# Estimation of the development of the Euro to Chinese Yuan exchange rate using artificial neural networks

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**Abstract.** The exchange rate is one of the most monitored economic variables, from the position of individual citizens or economists, financial institutions or entrepreneurs. In the long run, it is a reflection of the condition of the economy, and in the short and medium term it has a significant impact on the economy. The time series of currency development maps past developments, current status, and is also able to predict future developments. This article analyzes the time series of the development of EUR to Yuan exchange rate using artificial intelligence. It aims to evaluate this development and to indicate the prediction of the future development of EUR to Yuan.
**Key words:** time series, analysis, exchange rate, EUR, Yuan

## 1 Introduction

When talking about the development of currency rates, it is necessary to realize that numerical series are an essential part and an important aspect of the whole process. So why are the numerical series important? Numerical series map past developments, current status, and also allow you to generate predictions.

We can label the time series as observing data that is organized, from the perspective of time, from the past to the present. Time series analysis is mainly used for the aforementioned prediction of the future, which is created using different methods. An example of the analysis is the study of the modular structure of the global exchange network for which Mai [1] used correlation matrices. She found that the East Asian currency module is more closely correlated than the European currency module. The strong correlation is the result of strong joint currency movements in the region.

According to Kenneth [2], the link between the exchange rate and the economic fundamentals provides a new basis for empirical studies. Based on the situational analysis of the data and the empirical analysis of the commercial econometric model, we can see that increasing Chinese exports affect the Euro currency market [3]. The exchange rate is one of the most watched economic variables, whether from the position of individual citizens or economists, or financial institutions and entrepreneurs. While in the long run it is a reflection of the condition of the economy, in the short and medium term, it has a

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significant impact on it [4]. The exchange rate, as well as a number of other economic variables (eg gross domestic product, interest rates, etc.), can be tracked both in nominal terms and in real terms [5].

The economical view of the exchange rate often uses the real exchange rate optics, the product of the nominal exchange rate and the ratio between price levels abroad and the domestic economy [6]. Fundamentally, the currency crisis has been hit by the financial crisis, which has caused severe volatility in the currency areas of the fixed exchange rate regimes [7]. There are constant changes in the rates that are based on central banks around the world. Changes in rates can be influenced by both institutional tools and their trading on international foreign exchange markets. By buying and selling them, the country tries to get the currency into its target level [8]. Conversely, currencies tend to react to these activities by appreciating or depreciating the currency. Appreciation means the currency gains value. This situation is advantageous for importers, since they will buy more foreign currencies for the same amount of Czech currency. Depreciation is the opposite, and it is a devaluation of the currency itself, which will strengthen another currency. This situation concerns floating rates. Floating rates are determined by foreign exchange markets and are dependent on demand and supply [9].

This article will measure the development of the EUR compared to the Yuan, China's national currency. Yuan was added to the Special Drawing Rights (SDR) by the International Monetary Fund in 2016, which confirmed the success of China's economic development. This merge in practice means that the central banks of individual member states of the International Monetary Fund included Yuan, which raised the value of Chinese bonds on international markets [10]. Bond yields are estimated at CZK 24 trillion over the next five years. Some critics have spoken out sharply against the adoption of the Chinese national currency in the SDR, mainly because of the devaluation of the official Yuan exchange rate in 2015. The Chinese central bank weakened its currency by almost three and a half percent. Since 2005, it has been the biggest exchange rate change, and China has described it as a "one-off depreciation" [11]. The value of the currency is determined by the Chinese central bank, which sets the average exchange rate around which the market rate, irrespective of supply or demand, may deviate on a daily basis [12]. China, of course, is striving to make the most of international trade and uses Yuan as an alternative to the dollar and the euro [13].

