Estimation of the development of Czech Koruna to Chinese Yuan exchange rate using artificial neural networks

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Abstract. Through time series analysis, it is possible to obtain significant statistics and other necessary data characteristics. Prediction of time series allows predicting future values based on previously observed values. The exact prognosis of the time series is very important for a number of different areas, such as transport, energy, finance, economics, etc. It is within the topic of economy that the analysis and prediction of time series can also be used for exchange rates. The exchange rate itself can greatly affect the whole foreign trade. The aim of this article is therefore to analyze the exchange rate development of two currencies by analyzing time series through artificial neural networks. Experimental results show that neural networks are potentially usable and effective for exchange rate prediction.
Key words: artificial neural networks, exchange rate, time series, prediction, Czech crown, Yuan

1 Introduction

According to Sheikhan et al. [1], time series are characterized as sequences of spatially and de facto comparable observations that are time-based. Time series can also be defined as ordered sequences of values of variables at equally remote time intervals [2]. Time series analysis is a technique that involves the study of individuals or groups observed at the following moments. They are a series of data points in time order [3]. Through time series analysis, it is possible to obtain significant statistics and other necessary data characteristics. Prediction of time series allows predicting future values based on previously observed values [4]. The accurate prediction of time series is very important for a number of different areas, such as transport, energy, finance, economics, etc. [5]. The prognosis is considered to be the most important task of analyzing time series. Specifying a prediction problem is a basic step in the prognosis of time series. When predicting, it is necessary to have as accurate a picture as possible about the variables in the prediction, the availability of data, the nature of the data, and the prediction method and prognosis horizon [6].

The traditional view of the international economy lies in the fact that the exchange rate is a leading factor that can strongly affect foreign trade. Production fragmentation,

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widespread around the world as a result of recent globalization, may weaken the role of the exchange rate in international trade. Given that the Czech economy is very open, quantitative knowledge of the impact of the exchange rate on exports is valuable information for all actors in the economy [7].

International currency can be defined as one generally recognized in the world and used for trade agreements, investments, and foreign exchange reserves [8]. This paper will analyze the time series of the Czech currency development compared to the Chinese currency. The Czech crown (with the international abbreviation CZK) is the official currency of the Czech Republic. CZK 1 is composed of 100 hellers. Although hellers, as coins, have not been used since 2008, they are still included in the commodity prices. The final price is then rounded to the nearest value [9]. According to Cimburek and Řežábek [10], CZK in the Czech Republic, according to Czech legislation, is a legal tender that is generally accepted. Cash is easily available in the Czech Republic not only thanks to the CNB's distribution network, but also thanks to a dense network of banks, their branches and ATMs. The koruna is a safe currency and, thanks to its security features, ranks among the most successful ones in comparison with other currencies. An important role is played by the primary objective of the Czech National Bank as defined by the Constitution of the Czech Republic, namely price stability. The Czech Republic has been able to record a low-inflation environment for several consecutive years. A low-inflationary and stable economic environment may partially motivate certain demographic groups to accumulate cash and retain a certain portion of cash assets while maintaining the maximum liquidity requirement of these assets. As with most central banks, the CNB focuses primarily on the stability of consumer prices. In practice, price stability is generally not understood to mean price stagnation, but rather a modest growth. Price growth, consistent with price stability, should include the upward statistical upturn in the measurement of price growth and should also provide sufficient room for minor changes in price relations that are consistently occurring in every economy with an effective pricing system [11].

