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Comparison of Neural Networks and Regression Time Series in Estimating the Development of the Afternoon Price of Palladium on the New York Stock Exchange

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Abstract

Purpose of the article: Palladium is presently used for producing electronics, industrial products or jewellery, as well as products in the medical field. Its value is raised especially by its unique physical and chemical characteristics. Predicting the value of such a metal is not an easy matter (with regard to the fact that prices may change significantly in time).
Methodology/methods: To carry out the analysis, London Fix Price PM data was used, *i.e.* amounts reported in the afternoon for a period longer than 10 years. To process the data, Statistica software is used. Linear regression is carried out using a whole range of functions, and subsequently regression via neural structures is performed, where several distributional functions are used again. Subsequently, 1000 neural networks are generated, out of which 5 proving the best characteristics are chosen.
Scientific aim: The aim of the paper is to perform a regression analysis of the development of the palladium price on the New York Stock Exchange using neural structures and linear regression, then to compare the two methods and determine the more suitable one for a possible prediction of the future development of the palladium price on the New York Stock Exchange.
Findings: Results are compared on the level of an expert perspective and the evaluator's – economist's experience. Within regression time lines, the curve obtained by the least squares methods via negative-exponential smoothing gets closest to Palladium price line development. Out of the neural networks, all 5 chosen networks prove to be the most practically useful.
Conclusions: Because it is not possible to predict extraordinary situations and their impact on the palladium price (at most in the short term, but certainly not over a long period of time), simplification and the creation of a relatively simple model is appropriate and the result is useful.

Keywords: palladium, artificial neural networks, regression time series, prediction, multilayer perceptron network

JEL Classification: C32, C45, C53

Introduction

Palladium (chemical symbol Pd) is a shiny metal of silver color that is used mainly in production processes, especially in the manufacture of electronics and industrial products, but it can also be used for the production of jewelry. Palladium has the atomic number 46 in the Periodic Table of Elements. Most of the world's supplies of this precious metal come from mines located in the United States, Russia, South Africa and Canada (Barnes, Liu, 2012). Palladium together with rhodium, ruthenium, osmium, iridium and platinum forms a group of elements referred to as platinum-group metals. According to Colombo *et al.* (2008), palladium is a shiny, silver-white metal with a cubic structure. At normal temperatures, this element is highly resistant to corrosion in air and to acids. It produces many compounds and several complex salts. The author also notes that palladium has a great ability to absorb hydrogen.

Metals of the platinum group have many unique physical and chemical properties that make them absolutely exceptional and they are a crucial component in many technologies, industries and in the medical field (Ranganai, Kubheka, 2016). The high demand for these metals in industry has led to a growing interest in their resources (Bazarkina, Pokrovski, Hazemann, 2014).

Palladium is a truly a very rare metal, even more rare than gold or silver, as there is significantly less of it in the world (Balint *et al.*, 2012). The price of palladium is currently at around 800 USD per troy ounce. In the last few years, palladium has been gradually replacing platinum, which includes becoming more prominent in the production of catalysts (Grdeń *et al.*, 2008). This is because palladium is much cheaper than platinum, but has an unequivocally comparable quality of production (Pizzutilo *et al.*, 2017).

The London Platinum and Palladium Market (LPPM) oversees platinum and palladium trading. Twice a day, four members of the LPPM set the bid prices. The bid price is the price at which LPPM members have agreed to buy metals with "good delivery". Bidding prices are benchmarks for the market and hence for the industry. The offered prices affect the bid prices that customers request to pay for the metal. The platinum and palladium market values, as with all commodities, ultimately affect production costs (Kendall, 2004). Tools that can be used to estimate the price of palladium are, for example, regression time series or artificial neural networks. Both of these methods will be used in this article.