As in China, the shared currency of the European Union is managed by one institution, the European Central Bank. The Central Bank was established in 1998 by the Treaty on European Union and its seat is in Frankfurt. Its task is to manage the EU's single currency and to ensure price stability. Of the 27 member states, only 16 of them adopted a common Euro currency [14]. The development of the Euro currency is related to the development of other currencies with political and economic changes. The exchange rate mainly affects the two largest economic sectors, which are enterprises and households [15]. Long-term efficiency of the existence of the Euro requires wage and price flexibility and, above all, high labor mobility, in which the Chinese market stands out [16]. An essential part of the exchange rate is stable political integration, which is also dependent on a number of factors.

## 2 Data and methods

Data for analysis is available on the website of the World Bank [17] etc. The information on the exchange rate of the Euro and Yuan will be used for the analysis. 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 a total of 3,303 records of input data. The unit is the number of Yuans per 1 Euro. Descriptive characteristics of the data are given in Table 1.

**Table 1.** Characteristics of the datafile

| Samples | Data statistics | |
|---|---|---|
| | Case (Input variab.) | Euro to Chinese Yuan (output) (goal) |
| Minimum (Training) | 1.000 | 6.56070 |
| Maximum (Training) | 3303.000 | 10.29420 |
| Průměr (Training) | 1643.786 | 8.08101 |
| Standard deviation (Training) | 939.260 | 0.75919 |
| Minimum (Testing) | 11.000 | 6.56980 |
| Maximum (Testing) | 3302.000 | 10.25190 |
| Average (Testing) | 1664.707 | 8.06546 |
| Standard deviation (Testing) | 957.966 | 0.76986 |
| Minimum (Validation) | 20.000 | 6.58290 |
| Maximum (Validation) | 3297.000 | 10.30830 |
| Average (Validation) | 1677.677 | 8.09958 |
| Standard deviation (Validation) | 1438.254 | 1.20789 |
| Minimum (Overall) | 1.000 | 6.56070 |
| Maximum (Overall) | 3303.000 | 10.30830 |
| Average (Overall) | 1652.000 | 8.08147 |
| Standard deviation (Overall) | 953.638 | 0.76206 |

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. The independent variable will be time (or measuring designation - case). We will determine the Euro to Yuan 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 úreserve 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 the radial basic function, there will be at least 21 neurons in the 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 networks).

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[†] 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 Euro to Yuan exchange rate will be as low as possible (ideally zero).

## 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 neural networks

| Network name | Training performance | Testing perf. | Validation perf. | Training error | Testing error | Validation error | Training algorithm | Error function | Activation of hidd. lyr. | Output activ. funct. |
|---|---|---|---|---|---|---|---|---|---|---|
| RBF 1-24-1 | 0.983554 | 0.984770 | 0.984081 | 0.009370 | 0.009020 | 0.009390 | RBFT | Sum of sq. | Gauss | Identity |
| RBF 1-29-1 | 0.981894 | 0.981738 | 0.983707 | 0.010306 | 0.010730 | 0.009532 | RBFT | Sum of sq. | Gauss | Identity |
| RBF 1-30-1 | 0.984826 | 0.985312 | 0.984546 | 0.008650 | 0.008742 | 0.009129 | RBFT | Sum of sq. | Gauss | Identity |
| RBF 1-28-1 | 0.984362 | 0.984673 | 0.983238 | 0.008913 | 0.009007 | 0.009832 | RBFT | Sum of sq. | Gauss | Identity |
| RBF 1-26-1 | 0.983486 | 0.984695 | 0.984107 | 0.009407 | 0.009014 | 0.009311 | RBFT | Sum of sq. | 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 Euro to Yuan 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 | | |
|---|---|---|---|
|  | Balance (Training) | Balance (Testing) | Balance (Validation) |
| 1.RBF 1-24-1 | 0.983554 | 0.984770 | 0.984081 |
| 2.RBF 1-29-1 | 0.981894 | 0.981738 | 0.983707 |
| 3.RBF 1-30-1 | 0.984826 | 0.985312 | 0.984546 |
| 4.RBF 1-28-1 | 0.984362 | 0.984673 | 0.983238 |
| 5.RBF 1-26-1 | 0.983486 | 0.984695 | 0.984107 |