China had a range of currencies, most of which were denominated in the "Yuan" unit. Yuan in Chinese literally means "round object" or "round coin" [12]. Chinese Yuan (abbreviated CNY) is the official currency in China. 1 yuan is divided into 10 jiao and 1 jiao is divided into 10 fen [13]. Unlike other currencies, Chinese Yuan is subject to strict currency controls by the People's Bank of China [14]. CNY has evolved from a trading currency to an investment currency and now has the potential to be a global reserve currency. The growth of CNY as an international currency could balance the system controlled by the US dollar and contribute to regional and international financial stability [15]. If the Chinese policy were to return to effective monetary stability, it would strengthen the stability of the regional currency. This would create more favorable conditions for developing towards monetary co-operation [16], [17]. CNY rates can be considered as financial time series, characterized by high uncertainty, non-linearity and with different behaviors over time [18]. In this paper, artificial neural networks will be used to analyze the time series of the two aforementioned currencies. In this respect, for example, Liu et al. [19] conducted exchange rate predictions that were conducted using RBF neural networks. Detailed designs of the RBF neural network model architecture, transfer functions of the hidden layer nodes, input vectors, and output vectors have been performed with many tests. Experimental results show that the performance of RBF neural networks for the CNY exchange rate prediction is acceptable and effective.

2 Data and methods

Data for analysis are available on the World Bank website [20] etc. For the analysis, information on the Koruna (also referred to as "CZK") and Yuan (also referred to as

"RMB") exchange rate will be used. The timeframe for which the data will be available begins on October 6, 2009 and ends on October 21, 2018. We always record the daily exchange rate of both currencies. This is in total 3,303 records of input data. Unit is CZK per 1 RMB. The descriptive characteristics of the datafile are given in Table 1.

Table 1. Characteristics of the datafile

Samples	Data statistics	
	Date (Input variable)	Chinese Yuan to Czech Koruna (Output (goal))
Minimum (Training)	40092.00	2.485800
Maximum (Training)	43394.00	4.163000
Průměr (Training)	41734.79	3.265645
Standard deviation (Training)	939.26	0.392383
Minimum (Testing)	40102.00	2.496100
Maximum (Testing)	43393.00	4.155700
Average (Testing)	41755.71	3.272882
Standard deviation (Testing)	957.97	0.394309
Minimum (Validation)	40111.00	2.498900
Maximum (Validation)	43388.00	4.152900
Average (Validation)	41768.68	3.246446
Standard deviation (Validation)	1438.25	0.499822
Minimum (Overall)	40092.00	2.485800
Maximum (Overall)	43394.00	4.163000
Average (Overall)	41743.00	3.263852
Standard deviation (Overall)	953.64	0.392668

Source: Authors.

For data processing, DELL's Statistica version 12 will be used. For calculating neural structures, we use the Data Mining tool, specifically neural networks (ANS – Automated Neural Networks). We will generate multilayer perceptron networks and neural networks of basic radial functions.Time will be the independent variable (or designated measuring – case). We will determine the CZK to RMB exchange rate as the dependent variable. We divide the time series into three sets – training, testing, and validation. The first group will be 70% of input data. Based on the training set of data, we generate neural structures. In the remaining two sets of data, we always leave 15% of the input information. Both groups will serve us to verify the reliability of the found neural structure, or the found model. The delay of the time series will be 1. We will generate 100,000 neural networks. We will preserve 5 of them with the best characteristics[†]. In the hidden layer, we will have at least two neurons, at most 50. In the case of a radial basic function, there will be at least 21 neurons in the

[†] We will be orientated using the smallest square method. We will terminate network generation if there is no improvement, ie to reduce the sum of squares. So we will preserve those neural structures whose sum of squares of residuals to the actual development of the CZK to RMB exchange rate will be as low as possible (ideally zero).

hidden layer, at most 30. For the multiple perceptron network we will consider these distribution functions in the hidden layer and in the output layer:

- Linear,
- Logistic,
- Atanh,
- Exponential,
- Sinus.

Other settings are left by default (ANS – automated neural network).

3 Results

Based on the established procedure, 100,000 neural networks were generated. Five networks have been preserved, showing the best parameters. Their overview is given in Table 2.