As for artificial neural networks, they can be used for regression, classification, *etc.* (Sánchez, Melin, 2015). Their advantage is, in particular, the ability to work with large data, the accuracy of results or with simplicity using the obtained neural network (Mareček, 2016). The main disadvantage is the way individual models of artificial neural networks are created (Rowland, Vrbka, 2016). Neural networks generally have many advantages over conventional methods. They are able to analyze complex patterns quickly and with high precision. Neural networks are flexible in their own use (Santin, 2008). For example, these networks can be used to recognize images, to predict time series, to understand and to generate languages, *etc.* (Boguslauskas, Mileris, 2009). The disadvantage of neural networks is, according to Stehel, Vrbka, Rowland (2016), their demand for large input data, because to produce such an amount of data, a lot of test observations are needed, which is very uncomfortable for the user. The second main disadvantage is the process of optimizing the topology of hidden layers, which is time consuming and complicates the computation process (Hossain *et al.*, 2017).

1. Methods

The data for analysis are available on the websites of the New York Stock Exchange or the World Bank, *etc.* For the analysis, the London Fix price PM in the period between 3 January 2006 and 15 April 2016 will be used. Therefore, there are 2557 entries on the price of palladium. The key value for determining the reference price for palladium is the so-called London fix price, also referred to simply as London Fix, announced twice a day on the days palladium trading takes place in London. London Fix is set twice a day, in the morning at 09:45 it is called AM and in the afternoon at 14:00 it is referred to as PM of London Time. The price is set every working day excluding December 24 (if working day) and December 31 (if working day, no afternoon price). A time series of afternoon palladium prices has been selected for this paper.

The determination of the London Fix proceeds as follows: the chair of the fixing committee will propose an opening price that is close to the spot price. Subsequently, individual members of the committee contact their sales department and decide who and at what quantity will sell and buy palladium at the given price. Alternatively, they may slightly adjust the price so that the supply and demand for palladium of these five traders is even and there is no overlap between demand and supply. Then the London Fix is set. The London Fix process usually takes 10–20 minutes. The London Fix price is quoted in US Dollars (USD), British Pounds (GBP), and Euros (EUR) per troy ounce (Oz, *i.e.*, 31.1034807 grams). The descriptive characteristics of the data are given in Table 1.

Table 1. Characteristics of the data file.

Descriptive characteristic	Value in USD
Minimum value	164
Maximum value	911
Average value	540,6339851
Variance	40417,93698

Source: Author.

The development of price over time is assuredly interesting. Therefore, Figure 1

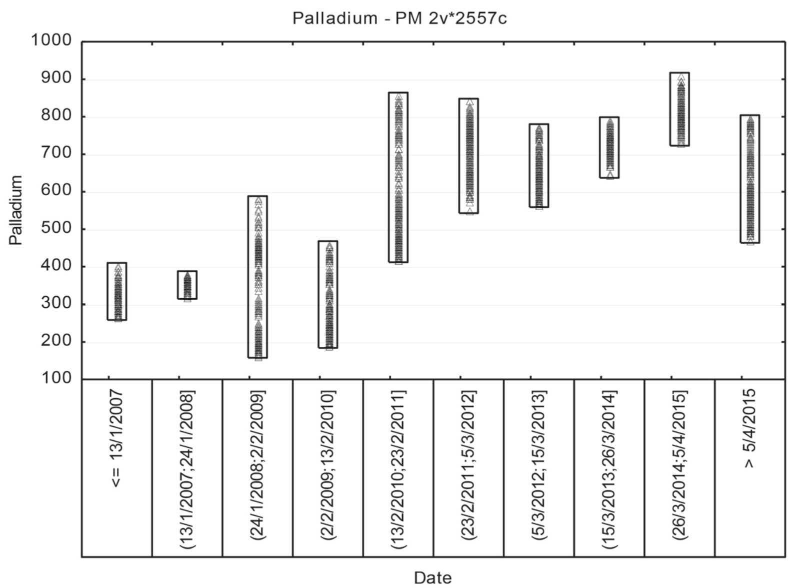

Figure 1. Graph of variance of palladium price (London Fix PM). Source: Author.

shows the variance of values in the individual periods of the monitored time period.

