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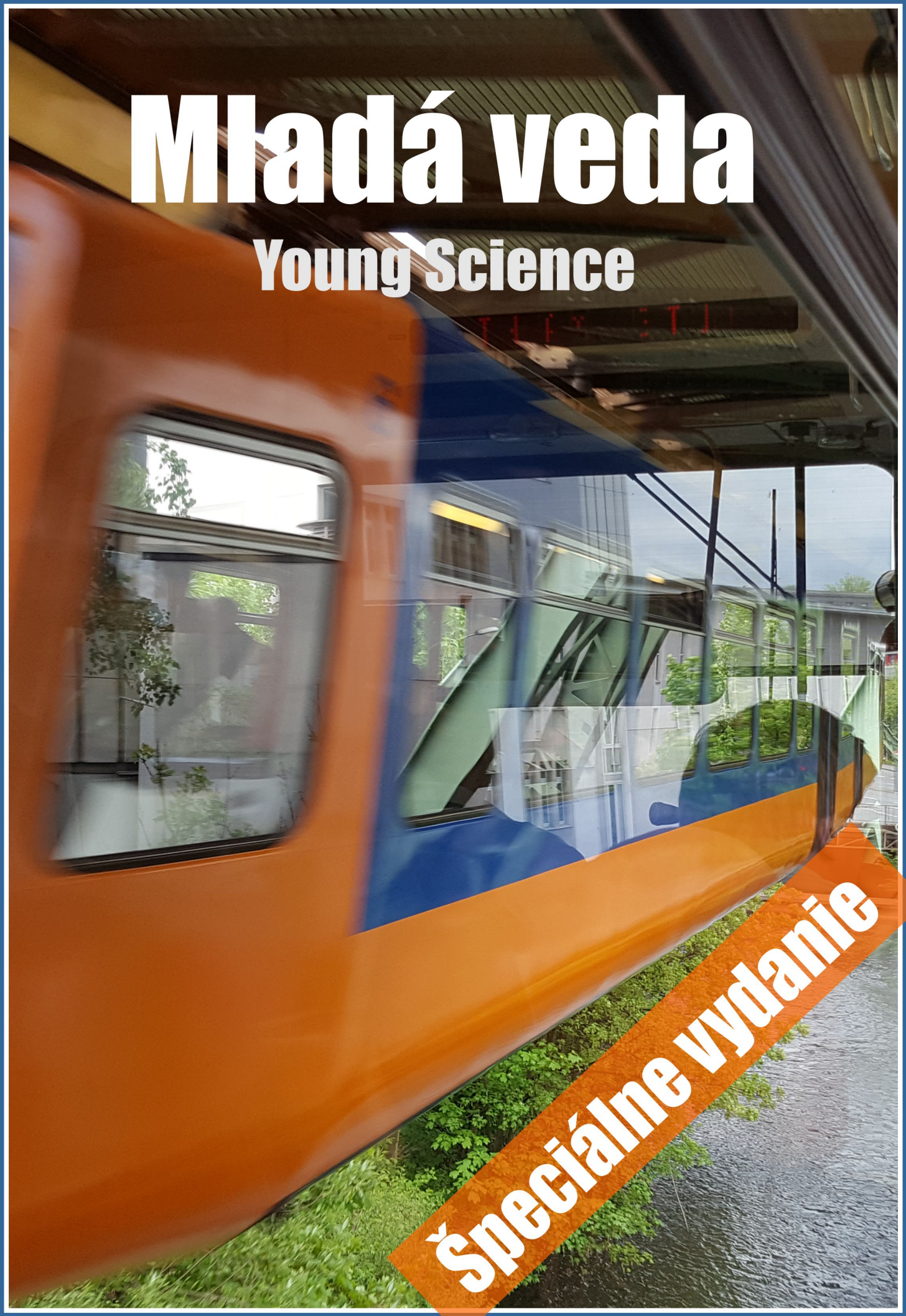

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KOMPARACE NEURONOVÝCH SÍTÍ A REGRESNÍCH ČASOVÝCH ŘAD PRO PREDIKCI VÝVOJE ODPOLEDNÍCH CEN PLATINY NA NEWYORSKÉ BURZE

