PREDICTING THE EURO TO CZECH CROWN EXCHANGE RATE

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Abstract: This paper explores the prediction of the exchange rate of the Czech Crown and its market position relative to larger currencies such as the Euro. The study examines the development of the EUR/CZK exchange rate from 2003 to 2023 using neural networks, revealing its volatile tendencies over twenty years. The analysis shows that the exchange rate fluctuated between 22 and 34 without a prolonged period of stagnation. Furthermore, a prediction for the exchange rate in the months of April, May, and June 2023 was conducted, indicating that most neural networks produced similar values and projected no significant increase or decrease. The paper emphasizes that the algorithm of neural networks relies on past values, implying that the actual exchange rate may differ significantly from the predicted outcome.

Keywords: Exchange Rate; Prediction; Euro; Czech Crown.

1 Introduction

The topic of this paper is a prediction of the exchange rate of a selected currency. Specifically, the authors focused on the currency pair Euro to the Czech crown. The euro was introduced 20 years ago and then quickly and confidently took its place as the world's second major currency. At that time, several works appeared that predicted that the euro in the next 10-15 years could surpass the US dollar as the dominant world currency. Currently, the use of the euro in the world is significantly wider than that of other currencies such as the pound and yen. However, the US dollar is still much more popular. Moreover, the last decade has seen a slowdown in the use of the euro in the world and even a decline in some segments in favour of the dollar (Polivach, 2020). The European Union is both an advocate and a symbol of multilateralism in international trade. The rise of the euro's international role may alleviate concerns about spill over brought about by the dollar-dominated global economy (Montfaucon, 2022).

Neck and Weyerstrass (2019) found that EU accession and the introduction of the euro bring a higher real gross domestic product, higher employment, and more sustainable public finances. The benefits of joining the euro area are due to productivity gains. The possibility of central banks issuing digital money is currently being discussed. On 2 October 2020, the European Central Bank presented a report on the issuance of a digital euro in the euro area. It is a way to respond to the growing interest in cryptocurrencies while assessing a possible new mechanism of governance and economic control. However, its benefits do not completely dispel the doubts it still raises (Fernandez, 2021).

Liquidity management is a key task of the central bank. In particular, the reasonable provision of banknotes requires understanding what drives currency demand. This challenge is even greater in the case of the European Monetary Union, where the euro continues to evolve into a well-established currency abroad. In this regard, a new indicator is proposed that reflects the development of foreign demand. In addition to the usual set of determinants, variables including financial and economic policy uncertainty are also considered. A full nominal distribution of banknotes is considered to reveal the diverse role played by several factors. External demand was found to be important for large denominations and that uncertainty was also important for cash demand. In addition, the ECB's recent announcement of the cessation of the issuance of top-denomination banknotes has reduced the overall demand for euro banknotes (Rua, 2020).

Gorman, Orlowski and Roessler (2020) found that the currencies of Central European countries that are not members of the euro area are increasingly moving together with the euro in foreign exchange markets. Gorman, Orlowski and Roessler (2020) from study the dynamics of cross elasticity between selected Central European currencies (Czech crown CZK, Polish zloty PLN, and Hungarian forint HUF) and euro exchange rates in US dollars based on daily data for the sample period from 4 January 2000 to 5 April 2019. They used the cross-elasticity model originally proposed and tested for EU currencies by Orlowski (2016). To test simultaneous currency movements over time, they used Bai-Perron regression with multiple breakeven points and two-state tests of Markov switching. Furthermore, Gorman, Orlowski and Roessler (2020) found evidence of increasing simultaneous movements of Central European currencies and the euro, which is particularly pronounced in times of financial distress. Current movements in local exchange rates with the euro are also more pronounced during the sovereign debt crisis in the eurozone periphery.

In 1999, when Belgium and Italy joined the euro, they were almost identical in two respects: both had a public debt of 110% of GDP and the same GDP per capita. In 2020, the situation in the two countries was hugely different. Sapir (2020) argues that Italy's troubles were not caused by the euro, as some suggest. On the contrary, as Belgium's experience suggests, Italy could have used the euro to make a fiscal adjustment large enough before the crisis to avoid the harsh adjustment that the crisis eventually necessitated. Radu and Horobet and Belascu (2021) evaluated in their article the benefits and risks of international investments in the Romanian stock market from the perspective of euro investors. They examined the share of exchange rate volatility in the overall risk of these investments over nine years, from January 2011 to December 2019, using monthly values of the Romanian leu and euro exchange rate and monthly values of the Romanian stock index. Radu, Horobet and Belascu (2021) found that the Romanian leu weakened against the euro on average, causing currency losses for the euro investor, which were offset by the average yield of the Romanian index, which was higher than the average yield of the euro area index over the period under review.

