the 2. RBF 1-29-1). The values of training performance are between 0.4 and 0.42. The error is always below 0.00002. It can thus be stated that compared to the absolute value of CNY/USD the value is minimal.

3.2 Results with one-day lag

The results of regression analysis with a one-day lag are shown in Table 3.

Table 3. Retained networks for time series with one-day lag

Index	Network	Training performance	Testing performance	Validation performance	Training error	Testing error	Validation error
1	RBF 1-25-1	0.367709	0.265241	0.423495	0.000016	0.000019	0.000017
2	RBF 1-27-1	0.412785	0.344563	0.432329	0.000015	0.000018	0.000017
3	RBF 1-25-1	0.434149	0.292056	0.427362	0.000015	0.000019	0.000017
4	RBF 1-30-1	0.448699	0.321214	0.421693	0.000015	0.000018	0.000017
5	RBF 1-26-1	0.411882	0.336311	0.431904	0.000015	0.000018	0.000017

Source: Own processing.

It results from the table that the retained networks contain 25-30 neurons in the hidden layer. The highest values are shown by the validation data set, where the value of the correlation coefficient is always above 0.42, while the lowest average values of the correlation coefficients are shown by the testing data set, namely between the value higher than 0.26 (1. RBF 1-25-1) and almost 0.35 (2. RBF 1-27-1). The training performance achieves the values of almost 0.37 – 0.45. The error is always lower than 0.00002. It can be stated that compared with the absolute value of CNY/USD the value is minimal. In general, however, the performance in the case of the individual neural networks and data sets is uneven.

3.3. Results with five-day lag

Another investigated time lag was a five-day lag. The results are shown in Table 4.

Table 4. Retained neural networks for time series with 5-day lag

Index	Network	Training performance	Testing performance	Validation performance	Training error	Testing error	Validation error
1	RBF 1-28-1	0.359699	0.428676	0.462018	0.000016	0.000018	0.000017
2	RBF 1-21-1	0.375812	0.449748	0.483160	0.000015	0.000018	0.000016
3	RBF 1-23-1	0.383388	0.387543	0.459824	0.000015	0.000019	0.000017
4	RBF 1-25-1	0.369094	0.448173	0.468541	0.000015	0.000018	0.000016
5	RBF 1-21-1	0.344893	0.422891	0.459610	0.000016	0.000018	0.000017

Source: Own processing.

It results from the table that the retained neural networks contain 21-28 neurons in the hidden layer. The performance of all retained neural structures is above 0.3. The highest values are shown by the validation data set, with the correlation coefficient value always above 0.46. The lowest average values are shown by the training data set correlation coefficient, namely the values between more than 0.34 (5. RBF 1-21-1) and more than 0.38 (3. RBF 1-23-1). The testing performance value is between more than 0.38 and almost 0.45. The error is always smaller than 0.00002. It can thus be stated that compared to the absolute value of CNY/USD the error is minimal.

3.4 Results with 10-day lag

The results of regression analysis of the Brent in USD/barrel and CNY/USD time series are shown in Table 5.

Table 5. Retained networks for time series with 10-day lag

Index	Network	Training performance	Testing performance	Validation performance	Training error	Testing error	Validation error
1	RBF 1-23-1	0.422277	0.289404	0.411383	0.000015	0.000018	0.000017
2	RBF 1-22-1	0.449527	0.335184	0.421136	0.000015	0.000018	0.000017
3	RBF 1-25-1	0.446497	0.281631	0.413589	0.000015	0.000018	0.000017
4	RBF 1-28-1	0.450363	0.285487	0.417970	0.000014	0.000018	0.000017
5	RBF 1-21-1	0.412808	0.271661	0.417731	0.000015	0.000018	0.000017

Source: Own processing.

It results from the table that the retained networks contain 21-28 neurons in the hidden layer. The highest values are shown by the training data set, where the correlation coefficient values are at the interval of more than 0.41 to more than 0.45, and the lowest average values are achieved by the testing data set, namely from more than 0.27 (5. RBF 1-21-1) to 0.33 (2. RBF 1-22-1). In this case, the performance values of networks and data sets are very low. The validation data set performance achieves the values between more than 0.41 to more than 0.42. The error is always smaller than 0.00002.

3.5. Results with 30-day lag

The last calculation concerns a 30-day time lag (Table 6).