COMPARISON OF NEURAL NETWORK AND REGRESSION TIME SERIES IN THE PREDICTION THE DEVELOPMENT OF THE AFTERNOON PLATINUM PRICE ON THE NEW YORK STOCK EXCHANGE

Marek Vochozka, Veronika Machová [1]

Autor Marek Vochozka působí jako rektor na Vysoké škole technické a ekonomické v Českých Budějovicích. Ve svém výzkumu se věnuje především tématům, jako jsou: Metody komplexního hodnocení podniku, umělé neuronové sítě, finanční analýza a predikce budoucího vývoje společnosti. Veronika Machová působí jako ředitelka Ústavu znalectví a oceňování Vysoké školy technické a ekonomické v Českých Budějovicích. Zaměřuje se na generátory hodnoty, hodnocení podniku, finanční analýzu a umělé neuronové sítě.

Author Marek Vochozka is a rector of Institute of Technology and Business in Ceske Budejovice. His research focuses mainly on topics such as: methods for comprehensive evaluation of the company, artificial neural networks, financial analysis and prediction of the future development of the company. Veronika Machová is the director of the School of Expertness and Valuation at the Institute of Technology and Business in Ceske Budejovice. Her focus is on value generators, evaluation of the company, financial analysis and artificial neural networks.

Abstract

Platinum is a durable, ductile and precious metal that is becoming a strategic commodity for industry in many countries around the world. In recent years, demand for platinum, thanks to its characteristics and high durability, has more than doubled. For investment purposes, platinum is easily available in the form of slits and, in some cases, in the form of coins. For a long time, it has also been used as a preserver of value. The scientific aim of this paper is to perform a regression analysis of platinum prices at the New York Stock Exchange using

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artificial neural structures and linear regression. The most appropriate method for predicting the future development of the platinum price at the New York Stock Exchange will be then determined. Based on the price development and the regression curve shape, and taking into account the simple linear regression, the closest curve to the platinum price development is the spline function. The most suitable neural networks selected are all multilayered perceptron networks with one hidden layer. The performance of all five preserved neuron structures is approximately identical. Considering the performance from a correlation coefficient point of view, the neural networks perform best and there is practically no difference among them. However, the analysis of residues, if employed, could undoubtedly determine the best of the preserved neural networks.
Key words: platinum, linear regression, artificial neural networks, regression analysis, price development

Abstrakt
Platina je odolným, tvárným a drahocenným kovem, který se stává strategickou komoditou pro průmysl v mnoha zemích světa. V posledních letech se poptávka po platině, díky jejím vlastnostem a vysoké odolnosti, více než zdvojnásobila. Pro investiční účely je platina snadno dostupná ve formě slitků a v některých případech i ve formě mincí. Již dlouhou dobu se tak využívá i jako uchovatel hodnoty. Cílem tohoto příspěvku je provést regresní analýzu ceny platiny na newyorské burze pomocí umělých neuronových struktur a pomocí lineární regrese. Určena bude nejvhodnější metoda pro případnou predikci budoucího vývoje ceny platiny na newyorské burze. Na základě hodnocení výsledků vývoje ceny a tvaru regresní křivky, při úvaze jednoduché lineární regrese, lze konstatovat, že nejblíže se vývoji ceny platiny přibližuje křivka proložená funkcí spline. Vybrané nejvhodnější neuronové sítě jsou pouze vícevrstvé perceptronové sítě s jednou skrytou vrstvou. Výkon všech pěti uchovaných neuronových struktur je přibližně totožný. Pokud se podíváme na výkon z pohledu koeficientu korelace, zůstávají k použití pouze neuronové sítě, mezi kterými není prakticky žádný rozdíl. Zajímavá by samozřejmě byla například analýza reziduí, která by zajisté určila z uchovaných neuronových sítí jednu nejlepší.
Klíčová slova: platina, lineární regrese, umělé neuronové sítě, regresní analýza, vývoj ceny

Introduction

Platinum is a chemical element with symbol Pt and atomic number 78. It is a very rare, dense, durable, malleable, precious and highly unreactive metal white in colour, which has become a strategic commodity for industry in many countries (Puddephatt, 2017). In the last 30 years, the demand for platinum has more than doubled, especially due to its properties and durability (Reith et al., 2014). However, sources of native platinum are limited and are becoming depleted fast (Soares et al., 2017). Platinum can be also obtained as a by-product of processing other metals, such as copper or nickel (Saternus et al., 2015). According to Marget et al. (2002), the deposits of this metal are located mostly in South Africa or in the Ural Mountains.