It is also necessary to work with information about future economic, political, or other developments. If their development can be predicted, they can then be projected into the monitored variable. Optically, the best option is linear regression, where the curve obtained by the least squares method using negative exponential appears by smoothing. In terms of the correlation coefficient, neural networks are applicable (Horák and Machová, 2019). Many authors have dealt with neural networks in connection with other currencies, such as Vrbka, Horák and Krulický (2022), who used the neural network method to predict the value of the Chinese currency and the influence of oil price developments on the world market. They concluded that fluctuations in oil prices on world markets would affect the CNY/USD price; However, it was not clear to what extent. Vochozka, Horák and Šuleř (2019) used artificial neural networks for exchange rate prediction, which have brought high-quality and valuable results in several research programs. Data on currency exchange rates for a period longer than 9 years (a total of 3303 input data) were used for the analysis. Vochozka, Horák and Šuleř (2019) found that when aligning time series, other variables (such as year, month, and day) had higher accuracy.

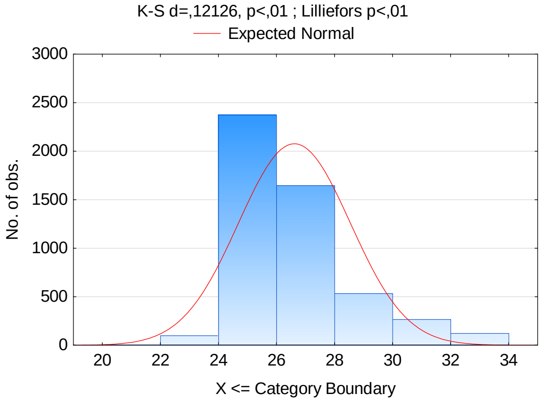
In the past, exchange rate forecasting models performed poorly outside the sample and were worse than the random walk model. Monthly panel data from 1973 to 2014 for ten OECD currency pairs are used for out-of-sample forecasts using artificial neural networks and XGBoost models. Most approaches show the significant and considerable informative value of directional forecasts. Moreover, evidence suggests that information regarding forecast timing is a key component of forecasting performance (Pfahler, 2022).

2 Materials and Methods

To analyse the problem, i.e., to predict the exchange rate of the selected currency (in this case EUR/CZK), the neural networks method will be used. It will be used to predict the price of the euro for the next 60 trading days. The data will be used from the Yahoo.com website from 200 3-2023, where the prices of a given currency are during each day that the currency was traded on the stock markets. Daily data from the New York Stock Exchange will be used. The New York Stock Exchange uses two indices. One is the NYSE Composite Index, which is used for all traded titles, and the other is the DJIA (Dow Jonas Industrial Average), which serves the 30 largest stock companies in the US. The New York Stock Exchange is traded every day from 9:30 a.m. to 4:00 p.m. local time (in the Czech Republic it is around 3:30 p.m. to 10:00 p.m.). The price is determined every business day, except when the U.S. is a public holiday.

The basic statistical characteristics of the used time series of the EUR/CZK price are shown in the following figures 1-3.

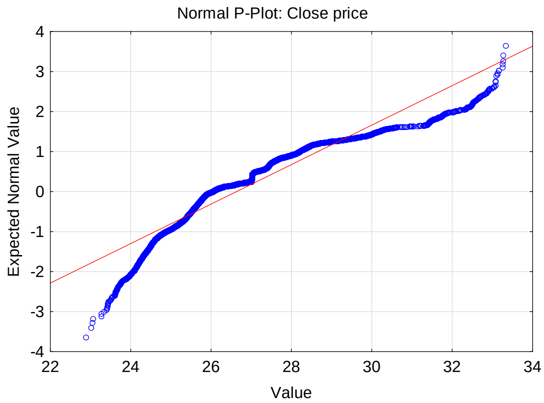
Figure 1: Basic data statistic – Histogram



Source: Authors

As you can see from the figure, the histogram has a normal distribution and the data that was used to construct the histogram was fine. The histogram should always have the shape of a "scoop". This histogram shows that the data was in the range of 22 to 34. 5047 data were used to construct this histogram.