For data processing, software Statistica in version 12 from the company DELL will be used. First, a linear regression will be performed. Neural networks will be used for regression next. The linear regression will be performed on the examined data sample for the following functions: Linear, Polynomial, Logarithmic, Exponential, Polynomial of weighted distances, Polynomial of negative-exponential smoothing.

The correlation coefficient, *i.e.* the dependence of the palladium price on time, will be calculated first. We will then be working with a level of reliability of 0.95.

Afterward regression will be performed using neural structures. We will generate multilayer perceptron networks and neural networks of radial basis functions. Time will be used as the independent variable. We will set the price of palladium as the dependent variable. We will divide the time series into three sets – training, testing, and validating. The first group will contain 70% of the input data. We will generate neural structures based on the training set of data. In the remaining two sets of data, we will consistently leave 15% of the input information. Both groups will serve us to verify the reliability of the found neural structure or the obtained model. The delay of the time series will be 1. We will generate 1000 neural networks. Of these 5 with the best characteristics will be kept. We will be orientating ourselves using the method of least squares. We will terminate network generation if there is no improvement, *i.e.* reduction in the sum of squares will not occur. We will therefore keep those neural structures for which the ratio of the squares sum of residues to the actual palladium development will be as low as possible (ideally zero). There will be a minimum of two neurons in the hidden layer of the multilayer perceptron networks and a maximum of 20. In the case of a radial basis function, there will be at least 21, at most 30, neurons in the hidden layer. For the multiple perceptron network we will consider the following distribution functions in the hidden layer and in the output layer: Identity, Logistic, Tanh, Exponential, Sine.

The rest of the settings will be kept default (under the tool ATS – automatic network creation).

Finally, we will compare the results of linear regression and regression obtained using neural networks. Comparison will not take place in the form of residual analysis (minimum, maximum values, variance of residues, *etc.*), but at the level of the expert view and experience of an evaluator, an economist.

2. Results

Results obtained by linear regression will be presented first. Artificial neural networks will follow immediately after.

2.1 Linear regression

The correlation coefficient is 0.7836. Such a value is, according to Sedlačík, Neubauer, Kříž, (2016), quite high to suppose that it represents a significant statistical effect of palladium on the development over time.

A scatter plot was constructed (see Figure 2), where the points were interleaved with a regression curve, in this case linear. The line parameters are clear from the figure.

The solid line represents a regression function. Figure 3 represents the interleaving of a scatter plot with a polynomial function. This is a second-degree polynomial. This is evident from the shape of the equation.

As in the case of a linear function, in this case, the solid line represents a regression curve. Figure 4 shows a scatter plot interleaved with a logarithmic function.

Figure 5 displays the scatter plot of the London Fix Price interleaved with an exponential function.

Figure 6 provides a scatter plot of palladium price development interleaved with the

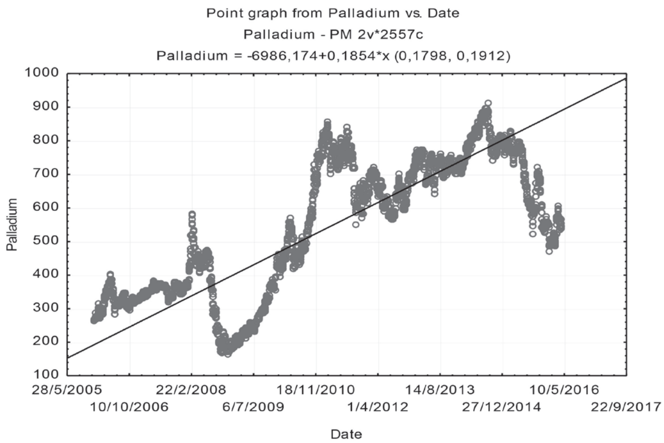

Figure 2. Scatter plot of the price of palladium interleaved with regression curve – linear function. Source: Author.