Platinum

Mudd (2012) describes native platinum as a mineral containing certain amount of iron. Zhang et al. (2017) adds that it is a non-magnetic metal characterized especially by good malleability. It can thus be classified as noble metal.

Due to its favourable properties, platinum is a very sought-after metal, rarely occurring in nature either in the form of native platinum or along with other elements of platinum metals in sand or drift (Kendall, 2004).

Patel et al. (2015) describe platinum production as a complex process, since native platinum contains about 25 % impurities. Zhang et al. (2017) claims that in order to obtain pure metal it is necessary to purify platinum from impurities. According to Rehren (2006), platinum must be heated or dissolved in aqua regia[2], where it gains the form of ground ore. For this process, calcium hydroxide is necessary, which allows precipitation of other metal substances except for platinum.

Platinum can be used especially in the pharmaceuticals, glass industry and chemical industry. To a limited extent, platinum is also used for jewellery production (Brenan, 2008). The use of platinum is also in the financial sector, but for shorter time than silver and gold (Ranganai et al., 2016). According to Alonso et al. (2012), platinum has become the metal which is nowadays necessary for car production due to its catalytic role, especially for the reduction of toxic gasses. It is therefore an excellent catalyst; it can be used at higher temperatures and is stable in many aggressive chemical environments. Currently, platinum accounts for 40-45% of the world demand (Almécija et al., 2016).

Like any commodity, platinum has its contract value and margin. As commodity contracts are usually adapted, each price movement has its own different value. In the platinum contract, the 10 cents movement equals 5 USD (Sun et al., 2011). According to Sverdrup et al. (2016), the world platinum price is given in Troy ounce. Platinum has been used for more than 300 years as a store of value. As for investment purposes, like silver and gold, this precious metal is readily accessible in the form of ingots and in some cases also in the form of coins. However, platinum is an industrially used metal, therefore it is subject to VAT.

Due to its beneficial properties, it is very important to analyse and predict platinum price and its future development. For this, artificial neural networks can be used.

Artificial neural networks

Artificial neural networks (ANN) seek to copy the processes in the human brain and the nervous system using computer systems (Stehel et al., 2016). The use of artificial neural networks is wide and currently, those are used especially for solving possible problems in future (Pao, 2008). These networks can be used for complicated operations which cannot be identified analytically. They are therefore used especially for modelling complex strategic solutions (Guresen and Kayakutlu, 2011).

[2] Aqua regia is fuming yellow-brown liquid used for dissolving hardly soluble noble metals. It is a mixture of concentrated nitric acid and hydrochloric acid.

According to Sánchez and Melina (2015), artificial neural networks have a wide variety of applications, they can be used in many fields and thanks to the growing volume of data gathered they are becoming increasingly popular. Neural networks can be used for classification, function approximation, and mainly for prediction of time series (Altun, Bilgila and Fidana, 2007). Time series analysis is the area in which neural networks can be widely used. Time series is defined as a sequence of spatially and factually comparable observations, which are arranged in terms of time (Sheikhan et al. 2013).

As for the neural networks and time series, great importance is attached to the nature of all data and purpose of the time series. Neural networks thus seek to depict the behaviour of time series and to predict the individual data points in the best possible way. Hu and Hwang (2002) claim that it is necessary to show the neural networks how to work with the time series properly.

In the real world, the inputs of many complex systems are time-varying processes or functions. In order to predict realistically the outputs of these systems with high precision and speed, many models of time series are predicted, which are based on the processes of neural networks. The effectiveness of the proposed time series and learning process seems to be an appropriate tool for predicting complex non-linear time series (Chen, Yang and Dong, 2006).
The objective of the contribution is to carry out a regression analysis of the development of platinum price on the New York stock exchange by means of neural networks and linear regression, then compare both methods to determine the method more suitable for a possible prediction of the future development of platinum price on New York stock exchange.