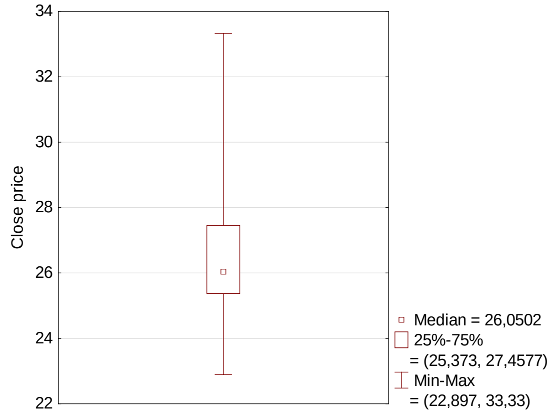
Figure 2: Basic data statistic – Normality test



Source: Authors

The normality test makes it possible to assess whether the observed values come from some known probability distribution. If the sample distribution of data coincides with the theoretical distribution, all points lie in a straight line. If the sample and theoretical distributions do not match, the displayed points will form a curve different from the straight line. This figure shows that the sample distribution almost coincides with the theoretical distribution. Only at the beginning and at the end are the values different from the straight line. From this point of view, the data used can therefore also be considered relevant.

Figure 3: Basic data statistic – Variance



Source: Authors

This figure shows that the variance was from 23 to 33, with the minimum value of 22.90 and the maximum value of 33.33. The median, in this case, was 26.05. It can also be seen that the highest values in the monitored period ranged from 25.37 to 27.46.

The data obtained will be evaluated using TIBECO's Statistica 13 software. First, we will create linear regression and as the next step, we will use neural networks for regression. We will examine the linear analysis on a sample for which we have determined the following functions: linear, polynomial, logarithmic, exponential, polynomial weighted distances, and polynomial negative exponential smoothing. First, the correlation coefficient will be calculated, that is, the dependence of the euro price on time, and a confidence level of 0.95 will be used, followed by regression using neural structures. Two types of networks will be constructed, namely MLP networks and RBF networks. For this purpose, 5047 data will be used, and the independent variable in our case will be time and the dependent variable will be the price of the currency. Time series (testing, training, and verification) will be divided into three groups. Each of these groups must contain a certain percentage of the data that will create neural structures. Training has 70% of the data, testing, and verification then 15% each. The test and verification groups are used to verify the reliability of the neural structure found. 1000 neural networks are used for the calculation and 10 neural networks are preserved. For MLP networks, a minimum of 2 neurons will be used, but the maximum will be 20 neurons, and for RBF networks, a minimum of 10 neurons will be used in the hidden layer, but the maximum will be 30 neurons. And for these two networks, the following functions will be used: linear, logistic, Atanh, Exponential, and Sine. We leave the other settings as default (within the ATS Automatic Mesh tool).

3 Results

Table 1 shows the 10 neural networks with the best characteristics out of 1000 generated neural structures.

Tab. 1: Summary of active networks (EUR/CZK – daily data 2003-2023)

Index	Net. Name	Train. Perf.	Test Perf.	Valid. Perf.	Train. Error	Test Error	Valid. Error	Train. Alg.	Error Function	Hidden Activation	Output Activation
1	MLP 1-13-1	0.983259	0.981622	0.985005	0.061198	0.065805	0.056042	BFGS 588	SOS	Tanh	Logistic
2	MLP 1-14-1	0.981610	0.979722	0.984382	0.067175	0.072506	0.058448	BFGS 389	SOS	Logistic	Logistic
3	MLP 1-18-1	0.981992	0.980536	0.984624	0.065789	0.069684	0.057616	BFGS 439	SOS	Logistic	Expon.
4	MLP 1-19-1	0.985094	0.984062	0.986784	0.054541	0.057205	0.049498	BFGS 461	SOS	Logistic	Logistic
5	MLP 1-15-1	0.982721	0.980997	0.985049	0.063147	0.068078	0.056036	BFGS 589	SOS	Logistic	Logistic
6	MLP 1-9-1	0.982586	0.980555	0.985019	0.063644	0.069689	0.056281	BFGS 1080	SOS	Tanh	Logistic
7	MLP 1-20-1	0.983067	0.981367	0.985398	0.061900	0.066719	0.054647	BFGS 639	SOS	Logistic	Expon.
8	MLP 1-19-1	0.982630	0.980622	0.984827	0.063476	0.069448	0.056836	BFGS 564	SOS	Logistic	Identity
9	MLP 1-20-1	0.986503	0.985521	0.988213	0.049423	0.051876	0.044085	BFGS 678	SOS	Tanh	Expon.
10	MLP 1-14-1	0.982813	0.980901	0.985182	0.062814	0.068398	0.055506	BFGS 827	SOS	Logistic	Logistic