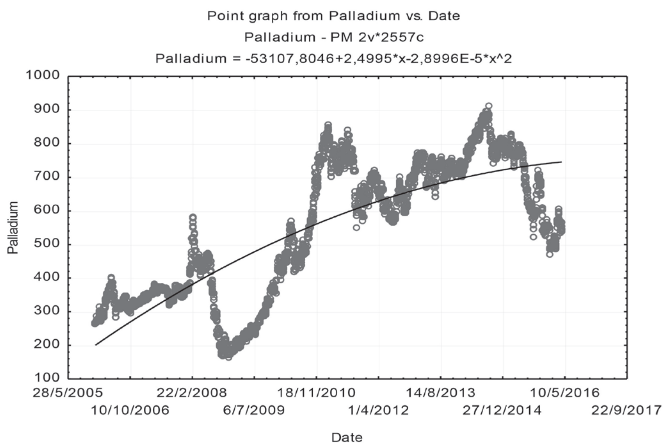

Figure 3. Scatter plot of the price of palladium interleaved with regression curve – polynomial function. Source: Author.

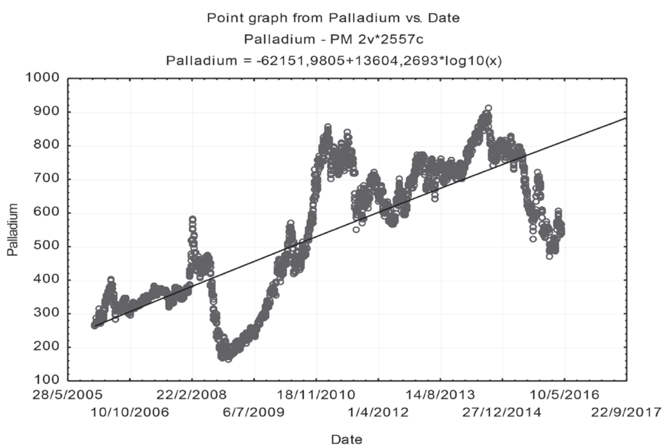

Figure 4. Scatter plot of the price of palladium interleaved with regression curve – logarithmic function. Source: Author.

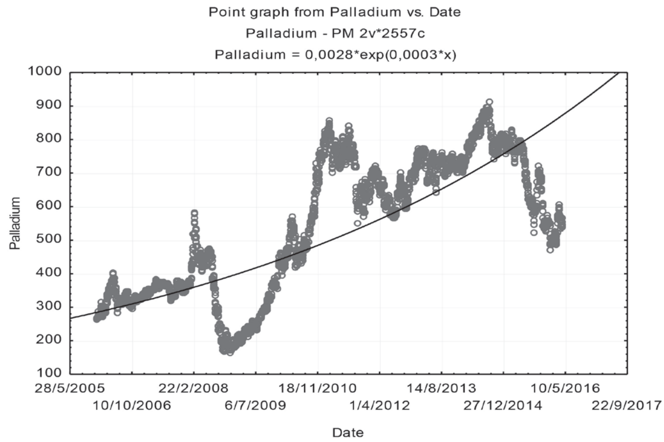

Figure 5. Scatter plot of the price of palladium interleaved with regression curve – exponential function. Source: Author.

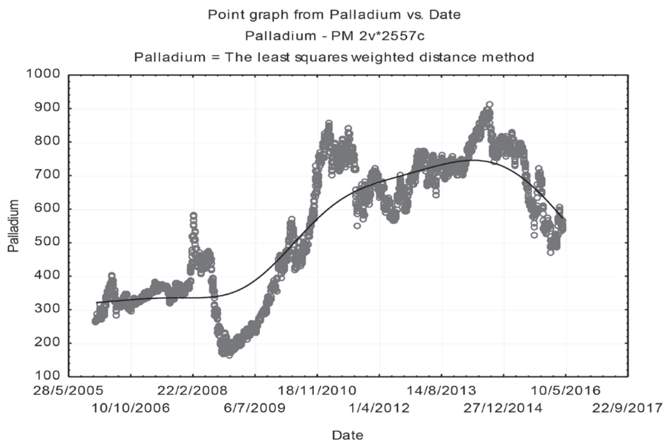

Figure 6. Scatter plot of palladium price interleaved with regression curve – function of weighted-distance least squares method. Source: Author.