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 ranges from more than 0.981 to over 0.984. The value of the correlation coefficient of testing data sets reaches the same values as the training set of data. The correlation coefficient of the validation data set of all neural networks is above 0.983. At the same time, let's that the error rate in all sets of data is in the

range of from nearly 0.009 to more than 0.01. 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 | Prediction statistics Output (goal): Euro to Chinese Yuan | | | | |
|---|---|---|---|---|---|
| | 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 |
| Minimum prediction (Training) | 6.85480 | 6.70498 | 6.85756 | 6.86930 | 6.79547 |
| Maximum prediction (Training) | 10.21765 | 9.92194 | 10.20493 | 10.14413 | 10.17991 |
| Minimum prediction (Testing) | 6.85511 | 6.70617 | 6.85749 | 6.86959 | 6.79648 |
| Maximum prediction (Testing) | 10.21718 | 9.92191 | 10.20358 | 10.14384 | 10.17832 |
| Minimum prediction (Validation) | 6.85528 | 6.70502 | 6.85825 | 6.87002 | 6.79581 |
| Maximum prediction (Validation) | 10.21006 | 9.92164 | 10.19128 | 10.14073 | 10.18000 |
| Minimum residues (Training) | -0.45897 | -0.70049 | -0.40403 | -0.39654 | -0.45631 |
| Maximum residues (Training) | 0.56285 | 0.41491 | 0.47297 | 0.49684 | 0.58830 |
| Minimum residues (Testing) | -0.47026 | -0.69190 | -0.38432 | -0.38399 | -0.43711 |
| Maximum residues (Testing) | 0.47346 | 0.40493 | 0.43641 | 0.45880 | 0.41700 |
| Minimum residues (Validation) | -0.45710 | -0.56530 | -0.35886 | -0.38681 | -0.42207 |
| Maximum residues (Validation) | 0.57571 | 0.42783 | 0.46780 | 0.50829 | 0.58714 |
| Minimum standard residues (Training) | -4.74158 | -6.90008 | -4.34425 | -4.20036 | -4.70472 |
| Maximum standard residues (Training) | 5.81469 | 4.08702 | 5.08551 | 5.26279 | 6.06549 |
| Minimum standard residues (Testing) | -4.95139 | -6.67959 | -4.11032 | -4.04606 | -4.60389 |
| Maximum standard residues (Testing) | 4.98511 | 3.90916 | 4.66740 | 4.83434 | 4.39212 |
| Minimum standard residues (Validation) | -4.71717 | -5.79008 | -3.75590 | -3.90102 | -4.37405 |
| Maximum standard residues (Validation) | 5.94113 | 4.38203 | 4.89604 | 5.12617 | 6.08474 |

Source: Authors.

Ideally, the individual statistics of the neural network are cross-sectionally same in all sets (minimum, maximum, residue, etc.). In the case of preserved neural networks, the differences in time series are minimal, both in absolute terms and in the case of residues. However, 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 Euro and Yuan as well as the development of predictions using individual generated and preserved networks (or even time series).