Table 6. Retained networks for time series with 30-day lag

Index	Network	Training performance	Testing performance	Validation performance	Training error	Testing error	Validation error
1	RBF 1-29-1	0.504936	0.417204	0.469858	0.000013	0.000015	0.000015
2	RBF 1-25-1	0.492835	0.402539	0.467906	0.000013	0.000016	0.000015
3	RBF 1-28-1	0.491749	0.426946	0.474171	0.000013	0.000015	0.000015
4	RBF 1-24-1	0.503934	0.421252	0.477249	0.000013	0.000015	0.000015
5	RBF 1-27-1	0.515606	0.481461	0.468058	0.000013	0.000014	0.000015

Source: Own processing.

The table shows that the retained networks contain 24-29 neurons in the hidden layer. All correlation coefficient values are above 0.40. The training data set coefficients achieve the values of more than 0.49 to almost 0.52. The lowest values are achieved by the testing data set correlation coefficients, namely from more than 0.40 (2. RBF 1-25-1) to more than 0.48 (5. RBF 1-27-1). The validation data set achieves the performance from almost 0.47 to almost 0.48. The error is never higher than 0.00002. In the case of the results for the time lag it must be noted that compared to other results, these achieve the lowest fluctuation in all three data sets.

3.6 Analysis of results

The analysis of the results given in Tables 2-6 clearly shows that, considering the overall performance of the retained neural networks, the correlation coefficient values, and all data sets error, the most successful is the set of results presented in Table 6. It declares certain (significant) dependence of CNY/USD exchange rate on the development of Brent in USD/barrel. This gives the response to the question whether Brent in USD/barrel affects the value of the CNY/USD, indicating that there is certain dependence. The influence is not decisive but it is not negligible. It can also be stated that the price of Brent in USD/barrel will be reflected in the CNY/USD exchange in approx. 30 days. Now it is necessary to assess which of the retained neural networks captures the relation between the Brent in USD/barrel and CNY/USD best.

Based on the correlation coefficients given in Table 6, where the absolute value in each set and ideally equalized values in all three data sets, the most successful appears to be the 5. RBF 1-27-1 neural network. Its suitability is mainly due to the performance of the testing data set, which is the highest one of all the retained networks. However, interesting data can be seen also in Table 7 showing the basic forecasts statistics.

Table 7. Basic statistics of forecasts (30-day lag)

Statistics	1.RBF 1-29-1	2.RBF 1-25-1	3.RBF 1-28-1	4.RBF 1-24-1	5.RBF 1-27-1
Minimal forecast (Training)	0.14318	0.14680	0.14586	0.14487	0.14386
Maximum forecast (Training)	0.16677	0.16676	0.16564	0.16341	0.16400
Minimal forecast (Testing)	0.14683	0.14680	0.14594	0.14620	0.14510
Maximum forecast (Testing)	0.16676	0.16675	0.16496	0.16336	0.16400
Minimal forecast (Validation)	0.14625	0.14683	0.14599	0.14798	0.14671
Maximum forecast (Validation)	0.16669	0.16676	0.16534	0.16341	0.16400
Minimal residuals (Training)	-0.01463	-0.01658	-0.01601	-0.01592	-0.01620
Maximum residuals (Training)	0.01449	0.01460	0.01280	0.01310	0.01403
Minimal residuals (Testing)	-0.01449	-0.01406	-0.01344	-0.01425	-0.01405
Maximum residua (Testing)	0.01227	0.01228	0.01082	0.01312	0.01202
Minimal residuals (Validation)	-0.01255	-0.01428	-0.01317	-0.01454	-0.01483
Maximum residuals (Validation)	0.01485	0.01246	0.01521	0.01308	0.01258
Minimal standard residua (Training)	-4.01689	-4.51769	-4.35931	-4.36985	-4.48091
Maximum standard residuals (Training)	3.97793	3.97692	3.48442	3.59497	3.88114
Minimal standard residuals (Testing)	-3.68314	-3.54739	-3.44145	-3.62991	-3.71718
Maximum standard residuals (Testing)	3.11746	3.09997	2.76965	3.34226	3.17966
Minimal standard residuals (Validation)	-3.25771	-3.70885	-3.44086	-3.80729	-3.84626
Maximum standard residuals (Validation)	3.85619	3.23586	3.97297	3.42616	3.26253

Source: Own processing.

The basic characteristics (at least those whose absolute values are given) are compared with the basic characteristics in Table 1 (showing the basic characteristics of the examined time series). Also, the residuals analysis is important. In this case, the comparison is vertical (that is, the same characteristic is compared for all data sets of each retained networks). The only network that slightly differs (in a negative way) is the network 3. RBF 1-28-1. Other retained networks show approximately the same performance.

Furthermore, we will deal with the sensitivity analysis of the individual networks. We will examine the sensitivity analysis of CNY/USD to Brent in USD/barrel (Table 8).