Source: Authors

As can be seen from Table 1, all the networks that have been preserved belong to MLP networks. It follows that the RBF networks met the performance parameters but had worse errors than the retained MLP networks. In the hidden layer, these stored networks had from 13 to 20 neurons and were created using the BFGS (Broyden-Fletcher-Goldfarb-Shanno) training algorithm, always in a different variant. To activate the hidden layer of neurons, the hyperbolic tangent and the logistic function had to be used, and three functions were used for the outer layer – logistic function, exponential function, and identity function. What is important is the correlation coefficient, which determines the performance of all stored networks in individual data sets.

Tab 2: Correlation coefficients (EUR/CZK – daily data 200 3-2023)

	Price Train	Price Test	Price Validation
1.MLP 1-13-1	0.983259	0.981622	0.985005
2.MLP 1-14-1	0.981610	0.979722	0.984382
3.MLP 1-18-1	0.981992	0.980536	0.984624
4.MLP 1-19-1	0.985094	0.984062	0.986784
5.MLP 1-15-1	0.982721	0.980997	0.985049
6.MLP 1-9-1	0.982586	0.980555	0.985019
7.MLP 1-20-1	0.983067	0.981367	0.985398
8.MLP 1-19-1	0.982630	0.980622	0.984827
9.MLP 1-20-1	0.986503	0.985521	0.988213
10.MLP 1-14-1	0.982813	0.980901	0.985182

Source: Authors

The value of the correlation coefficient should always ideally be 1, which is why they try to find the neural network that most closely corresponds to this value. It is also important that all groups (training, testing and verification) have the same performance. It is therefore obvious that all structures that were created using the training data set are valid and subsequently verified on the next two data sets. It is also essential that in all data sets the neural network shows minimal error. As can be seen from Table 2, in all cases the value of correlation coefficients is higher than 0.979 for all neural networks and the differences between individual neural networks are minimal. It can therefore be said that the data is of extremely high quality. Also especially important is Table 3, which records the analysis of prediction statistics.

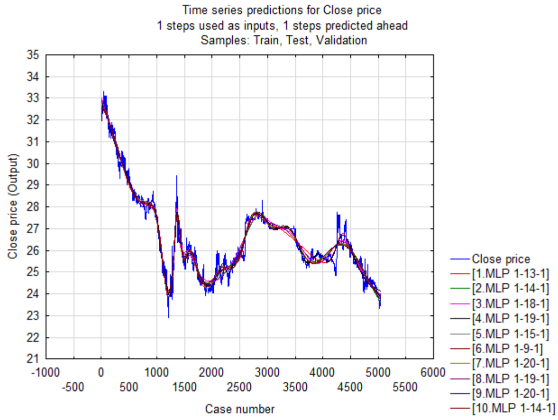
Tab. 3: Predictions statistics (EUR/CZK – daily data 2003-2023)