It is clear from the graph that all neural networks predict the evolution of the Euro to Yuan exchange rate at individual intervals slightly differently. However, what is important is no the 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. In this respect, all preserved neural networks seem very interesting at first glance. They respect the basic guidelines of the curve assessing the evolution of the Euro to Yuan exchange rate, and at the same time tend to perceive the extremes of this curve.
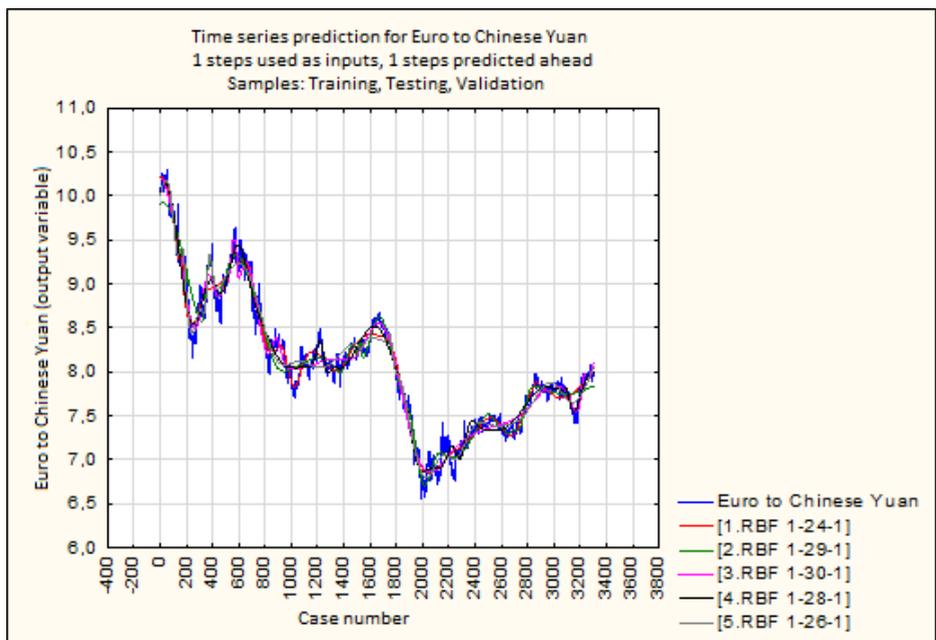


**Fig. 1.** Link graph – Development of the Euro to Yuan exchange rate predicted by neural networks compared to the actual exchange rate in the monitored period
Source: Authors.

Given that the chart in Figure 1 includes 3,303 records of data on the Euro to Yuan 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 Euro to Yuan exchange rate at the interval of the last 100 days of the reference period, ie from July 14 to October 21, 2018.
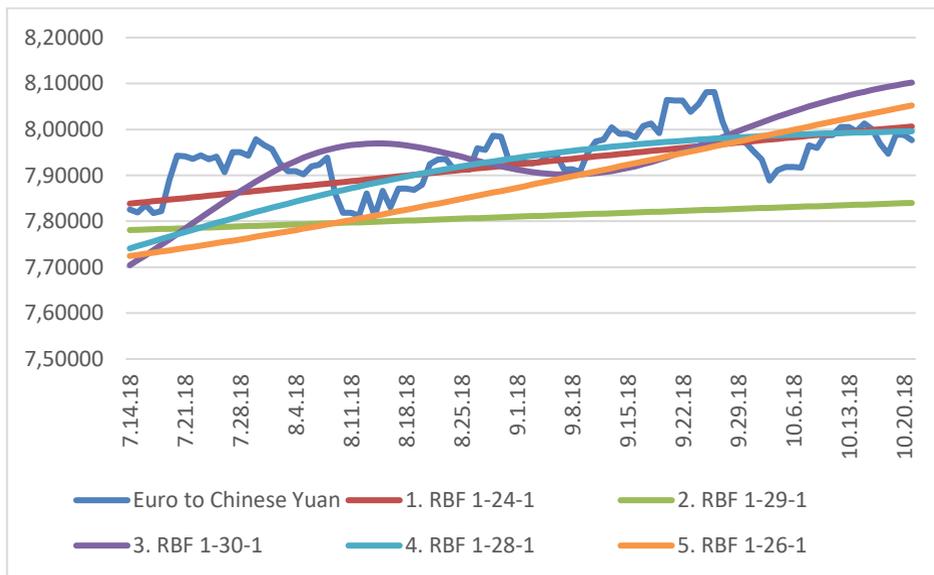
**Fig. 2.** Link graph – Development of the Euro to Yuan exchange rate predicted by neural networks compared to actual exchange rates from July 14 to October 21, 2018
Source: Authors.