Table 8. Sensitivity analysis of CNY/USD to Brent in USD/barrel

Networks	Brent in USD/barrel
1.RBF 1-29-1	1.551800
2.RBF 1-25-1	1.602996
3.RBF 1-28-1	1.320312
4.RBF 1-24-1	1.529973
5.RBF 1-27-1	1.543923
Average	1.509801

Source: Own processing.

Based on the results of the analysis, the network with the highest sensitivity of CNY/USD to changes in Brent in USD/barrel appears to be 2. RBF 1-25-1. For better illustration, see Figure 3.

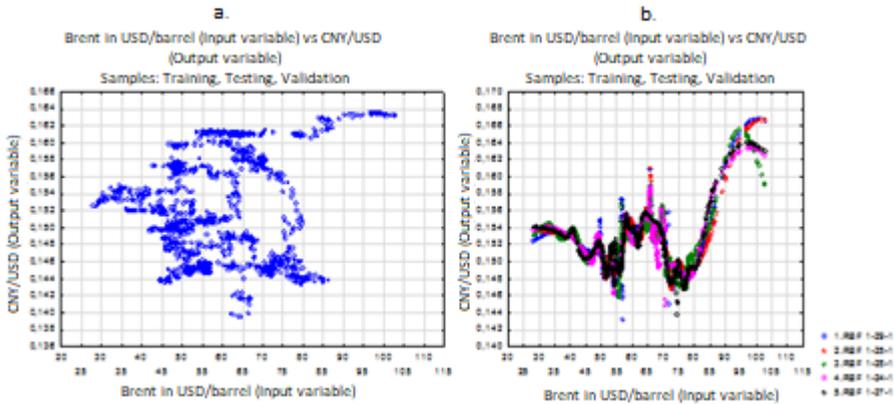


Fig. 3. Comparison of data distribution for real relationship between CNY/USD and Brent in USD/barrel and forecast

Source: Own processing.

Figure a. shows the actual distribution of time series data, where Brent in USD/Barrel is on the axis X and CNY/USD (without time sequence) on the axis Y . Figure b. shows the value of forecasts, which seems to indicate that the values follow the development over time but this is not true.

It follows from the figure that:

1. None of the neural networks is able to forecast the actual development of the CNY/USD exchange rate depending on Brent in USD/barrel completely.
2. It is clear that there is dependence between the CNY/USD time series and Brent in USD/barrel.

4 Conclusion

The objective of the contribution was to identify possible relationship between the price of Brent oil (Brent in USD/barrel) and the Chinese Yuan to American dollar (CNY/USD) exchange rate by means of artificial neural networks of the radial basis function (RBF).

Within the experiment, a total of 50,000 artificial RBF neural networks were generated. In each setting based on the time lag of the impact on the CNY/USD exchange rate (0, 1, 5, 10 and 30 days), five artificial neural structures with the best characteristics were retained. Subsequently, the results were analysed with regard to the objective of the contribution. It can be concluded as follows:

1. There is a dependence of CNY/USD on Brent in USD/barrel. It is not a majority one but is measurable.
2. None of the 50,000 generated RBF neural networks is capable of forecasting the actual development of the CNY/USD exchange rate depending on Brent in USD/barrel completely.
3. Time lag of the influence of Brent in USD/barrel on CNY/USD is almost 30 days. It is obvious that the time lag is not constant in the entire course of the monitored time interval.

It is thus evident that the CNY/USD price will play a significant role in creating China's real product.

Given that it has already been proven that the CNY/USD exchange depends on Brent in USD/barrel, it is important to focus the further research on finding out the time lag with which the price of Brent in USD/barrel is actually reflected in the price of CNY/USD.