Methods

The data for analysis will be obtained from the web pages of New York stock exchange or the World Bank etc. For the analysis, London Fix price AM between January 3, 2006 and April, 15, 2016 will be used. In total, it is the volume of 2570 data on platinum price. The key value for setting the reference price for platinum is so-called London fix price (often referred to as London Fix). It is announced on the days when platinum is traded in London, twice a day. The morning fix (referred to as AM) is announced at 09:45. The afternoon fix (referred to as PM) is announced at 14:00. Except December 24 (if it is a working day) and December 31 – it is announced on in the morning, if the last day of December is a working day. For the purpose of this contribution, only afternoon platinum prices will be used. The morning prices will not be used. The descriptive characteristics of the data are showed in Table 1.

Descriptive characteristics	Value in USD
Minimum value	763
Maximum value	2273
Average value	1389.91148
Dispersion of values	82182.7758

Table 1 – Characteristics of data set
Source: Own

What is interesting is the development of platinum price over time. Figure 1 therefore shows the dispersion of the values in the individual periods of the monitored period.

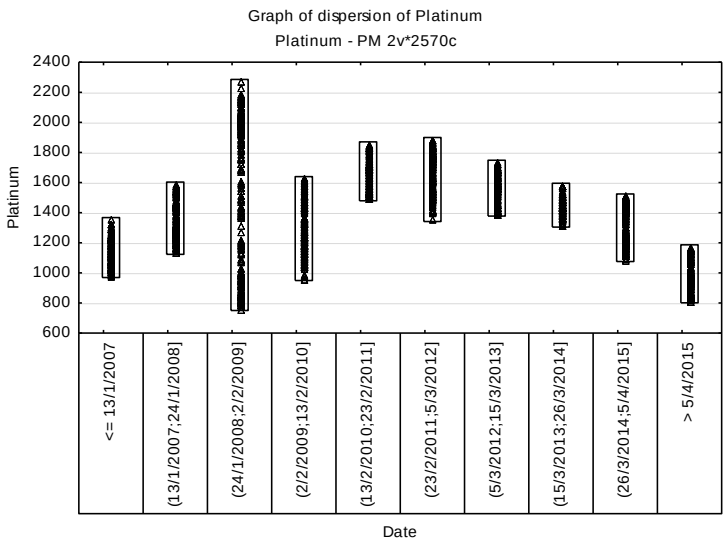

Figure 1 – Graph of dispersion of platinum price values (London Fix PM)
Source: Own

Setting London Fix starts at the moment when the fixation committee suggests an opening price that is close to the spot price. The process then continues with the individual committee members contacting their sales departments and deciding who and what amount of platinum to sell and buy at a given price. They are able to slightly coordinate the price so that the supply and demand for platinum from the largest trades is balanced and there is no excess supply or demand. Subsequently, London Fix is set. The process of setting London Fix usually takes 10-20 minutes. The London Fix price is in US dollars (USD), UK pounds (GBP) and euros (EUR) for one Troy ounce (Oz, that is, 31.1034807 grams).

For the data processing, DELL Statistica V12 will be used. First, linear regression will be carried out. Subsequently, artificial neural networks will be used for regression.

Linear regression will be carried out on the examined data sample for the following functions:

- Linear,
- Polynomial,
- Logarithmic,
- Exponential,
- Spline,
- Multinomial of distance weighing,
- Multinomial of negative-exponential smoothing.

First, correlation coefficient will be calculated, that is, the dependence of the platinum price on time. Then we will work with the significance level 0.95.

Subsequently, regression analysis will be carried out using neural networks. Multilayer perceptron networks and radial basis function network will be generated. Time will be the

independent variable, while the platinum price will be the dependent variable. The time series will be divided into three sets – training, testing and validation. The training sample will contain 70% of the input data (based on this data set, neural structures will be generated). Both testing and validation sample will contain 15% of the input data. Both these sets will serve for verification of the reliability of the generated neural structure or the model. The delay in time series will be set to 1. In total, 1,000 neural networks will be generated, out of which 5 with the best characteristics will be retained. The hidden layer will contain at least two neurons, but no more than 20. The hidden layer of the radial basis neural networks will contain no less than 21 neurons and no more than 30 neurons. For the multilayer perceptron network, the distribution linear function, logistic function, atanh, exponential and sinus functions will be considered in the hidden and output layer. Other settings will be default (according to the automatic network creation tool).