Table 2. Overview of preserved nerual networks

Network name	Training perf.	Testing perf.	Valid. perf.	Train. error	Test. error	Valid. error	Train. Algor.	Error function	Activ. of hidd. lyr	Output activ. funct.
RBF 1-30-1	0.983490	0.983020	0.984843	0.002516	0.002616	0.002319	RBFT	Sum of squares	Gauss	Identity
RBF 1-26-1	0.984841	0.985412	0.984883	0.002312	0.002255	0.002309	RBFT	Sum of squares	Gauss	Identity
RBF 1-25-1	0.986071	0.986443	0.985769	0.002126	0.002109	0.002179	RBFT	Sum of squares	Gauss	Identity
RBF 1-26-1	0.985491	0.985337	0.984503	0.002213	0.002262	0.002367	RBFT	Sum of squares	Gauss	Identity
RBF 1-30-1	0.984297	0.983784	0.984732	0.002394	0.002499	0.002339	RBFT	Sum of squares	Gauss	Identity

Source: Authors.

These are only the neural networks of the basic radial function. The input layer has only one variable - time. In the hidden layer, neural networks contain 24 to 30 neurons. In the output layer, we have logically a single neuron, and the only output variable is the CZK to RMB exchange rate. For all networks, the RBFT training algorithm was applied. All neural structures used the same function to activate the hidden neuron layer, namely the Gaussian curve. They also use the same function to activate the outer layer of the neurons, and this function is identity (see Table 2).

Training, testing and validation performance is also interesting. In general, we are looking for a network that has the same performance in all sets of data (we recall that the distribution of data into sets was random). The error should be as minimal as possible.

The performance of individual sets of data is expressed as a correlation coefficient. The values of the individual data sets according to specific neural networks are presented in Table 3.

Table 3. Correlation coefficients of individual data sets

	Correlation coefficients		
	Chinese Yuan to Czech Koruna (Training)	Chinese Yuan to Czech Koruna (Testing)	Chinese Yuan to Czech Koruna (Validation)
1.RBF 1-30-1	0.983490	0.983020	0.984843
2.RBF 1-26-1	0.984841	0.985412	0.984883
3.RBF 1-25-1	0.986071	0.986443	0.985769
4.RBF 1-26-1	0.985491	0.985337	0.984503
5.RBF 1-30-1	0.984297	0.983784	0.984732

Source: Authors.

The table shows that the performance of all preserved neural structures is approximately identical. Slight differences do not affect the performance of individual networks. The correlation coefficient of all training data sets is above 0.983. The value of the correlation coefficient of the testing data sets reaches the same values as the training set of data, ie always more than 0.983. The correlation coefficient of the validation data set for all neural networks is above 0.984. Also, let's recall that the error is always slightly above 0.002 for all sets of data. Differences in the error of aligned time series in the individual datasets are almost negligible.

In order to select the most suitable neural structure, we need to analyze the results obtained. Table 4 provides the basic statistical characteristics of each set of data for all neural structures.

Table 4. Statistics of individual sets of data according to preserved neural structures

Statistics	Output (goal): Chinese Yuan to Czech Koruna				
	1.RBF 1-30-1	2.RBF 1-26-1	3.RBF 1-25-1	4.RBF 1-26-1	5.RBF 1-30-1
Minimum prediction (Training)	2.58183	2.55340	2.52919	2.52734	2.62556
Maximum prediction (Training)	4.04950	4.09743	4.00225	4.00540	3.95151
Minimum prediction (Testing)	2.58355	2.55342	2.52917	2.52741	2.62557
Maximum prediction (Testing)	4.04944	4.09741	4.00223	4.00544	3.95152
Minimum prediction (Validation)	2.58184	2.55531	2.53062	2.52749	2.62600
Maximum prediction (Validation)	4.04951	4.09682	4.00226	4.00505	3.95129
Minimum residues (Training)	-0.22414	-0.21614	-0.30694	-0.24314	-0.28141
Maximum residues (Training)	0.37317	0.23107	0.22900	0.21521	0.29266
Minimum residues (Testing)	-0.21388	-0.18746	-0.28546	-0.22842	-0.26051
Maximum residues (Testing)	0.37307	0.23378	0.22341	0.20519	0.29323
Minimum residues (Validation)	-0.21094	-0.17494	-0.17479	-0.20650	-0.23232
Maximum residues (Validation)	0.26023	0.22773	0.18504	0.21784	0.21065
Minimum standard residues (Training)	-4.46833	-4.49505	-6.65757	-5.16815	-5.75120
Maximum standard residues (Training)	7.43936	4.80567	4.96689	4.57450	5.98108
Minimum standard residues (Testing)	-4.18178	-3.94719	-6.21611	-4.80292	-5.21090
Maximum standard residues (Testing)	7.29438	4.92251	4.86501	4.31438	5.86540
Minimum standard residues (Validation)	-4.38041	-3.64037	-3.74445	-4.24472	-4.80316
Maximum standard residues (Validation)	5.40392	4.73891	3.96396	4.47779	4.35511