	1.MLP 1-13-1	2.MLP 1-14-1	3.MLP 1-18-1	4.MLP 1-19-1	5.MLP 1-15-1	6.MLP 1-9-1	7.MLP 1-20-1	8.MLP 1-19-1	9.MLP 1-20-1	10.MLP 1-14-1
Minimum Prediction (Train)	23.87282	23.62950	23.95749	24.00041	23.82133	23.86179	23.74859	23.88438	23.83938	23.72466
Maximum Prediction (Train)	32.73145	32.60002	33.05219	32.80494	32.74624	32.57954	32.82503	32.89649	32.86068	32.65979
Minimum Prediction (Test)	23.87311	23.64474	23.96496	24.00059	23.83381	23.87342	23.76116	23.88442	23.85556	23.73884
Maximum Prediction (Test)	32.68272	32.53948	32.89751	32.72720	32.67767	32.52166	32.73476	32.78598	32.86059	32.59220
Minimum Prediction (Validation)	23.87217	23.62698	23.95626	24.00261	23.81926	23.85986	23.74651	23.89689	23.83669	23.72231
Maximum Prediction (Validation)	32.67549	32.53089	32.87668	32.71610	32.66788	32.51344	32.72215	32.77078	32.86078	32.58263
Minimum Residual (Train)	-1.24302	-1.30282	-1.38997	-1.23659	-1.36102	-1.36446	-1.32998	-1.36280	-1.19276	-1.34303
Maximum Residual (Train)	1.95751	1.78228	1.60347	1.87788	1.66408	1.87065	1.72503	1.93883	1.68021	1.84357
Minimum Residual (Test)	-1.31383	-1.36118	-1.45225	-1.27898	-1.41968	-1.42415	-1.38962	-1.42401	-1.26296	-1.40126
Maximum Residual (Test)	1.25902	1.41368	1.26696	1.29779	1.35332	1.33432	1.36699	1.31157	1.32128	1.37713
Minimum Residual (Validation)	-1.09614	-1.28625	-1.38249	-1.23448	-1.38158	-1.30784	-1.35934	-1.22460	-1.27052	-1.27911
Maximum Residual (Validation)	1.32473	1.40772	1.27925	1.35995	1.34744	1.33320	1.36706	1.31826	1.38264	1.37234
Minimum Standard Residual (Train)	-5.02468	-5.02665	-5.41912	-5.29499	-5.41613	-5.40860	-5.34563	-5.40912	-5.36524	-5.35870
Maximum Standard Residual (Train)	7.91285	6.87655	6.25151	8.04092	6.62212	7.41507	6.93346	7.69546	7.55786	7.35583
Minimum Standard Residual (Test)	-5.12166	-5.05508	-5.50143	-5.34744	-5.44112	-5.39477	-5.37985	-5.40360	-5.54510	-5.35790
Maximum Standard Residual (Test)	4.90801	5.25003	4.79951	5.42609	5.18681	5.05449	5.29224	4.97692	5.80112	5.26566
Minimum Standard Residual (Validation)	-4.63030	-5.32035	-5.75958	-5.54869	-5.83637	-5.51283	-5.81497	-5.13670	-6.05114	-5.42926
Maximum Standard Residual (Validation)	5.59588	5.82282	5.32948	6.11267	5.69215	5.61969	5.84795	5.52956	6.58514	5.82496

Source: Authors

This table shows the analysis of prediction statistics. Residue levels can be seen here. Residues should ideally approach the value of 0, meaning that the input data's value corresponds to the predicted value. Here we see that they show some network residues and the; therefore, they cannot be said to be accurate. In the following Figure 1, these residues are shown graphically, where all the networks and the actual value history of the currency are.

Figure 4: Evolution of the Euro price vis-à-vis the Czech crown



Source: Authors

Figure 4 shows that all neural networks in total managed to exactly copy the actual price movement. The coloured lines represent the ten preserved neural networks. But these neural networks cannot capture local minimum and maximum extreme fluctuations. For example, at 1200, there was an extreme downward swing, when the price of the euro fell, and neural networks did not notice this swing. This is because the Global Financial Crisis began in 2008. The figure also shows that the price of the euro fell from 2003 until 2008. Then it rose again very quickly. And it can also be seen that until 2023, the price of the euro has continued to fluctuate up and down. It is questionable to what extent they are the result of a turbulent environment that none of the preserved neural networks could reliably describe. However, despite this fact, we can accept the statement that all preserved neural networks are applicable in practice.

4 Discussion

Following the training of neural networks, predictions of oil prices for the next 60 trading days were made. In Table 4 you can see how the price will move just for the mentioned 60 trading days.