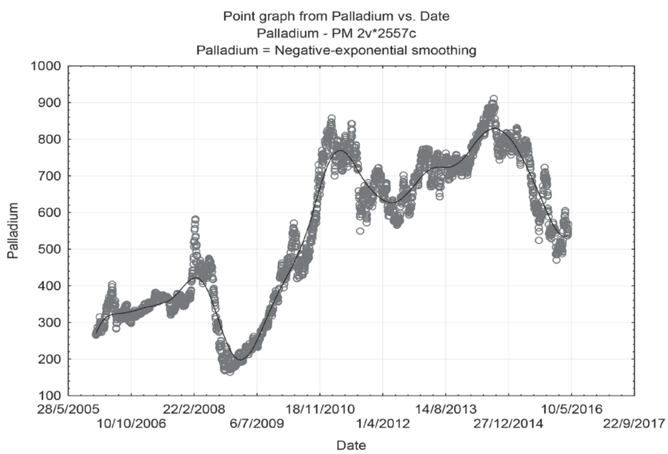

Figure 7. Scatter plot of palladium price interleaved with regression curve – function of least squares method – negative exponential smoothing. Source: Author.

function obtained using the method of weighted-distance least squares.

Figure 7 provides interleaving with the function obtained using the method of least squares by negative-exponential smoothing.

As stated above, the correlation coefficient indicates a relatively significant statistical dependence of the target variable on the development over time. If we evaluated the results solely by optically comparing the development of London Fix Price PM (afternoon prices of palladium) and the shape of the regression curve while taking into account simple linear regression, we could certainly say that the curve most accurately presenting development is the one obtained by the least squares method via negative-exponential smoothing. Following next is the curve also determined by the least squares method, in this case acquired via weighted distances. They both copy the basic development of the palladium price. The other curves differ substantially from the actual development. The curve obtained by the weighted-distance least squares method copies the price of palladium roughly, minimally deviating from the actual development and capturing the global extremes of such development. Conversely, the curve obtained by the least squares method via negative-exponential smoothing tracks not only the global extremes of London Fix Price PM, but also the local extremes of this development. Optically, the feature seems to be effective in terms of predicting the London Fix Price PM. However, the results can never be relied on 100%.

2.2 Neural structures

Based on the established procedure, 1000 neural networks were generated, of which 5 networks with the best parameters were preserved. Their overview is given in Table 2.

This solely concerns multilayer perceptron networks with one hidden layer. There is only one variable in the input layer – time. In the hidden layer, the neural networks contain 4 to 10 neurons. In the output layer, we

Table 2. Overview of preserved neural networks.

Index	Network name	Training perf.	Testing perf.	Valid. perf.	Training error	Testing error	Validating error	Training algorithm	Error function	Activation of hidden layer	Output activation layer
1	MLP 1-4-1	0.998535	0.998527	0.998933	58.78338	60.35577	43.53849	BFGS (Quasi-Newton) 552	Sum. sqr.	Logistic	Exponential
2	MLP 1-4-1	0.998534	0.998527	0.998933	58.80094	60.35907	43.54301	BFGS (Quasi-Newton) 249	Sum. sqr.	Tanh	Exponential
3	MLP 1-8-1	0.998535	0.998530	0.998933	58.78806	60.18313	43.58941	BFGS (Quasi-Newton) 105	Sum. sqr.	Tanh	Exponential
4	MLP 1-5-1	0.998537	0.998532	0.998933	58.70793	60.13783	43.52778	BFGS (Quasi-Newton) 500	Sum. sqr.	Tanh	Tanh
5	MLP 1-10-1	0.998540	0.998539	0.998934	58.55750	59.85375	43.53938	BFGS (Quasi-Newton) 197	Sum. sqr.	Tanh	Logistic

Source: Author.