Source: Authors.

Ideally, individual neural network statistics are cross-sectionally (minimum, maximum, residue, etc.) similar in all sets of one particular neural structure. In the case of stored neural networks, the differences in time series are minimal, both in absolute terms and in the case of residues. For this reason, we are not able to clearly identify which of the preserved neural networks has the most appropriate results. All neural structures appear to be usable in practice.

Figure 1 is a graph showing the actual development of the CZK to RMB exchange rates as well as the development of predictions of the generated and preserved networks (or time series).

The graph shows that all neural networks predict a slight change in the development of the CZK to RMB exchange rate at individual intervals. However, the similarity between the predictions of individual networks, but the similarity (or the degree of consistency) with the actual development of the exchange rate of both currencies is not important. In this respect, all stored neural networks seem very interesting at first glance. They respect the basic guidelines of the curve assessing the development of the CZK to RMB exchange rate and at the same time tend to perceive the extremes of this curve.

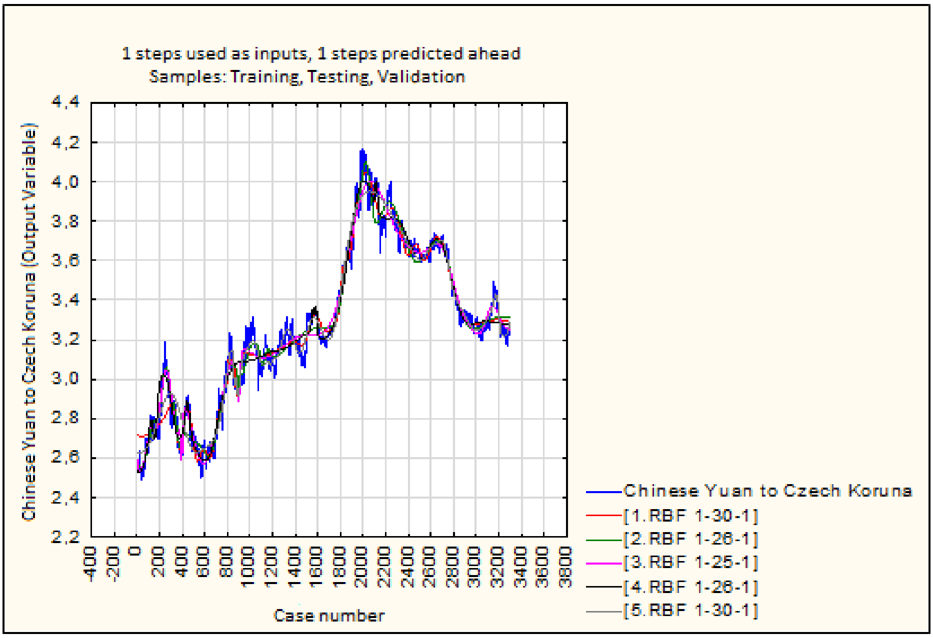

Fig. 1. Link graph – The development of the CZK to RMB exchange predicted by neural networks compared to the real exchange rate in the reference period
Source: Authors.