It can be seen from the graph that none of the preserved neural networks can fully copy the actual exchange rate of Euro to Yuan in the observed interval. The truth is, however, that the perceived closest to reality is the network 1.RBF 1-24-1. At the beginning of the period under review, it is almost the same as the actual value of Yuan, and at the end of the period under review, it is not too different from the target value. The difference in both cases is in the hundredths of a Yuan. But even from this perspective, the least accurate network, 3.RBF 1-30-1 differ from the actual exchange rate by less than 0.15 Yuan. The examination of residues also appears interesting. The development of residues in the period from 14 July to 21 October 2018 is the subject of Figure 3.
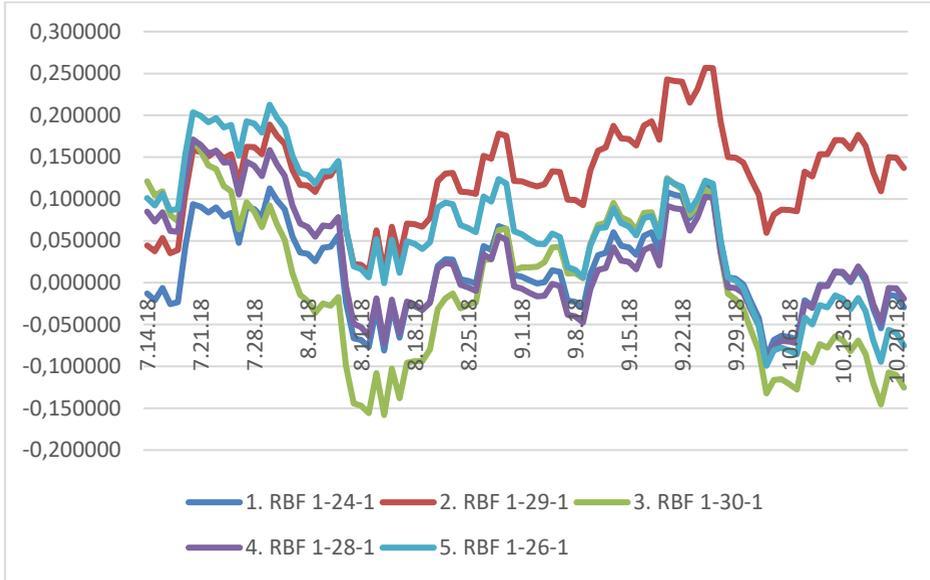
**Fig. 3.** Development of residues of aligned time series from 14 July to 21 October 2018
Source: Authors.

The graph shows that the sum of the residues approaching zero can be recorded in the observed period for all neural networks except the 2.RBF 1-29-1 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 aligned 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 | 10.753689 | 1.369654 | 10.598169 | 4.290912 | 0.676559 |

Source: Authors.

When we ignore the individual fluctuations of residues throughout the whole monitored period, the sum of the residues will ideally be zero. The closest to zero is the sum of the fifth neural network, for which it is almost 0.676. On the contrary, the highest sums are shown by 1. RBF 1-24-1 and 3. RBF 1-30-1. Always above the value of 10. The last analysis would then show that the most successful time series is 5. RBF 1-26-1. However, we must realize that in the case of 3303 measurements, the sum of residues at the value of 10 is absolutely minimal. Therefore, we maintain that the most successful neural structure is the network 1.RBF 1-24-1.

## 4 Conclusion

The aim of the paper was to align the time series mapping the Euro to Chinese Yuan exchange rate using artificial neural networks to find an artificial neural structure with 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 neuron structures show above-average performance (higher than the desired 0.95) and present a minimal rate of error. Still, we analyzed five preserved neural networks. We cared about which time series is more successful than the others. We concluded that the most successful network is the neural structure of 1.RBF 1-24-1. Although having the second highest sum of residues, in the case of basic statistics, it keeps up with other preserved networks. At the same time, we must state that it is the most similar to the actual development of the Euro and Yuan exchange rate. This network offers performance in training, test, and validation sets 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 rates of Euro to Yuan in days and weeks.

It is often a major mistake for neural networks to overtrain. This means that networks have excellent characteristics – minimum 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 1.RBF 1-24-1 network gives even more accurate results than other networks.

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