Table 3. Correlation coefficients of individual sets of data.

	Palladium Training	Palladium Testing	Palladium Valid.
MLP 1-4-1	0.998535	0.998527	0.998933
MLP 1-4-1	0.998534	0.998527	0.998933
MLP 1-8-1	0.998535	0.998530	0.998933
MLP 1-5-1	0.998537	0.998532	0.998933
MLP 1-10-1	0.998540	0.998539	0.998934

Source: Author.

logically have a single neuron and a single output variable – the London Fix Price. For all nets, the Quasi-Newton training algorithm was applied. The different artificial structures also differ from one another in the type of activation functions used in the hidden and in the output layer of neurons (see Table 2).

The training, testing and validation performance is also interesting. In general, we are looking for a network with a performance across all datasets (we emphasize that the division into datasets occurred randomly) that is ideally the same and of an adequate height. At the same time, the error should be as small as possible.

The performance of individual data sets is expressed as a correlation coefficient. The values of the individual data sets in accordance with specific neural networks are shown in Table 3.

It is evident from the table that the performance of all preserved neuronal structures is nearly identical. Slight differences do not affect the performance of individual networks.

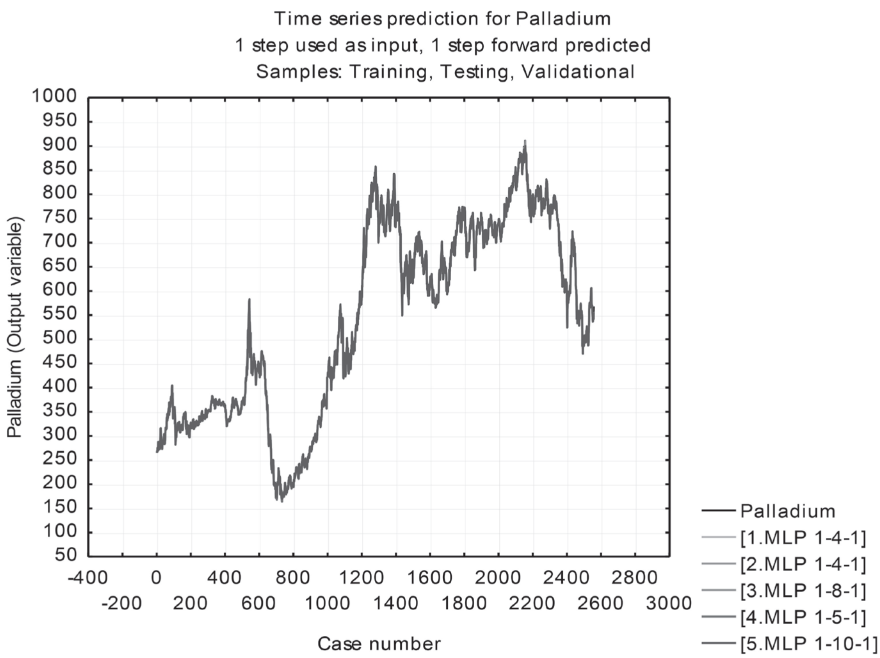

Figure 8. Line graph – the development of palladium prices predicted by neural networks compared to the actual price in the observed period. Source: Author.

Figure 8 represents a line graph that displays the actual development of the London Fix Price (marked as Palladium in the figure) and the development of predictions by individual generated networks simultaneously (these are marked by the order number given in Table two and the number of neurons in each layer).