Given that the graph in Figure 1 includes 3,303 records of data on the CZK to RMB exchange rate, it may appear to be unclear. Therefore, it is appropriate to demonstrate the situation at the selected data interval. The graph in Figure 2 provides a comparison of the actual development of the CZK to RMB exchange rate at the interval of the last 100 days of the reference period, ie from July 14 to October 21, 2018.

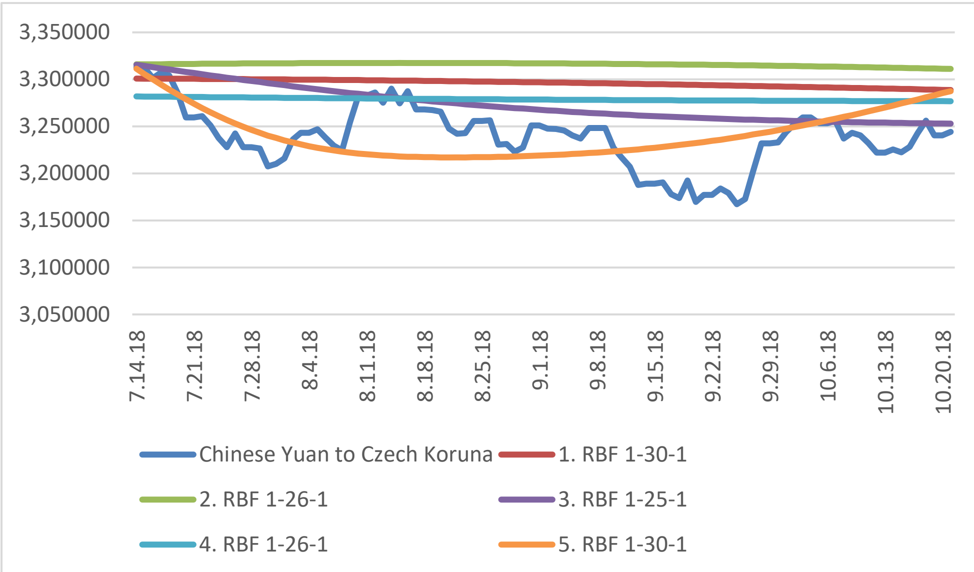

Fig. 2. Link graph – The development of the CZK to RMB exchange rate predicted by neural networks compared to the actual exchange rate in the period from 14 July to 21 October 2018
Source: Authors.

It is clear from the graph that none of the preserved neural networks can fully copy the development of the CZK to RMB exchange rate at the observed interval. The truth, however, is that the network 3.RBF 1-25-1 and the 5.RBF 1-30-1 network are the closest to reality. At the beginning of the monitored period, it almost coincides with the actual RMB value. We can identify a greater difference at the end of the reference period. The difference amounts to approximately 0.08 CZK per RMB. But even from this point of view, the least accurate network 2.RBF 1-26-1 differs from the actual rate by less than 0.011 CZK. Therefore, the examination of residues examination also appears interesting. The development of residues in the period from 14 July to 21 October 2018 is the subject of Figure 3.