Tab. 4: Euro price prediction for the month of April, May, and June 2023

	1. Close price_(t)	2. Close price_(t)	3. Close price_(t)	4. Close price_(t)	5. Close price_(t)	6. Close price_(t)	7. Close price_(t)	8. Close price_(t)	9. Close price_(t)	10. Close price_(t)
04.04.2023	23.51327	23.68012	24.04678	23.67294	23.72831	23.53376	23.57027	24.14276	23.79851	23.08824
05.04.2023	23.50555	23.67757	24.04554	23.66814	23.72408	23.52942	23.56639	24.14186	23.79602	23.07901
06.04.2023	23.49780	23.67504	24.04429	23.66332	23.71985	23.52507	23.56250	24.14095	23.79354	23.07010
07.04.2023	23.49002	23.67250	24.04305	23.65848	23.71562	23.52072	23.55862	24.14005	23.79106	23.06148
10.04.2023	23.46648	23.66492	24.03932	23.64384	23.70291	23.50766	23.54696	24.13735	23.78363	23.03745
11.04.2023	23.45857	23.66240	24.03808	23.63892	23.69867	23.50330	23.54307	24.13645	23.78116	23.03002
12.04.2023	23.45063	23.65988	24.03683	23.63398	23.69443	23.49894	23.53918	24.13555	23.77869	23.02289
13.04.2023	23.44266	23.65736	24.03559	23.62901	23.69019	23.49458	23.53530	24.13466	23.77623	23.01605
14.04.2023	23.43466	23.65485	24.03435	23.62403	23.68594	23.49021	23.53141	24.13376	23.77376	23.00948
17.04.2023	23.41046	23.64733	24.03061	23.60894	23.67320	23.47710	23.51974	24.13109	23.76639	22.99142
18.04.2023	23.40233	23.64483	24.02937	23.60387	23.66895	23.47273	23.51585	24.13020	23.76393	22.98592
19.04.2023	23.39417	23.64234	24.02812	23.59878	23.66470	23.46835	23.51196	24.12932	23.76148	22.98067
20.04.2023	23.38598	23.63984	24.02688	23.59367	23.66045	23.46397	23.50807	24.12843	23.75903	22.97568
21.04.2023	23.37776	23.63735	24.02563	23.58853	23.65620	23.45959	23.50417	24.12755	23.75659	22.97092
24.04.2023	23.35289	23.62990	24.02189	23.57299	23.64345	23.44642	23.49250	24.12490	23.74926	22.95801
25.04.2023	23.34454	23.62742	24.02065	23.56776	23.63920	23.44203	23.48860	24.12402	23.74683	22.95414
26.04.2023	23.33616	23.62495	24.01940	23.56251	23.63495	23.43764	23.48471	24.12315	23.74439	22.95047
27.04.2023	23.32774	23.62248	24.01816	23.55724	23.63070	23.43324	23.48082	24.12227	23.74196	22.94700
28.04.2023	23.31929	23.62001	24.01691	23.55195	23.62645	23.42884	23.47692	24.12140	23.73953	22.94372
01.05.2023	23.29376	23.61262	24.01317	23.53593	23.61371	23.41563	23.46524	24.11878	23.73226	22.93494
02.05.2023	23.28519	23.61017	24.01192	23.53054	23.60946	23.41122	23.46134	24.11791	23.72985	22.93235
03.05.2023	23.27658	23.60771	24.01068	23.52513	23.60522	23.40681	23.45744	24.11705	23.72743	22.92991
04.05.2023	23.26794	23.60526	24.00943	23.51970	23.60098	23.40240	23.45355	24.11618	23.72502	22.92761
05.05.2023	23.25927	23.60282	24.00818	23.51424	23.59674	23.39798	23.44965	24.11531	23.72261	22.92546
08.05.2023	23.23306	23.59549	24.00444	23.49773	23.58403	23.38472	23.43796	24.11273	23.71539	22.91976
09.05.2023	23.22426	23.59306	24.00319	23.49218	23.57980	23.38029	23.43406	24.11187	23.71299	22.91810
10.05.2023	23.21543	23.59063	24.00194	23.48660	23.57557	23.37586	23.43016	24.11101	23.71060	22.91655
11.05.2023	23.20657	23.58820	24.00069	23.48100	23.57134	23.37143	23.42626	24.11015	23.70820	22.91510
12.05.2023	23.19767	23.58578	23.99944	23.47537	23.56712	23.36700	23.42236	24.10930	23.70581	22.91375