It is clear from the graph that all neural networks predict the development of the London Fix Price PM very similarly. However, the similarity of the predictions of individual networks is not important, unlike the similarity (or degree of consistency) with the actual development of the palladium price. In this respect, it can be stated that the preserved neural networks appear very interesting at first glance. They respect global curve extremes evaluating the development of palladium prices, but also tend to register the local extremes of this curve.

3. Discussion and Conclusion

Precious metals have long been used as coins. The reasons are several, for example:

- They are subject to thesaurus (they accumulate large values).
- They can be divided.
- They're rare.

These are the reasons why their role is irreplaceable even today, when we use money and even virtual money. The volume of money in circulation is managed by the central banks or governments. They affect the economic environment according to what goals they are pursuing. The volume of precious metals is more or less final (unless we take into account extraordinary findings in nature). This does not devalue them. On the contrary, in times of economic crises, they become more important and are even more bearable – money is losing by inflation, while precious metals still retain their value. Thus, in the time of the economic crisis, investors convert their resources into objects of lasting value (works of art and precious metals). Thus, the cycle of growth and decline in the price of precious metals, which resembles the shape of a cycle in time only differently time-settled, can be noticed. If compared to the business cycle, it is delayed for several years or even is inverse (investors buy precious metals when the value is relatively high). Once the economic crisis is over, investors buy assets in the form of securities (both debt and equity) and start to take more risks. The price of precious metals can be determined, as in the case of other assets, by several types of methods, including psychological (behavioral) and mathematical-statistical methods. The second case is the subject of this article. However, we can say that the price of precious metals is also derived from investors' expectations. These situations create discrepancies between the application of mathematical-statistical methods and reality.

As a general principle, each prediction is determined with a certain probability (with a probability of at least 0.95%) of being implemented. At the moment we predict the future development of any variable, we are attempting, based on data from past periods, to estimate the future development of this variable. Although we can include most of the factors influencing the target variable in the model, reality is always simplified. We work with a certain degree of probability that some of our predicted scenarios will be realized. In the case of linear regression, as well as regression using neural networks, the simplification that occurs is quite substantial. We only work with two quantities – input (time) and output (London Fix Price). Thus, we are completely overlooking other input quantities, which undoubtedly influence the final price of palladium (the development of the national economy, the political situation of the state, the legal environment, market barriers, *etc.*). Yet, or precisely because there are a myriad of factors influencing the price of palladium, we have to consider whether our work with time series does not simplify the development of the target variable too much, or vice versa, the other variables are so insignificant that the input quantity (time) and output quantity (London Fix Price) are completely sufficient. Because it is not possible to predict extraordinary situations and their impact on the palladium price (at most in the short term, but certainly not over a long period of time), simplification and the creation of a relatively simple model is appropriate and the result is useful.

We can determine the price of palladium based on statistical methods, causal methods and intuitive methods. In this example, we have been comparing statistical methods. However, they only gave us a possible framework for the development of the price of palladium. It is important to subsequently work with information on the possible future development of the economic, political or legal environment. If we can predict its development, we can then project it into the palladium price. At the same time, however, the figure of the evaluator – an economist becomes involved, who, on the basis of their knowledge and experience, corrects the price that has been approximately determined by statistical methods and specified on the basis of causal links.

The aim of the paper was to perform a regression analysis on the development of the palladium price on the New York Stock Exchange using linear regression and neural networks, then compare the two methods and identify the more suitable one for a possible prediction of the future development of the palladium price on the New York Stock Exchange. The purpose of the text was to address nothing more than a comparison of two statistical tools. The economic explanation is given rather by the research.

Optically, the curve obtained by the method of least squares via negative-exponential smoothing appeared to be the best from the linear regression options. Among the neural networks, all preserved structures proved to be usable in practice. If we look at performance from the perspective of correlation coefficient, only neural networks remain usable, among which there is virtually no difference.

An analysis of residues would certainly be interesting. It would undoubtedly help determine the best of preserved neural networks. However, this was not the goal of this paper, and the analysis of residues could therefore be the subject of further research.

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