Finally, the results of linear regression and regression by means of artificial neural networks will be compared. In this case, comparison will not be in the form of residuals analysis (minimum and maximum values, dispersion of values of residuals etc.), but at the expert level and the experience of the evaluator, an economist.

Results

This part presents a summary of the results obtained by means of linear regression and regression using neural networks.

Linear regression

The correlation coefficient is -0.0658, which means only insignificant statistical dependence of the platinum price on the development over time. Points are fitted by regression curve, linear in this case. The line parameters can be seen in Figure 2.

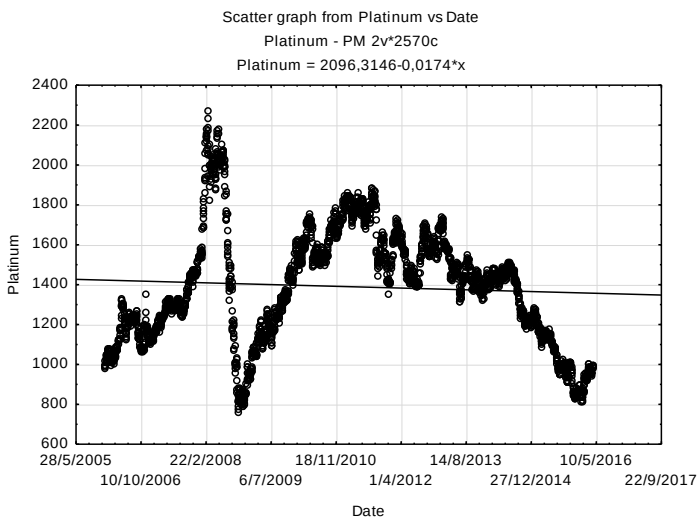

Figure 2 – Platinum price scatter graph fitted by regression curve – linear function
Source: Own

The solid line represents regression function. Figure 3 shows fitting of the London Fix Price scatter graph by the polynomial function.

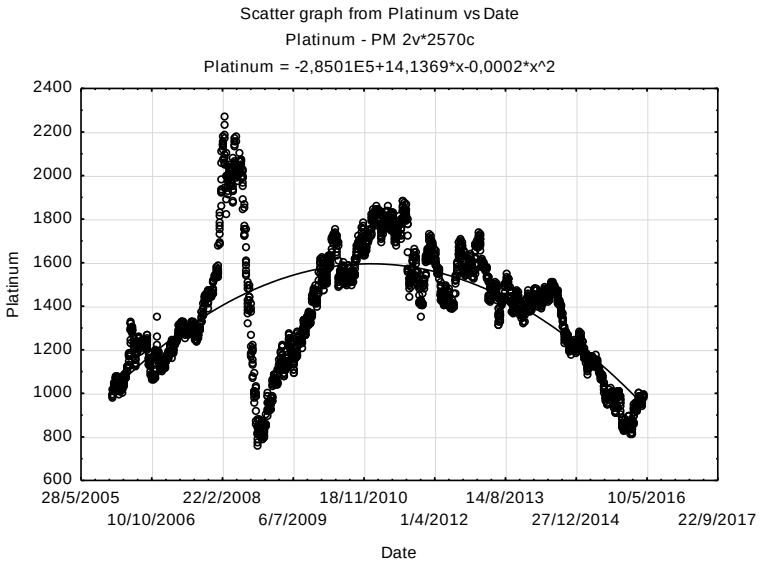

Figure 3 – Platinum price scatter graph fitted by regression line – polynomial function
Source: Own

As in the case of linear function, the solid red line represents the regression curve. Figure 4 shows the scatter graph fitted by logarithmic function.