References

1. W. Qiang, A. Lin, C. Zhao, Z. Liu, M. Liu, X. Wang, The impact of international crude oil price fluctuation on the exchange rate of petroleum-importing countries: a summary of recent studies. *Natural Hazards*, **95**(1-2), 227-239 (2019)
2. J. Chai, Y. Wang, S. Wang, Y. Wang, A decomposition – integration model with dynamic fuzzy reconstruction for crude oil price prediction and the implications for sustainable development. *Journal of Cleaner Production*, **229**, 775-786 (2019)
3. S. Liu, W. Fang, X. Gao, F. An, M. Jiang, Y. Li, Long-term memory dynamics of crude oil price spread in non-dollar countries under the influence of exchange rates. *Energy*, **182**, 753-764 (2019)
4. C.P. Zhang, X. Cao, Y.N. Zhao, J. Zhang, L. Yu, Research on the Impact of International Crude Oil Price Fluctuation and Oil Import to China's GDP. *2013 International Conference on Management Science and Engineering(ICMSE)*, pp. 1168-1173 (2013)
5. J. Baek, H.Y. Kim, On the relation between crude oil prices and exchange rates in sub-saharan African countries: A nonlinear ARDL approach. *Journal of International Trade & Economic Development*, 1-12 (2019)
6. F. Novotný, The Link Between the Brent Crude Oil Price and the US Dollar Exchange Rate. *Prague Economic Papers*, **21**(2), 220-232 (2012)
7. D.E. Kayalar, C.C. Küçüközmen, A.S. Selcuk-Kestel, The impact of crude oil prices on financial market indicators: copula approach. *Energy Economics*, **61**, 162-173 (2017)
8. M. Vochozka, J. Horák, P. Šuleř, Equalizing Seasonal Time Series Using Artificial Neural Networks in Predicting the Euro–Yuan Exchange Rate. *Journal of Risk and Financial Management*, **12**(2) (2019)
9. J. Horák, T. Krulický, Comparison of exponential time series alignment and time series alignment using artificial neural networks by example of prediction of future development of stock prices of a specific company. *SHS Web of Conferences: Innovative Economic Symposium 2018 – Milestones and Trends of World Economy*, **61** (2019)
10. P. Šuleř, Using Kohonen's neural networks to identify the bankruptcy of enterprises: Case study based on construction companies in South Bohemian region. *Proceedings of the 5th International conference Innovation Management, Entrepreneurship and Sustainability*, pp. 985-995 (2017)
11. Z. Rowland, J. Vrbka, Using Artificial Neural Networks for Prediction of Key Indicators of a Company in Global World. *Globalization and Its Socio-Economic Consequences, 16TH International Scientific Conference Proceedings*, pp. 1896-1903 (2016)
12. V. Machová, Z. Rowland, Value generators of enterprises in the processing industry. *Proceedings of the 6th International conference Innovation Management, Entrepreneurship and Sustainability*, pp. 624-634 (2018)
13. R. Adhikari, R.K. Agrawal, A combination of artificial neural network and random walk models for financial time series forecasting. *Neural Computing and Applications*, **24**(6), 1441-1449 (2014)
14. A. R. Sayadi, S. M. M. Tavassoli, M. Monjeziand, M. Rezaei, Application of neural networks to predict net present value in mining projects. *Arabian Journal of Geosciences*, **7**(3), 1067–1072 (2012)

15. A. Hogenboom, W. Ketter, J. Van Dalen, U. Kaymak, J. Collins, A. Gupta, Adaptive Tactical Pricing in Multi-Agent Supply Chain Markets Using Economic Regimes. *Decision Sciences*, **46**(4), 791-818 (2015)
16. M. Šnorek, *Neural networks and neurocomputers*. 1st ed. Prague: Publishing CVUT (2002)
17. Z. Rowland, P. Šuleř, M. Vochozka, Comparison of neural networks and regression time series in estimating the Czech Republic and China trade balance. *SHS Web of Conferences: Innovative Economic Symposium 2018 – Milestones and Trends of World Economy*, **61** (2019)
18. K. Valášková, T. Klieřtik, L. řvábová, P. Adamko, Financial risk measurement and prediction modelling for sustainable development of business entities using regression analysis. *Sustainability*, **10**(7) (2018)
19. Y. Mai, H. Chen, J.Z. Zou, Currency co-movement and network correlation structure of foreign Exchange market. *Physica A-Statistical Mechanics and its Applications*, **492**, 65-74 (2018)
20. J. Vrbka, Z. Rowland, Stock price development forecasting using neural networks. *SHS Web of Conferences: Innovative Economic Symposium 2018 – Strategic Partnerships in International Trade*, **39** (2017)
21. F. Rodrigues, I. Markou, F.C. Pereira, Combining time-series and textual data for taxi demand prediction in event areas: A deep learning approach. *Information Fusion*, **49**, 120-129 (2019)
22. T. Klieřtik, M. Miřánková, K. Valášková, L. řvábová, Bankruptcy prevention: New effort to reflect on legal and social changes. *Science and Engineering Ethics*, **24**(2), 791-803 (2018)
23. P. Rostan, A. Rostan, The versatility of spectrum analysis for forecasting financial time series. *Journal of Forecasting*, **37**(3), 327-339 (2018)
24. M. Vochozka, Using the Radial Basic Function neural network for determining the financial plan of a company. *Management 2016: International Business and Management, Domestic Particularities and Emerging Markets in the Light of Research*, pp. 331-337 (2016)
25. J. Vrbka, Z. Rowland, Stock price development forecasting using neural networks. *SHS Web of Conferences: Innovative Economic Symposium 2018 – Strategic Partnerships in International Trade*, **39** (2017)
26. World Bank [online], Available at: <https://www.worldbank.org/> (2019)