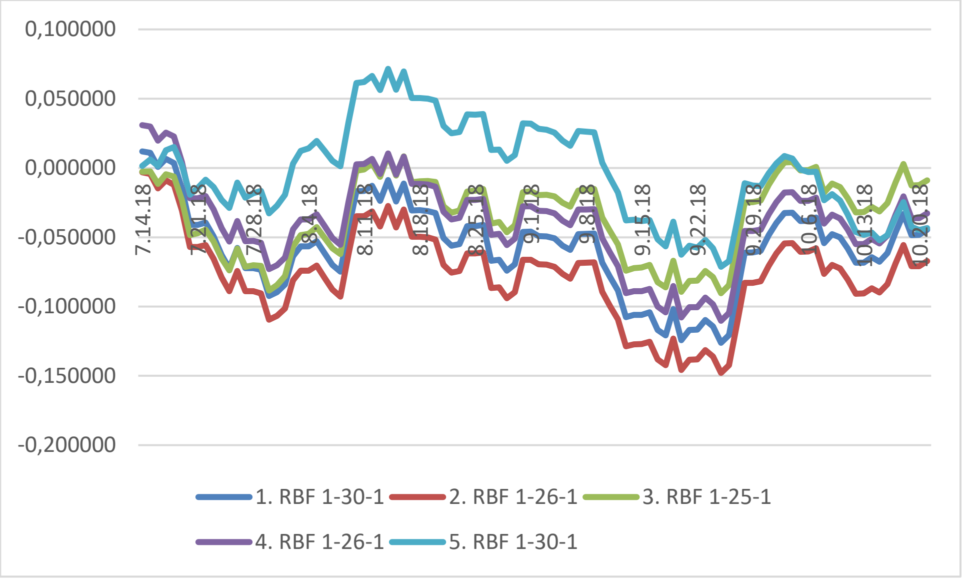

Fig. 3. Development of residues of aligned time series from 14 July to 21 October 2018
Source: Authors.

The graph shows that the sum of the residues approaching zero can be recorded in the observed period for all neural networks except the 5.RBF 1-30-1 network. In this case, residues produce relatively high positive values. To illustrate the situation, Table 5 offers the sum of the residuals of all aligned time series.

Table 5. Sum of the residues of the individual time series

	1. RBF 1-24-1	2. RBF 1-29-1	3. RBF 1-30-1	4. RBF 1-28-1	5. RBF 1-26-1
Sum of residues	0.150758	-1.025922566	-3.350398611	-1.785245346	-3.244516106

Source: Authors.

If the individual fluctuations of residues are to be eliminated throughout the whole investigation period, the absolute sum of the residues will ideally be zero. The closest to zero is the absolute sum of residues of the second neural network, which is almost -1,026. Conversely, the highest absolute values of the sum of residues are 3. RBF 1-30-1 and 5. RBF 1-26-1. Always above the value of 3. However, we must realize that in the case of 3303 measurements, the absolute value of the sum of residues at 3 is minimal. Therefore, we maintain that the most successful neural structures are the 3.RBF 1-25-1 and 5.RBF 1-30-1 networks.

4 Conclusion

The aim of the paper was to align the time series mapping the CZK to RMB exchange rate using artificial neural networks and to find such an artificial neural structure that would show a performance greater than 0.95.

In general, each prediction is given by a certain degree of probability with which it is to be fulfilled. As we predict the future development of any variable, we try to estimate the future development of this variable on the basis of previous years' data. Although we can include most of the factors influencing the target variable in the model, we always simplify reality, and we always work with a certain degree of probability that some of the predicted scenarios will be fulfilled.

In the case of our contribution, we aimed to predict the relationship between two currencies. We have not taken into account any other variables than time. We have not addressed growth, possibly a fall in gross domestic product, the volume of mutual transactions, the relationship of other countries to the currencies analyzed, the volume of mutual tourism and many others. We only dealt with the machine prediction of the future development of the two-currency exchange rate. Therefore, we performed the time series alignment using neural networks. All neural structures show above-average performance (higher than the desired 0.95) and present minimal error. Still, we analyzed five preserved neural networks. We cared about the time series that is more successful than the others. We concluded that the most successful networks are the network 3.RBF 1-25-1 and the network 5.RBF 1-30-1. Having the second highest sum of residues, in the case of basic statistics, keeps up with other preserved networks. At the same time, however, we must state that it is most similar the actual development of the CZK to RMB exchange rate. This network offers performance in a training, test, and validation set of data always above the 0.98 correlation coefficient. It also shows minimal error. So we can conclude that the aim of the paper has been met. We have generated a high-performance neural network with the ability to predict the exchange rate between CZK and RMB in days and weeks.

It is often a major mistake for neural networks to overcome them. This means that networks have excellent characteristics - minimal error and very high performance. Yet their results tend to be pointless. In this case, they were not. All preserved networks are usable with a certain degree of accuracy, and as previously noted, the 3.RBF 1-25-1 network and the 5.RBF 1-30-1 network give even more accurate results than other networks.

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