15.05.2023	23.17079	23.57852	23.99570	23.45834	23.55447	23.35369	23.41066	24.10674	23.69865	22.91022
16.05.2023	23.16176	23.57611	23.99445	23.45262	23.55026	23.34925	23.40676	24.10589	23.69627	22.90921
17.05.2023	23.15271	23.57370	23.99320	23.44687	23.54605	23.34481	23.40286	24.10504	23.69390	22.90826
18.05.2023	23.14362	23.57129	23.99195	23.44109	23.54185	23.34036	23.39896	24.10419	23.69152	22.90739
19.05.2023	23.13449	23.56889	23.99070	23.43529	23.53765	23.33591	23.39506	24.10334	23.68915	22.90657
22.05.2023	23.10693	23.56170	23.98695	23.41773	23.52509	23.32255	23.38335	24.10081	23.68205	22.90447
23.05.2023	23.09768	23.55930	23.98570	23.41182	23.52091	23.31809	23.37945	24.09997	23.67969	22.90387
24.05.2023	23.08840	23.55692	23.98445	23.40589	23.51673	23.31363	23.37554	24.09913	23.67733	22.90332
25.05.2023	23.07908	23.55453	23.98320	23.39993	23.51256	23.30917	23.37164	24.09829	23.67498	22.90281
26.05.2023	23.06974	23.55215	23.98195	23.39395	23.50840	23.30470	23.36773	24.09745	23.67262	22.90234
29.05.2023	23.04150	23.54502	23.97820	23.37583	23.49594	23.29130	23.35602	24.09494	23.66559	22.90113
30.05.2023	23.03202	23.54265	23.97694	23.36974	23.49179	23.28682	23.35212	24.09411	23.66325	22.90079
31.05.2023	23.02251	23.54029	23.97569	23.36362	23.48766	23.28234	23.34821	24.09328	23.66091	22.90048
01.06.2023	23.01296	23.53792	23.97444	23.35748	23.48353	23.27787	23.34431	24.09245	23.65857	22.90019
02.06.2023	23.00339	23.53556	23.97319	23.35131	23.47940	23.27338	23.34040	24.09162	23.65624	22.89992
05.06.2023	22.97447	23.52850	23.96944	23.33262	23.46708	23.25993	23.32868	24.08913	23.64927	22.89925
06.06.2023	22.96476	23.52615	23.96818	23.32634	23.46298	23.25544	23.32478	24.08831	23.64695	22.89906
07.06.2023	22.95503	23.52381	23.96693	23.32002	23.45889	23.25094	23.32087	24.08749	23.64463	22.89889
08.06.2023	22.94526	23.52147	23.96568	23.31368	23.45481	23.24645	23.31696	24.08666	23.64232	22.89873
09.06.2023	22.93545	23.51913	23.96443	23.30732	23.45074	23.24195	23.31305	24.08584	23.64001	22.89859
12.06.2023	22.90585	23.51213	23.96067	23.28804	23.43856	23.22845	23.30133	24.08339	23.63309	22.89822
13.06.2023	22.89592	23.50980	23.95942	23.28156	23.43452	23.22394	23.29742	24.08257	23.63079	22.89812
14.06.2023	22.88595	23.50748	23.95817	23.27504	23.43049	23.21943	23.29351	24.08176	23.62850	22.89802
15.06.2023	22.87595	23.50516	23.95692	23.26850	23.42646	23.21492	23.28961	24.08094	23.62621	22.89794
16.06.2023	22.86592	23.50284	23.95566	23.26193	23.42245	23.21041	23.28570	24.08013	23.62392	22.89786
19.06.2023	22.83564	23.49591	23.95191	23.24204	23.41046	23.19685	23.27397	24.07770	23.61707	22.89766
20.06.2023	22.82548	23.49360	23.95066	23.23535	23.40648	23.19233	23.27006	24.07689	23.61479	22.89761
21.06.2023	22.81529	23.49130	23.94940	23.22863	23.40251	23.18781	23.26615	24.07608	23.61252	22.89756
22.06.2023	22.80506	23.48900	23.94815	23.22188	23.39855	23.18328	23.26224	24.07528	23.61025	22.89751
23.06.2023	22.79480	23.48671	23.94690	23.21510	23.39460	23.17875	23.25833	24.07447	23.60798	22.89747
26.06.2023	22.78451	23.48441	23.94565	23.20829	23.39066	23.17422	23.25442	24.07367	23.60572	22.89743

Source: authors

In Table 4 it is possible to see how the price of oil will move in the period from 4.04.2023 to 24.06.2023. Most neural networks show remarkably similar values. And the fact that the price of the EUR to CZK will be around 23.5 in the coming months. Only the 3rd and 8th neural networks show a higher price, about 24 CZK. Interestingly, there are no major price fluctuations in either of the neural networks. All of them have a higher price at the beginning of the period, which decreases during the monitored period and increases again towards the end of most neural networks.

5 Conclusion

The topic of this paper was the prediction of the exchange rate of a selected currency and the euro currency was chosen. It has been found that the euro has an extraordinarily strong market position but cannot yet compete sufficiently with larger currencies such as the US dollar. This work also investigated the development of the euro price from 2003 to 2023 using neural networks. It was found that the euro had very volatile tendencies over twenty years and that there was hardly any period when the price was stagnant but still fluctuated between 22 and 34. A prediction of the euro price for three months ahead was also prepared. Specifically, for the months of April, May, and June 2023. It was found that most neural networks had similar values, and the price of the euro did not increase or decrease dramatically. This is because the algorithm of neural networks takes the previous values from the past days and follows them. It is therefore possible that in the end, the price of the euro will be completely different.

References

1. FERNANDEZ, F.H., 2021. Towards a European digital currency. The Euro 2.0. *Revista de Derecho Comunitario Europeo*. 70, 1007-1033. ISSN 1138-4026. Available at: doi:10.18042/cepc/rdce.70.06

2. GORMAN, M., ORLOWSKI, L. a ROESSLER, M., 2020. Dynamic interactions between Central European currencies and the euro. *Economic Systems*. 44(3). ISSN 0939-3625. Available at: doi:10.1016/j.ecosys.2020.100781

3. HORÁK, J. a MACHOVÁ, V., 2019. Comparison of neural networks and regression time series on forecasting development of US imports from the PRC. *Littera Scripta*. 12(1), 1-15. ISSN 1805-9112. Available at: https://www.littera-scripta.com/wp-content/uploads/2020/03/Horak_Machova-citace-1-form-oprava-%C4%8D%C3%ADsla-str%C3%A1nek.pdf

4. MONTFAUCON, A. F., 2022. Euro usage in international trade amidst threats to multilateralism: evidence from Malawian imports. *Empirica*. 49(2), 485-507. ISSN 0340-8744. Available at: doi:10.1007/s10663-021-09523-8

5. NECK, R. a WEYERSTRASS, K., 2019. Macroeconomic Effects of Serbia's Integration in the EU and the Euro Area. *International Advances in Economic Research*. 25(3), 277-292. ISSN 1083-0898. Available at: doi:10.1007/s11294-019-09748-1

6. PFAHLER, J.F., 2022. Exchange Rate Forecasting with Advanced Machine Learning Methods. *Journal of Risk and Financial Management*. 15(1). ISSN 1911-8066. Available at: doi:10.3390/jrfm15010002

7. POLIVACH, A., 2020. International role of Euro and European integration. *Mirovaya Ekonomika I Mezhdunarodnye Otnosheniy*. ISSN 0131-2227. Available at: doi:10.20542/0131-2227-2020-64-5-33-41

8. RADU, M., HOROBET, A. a BELASCU, L., 2021. Romanian Equity Investments And Currency Risk: A Euro-Based Perspective. *Studies In Business And Economics*. 16(1), 162-176. ISSN 1842-4120. Available at: doi:10.2478/sbe-2021-0013

9. RUA, A., 2020. Modelling currency demand: the case of the euro. *Empirical Economics*. 61(4), 1865-1881. ISSN 0377-7332. Available at: doi:10.1007/s00181-020-01939-8

SAPIR, A., 2020. High Public Debt in the Euro Area: A Tale of Belgium and Italy. *Jcms-Journal of Common Market Studies*. 58(3), 672-687. ISSN 0021-9886. Available at: doi:10.1111/jcms.12950

10. VOCHOZKA, M., HORÁK, J. A ŠULEŘ P., 2019. Equalizing Seasonal Time Series Using Artificial Neural Networks in Predicting the Euro–Yuan Exchange Rate. *Journal of Risk and Financial Management*. 12(2). ISSN 1911-8074. Available at: doi:10.3390/jrfm12020076

11. VRBKA, J., HORÁK, J. a KRULICKÝ, T., 2022. The Influence of Word Oil Prices on the Chinese Yuan Exchange Rate. *Entrepreneurship and Sustainability Issues*. 9(4), 439-462. ISSN 2345-0282. Available at: doi:10.9770/jesi2022.9.4(24)

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Primary Paper Section: A

Secondary Paper Section: AH