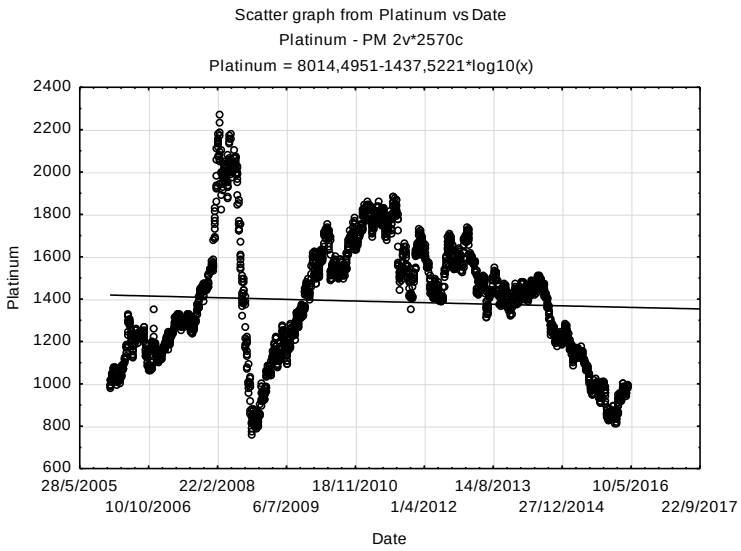

Figure 4 – Platinum price scatter graph fitted by regression line - logarithmic function
Source: Own

Figure 5 shows the platinum price development scatter graph fitted by exponential function.

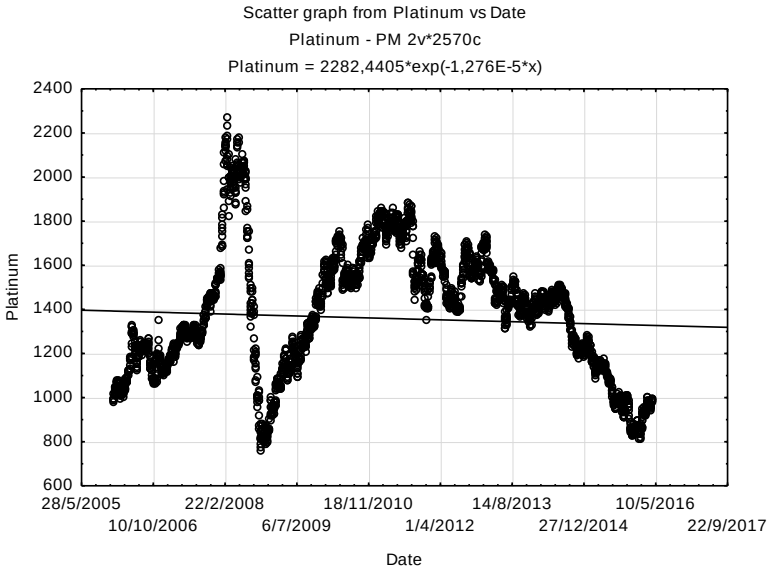

Figure 5 – Platinum price scatter graph fitted by regression line – exponential function
Source: Own

The platinum price development scatter graph fitted by the spline function is seen in Figure 6.

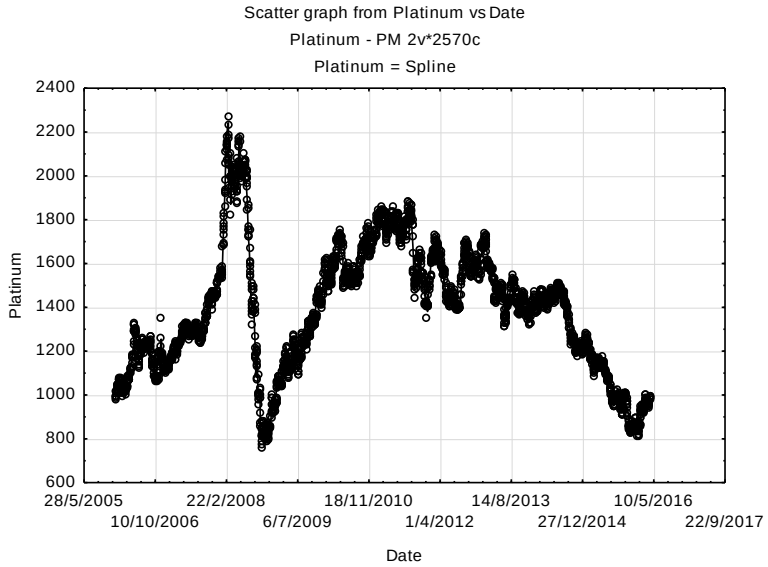

Figure 6 – Platinum price scatter graph fitted by regression curve – spline function
Source: Own

The platinum price development scatter graph fitted by the function obtained by means of the least squares method is showed in Figure 7.

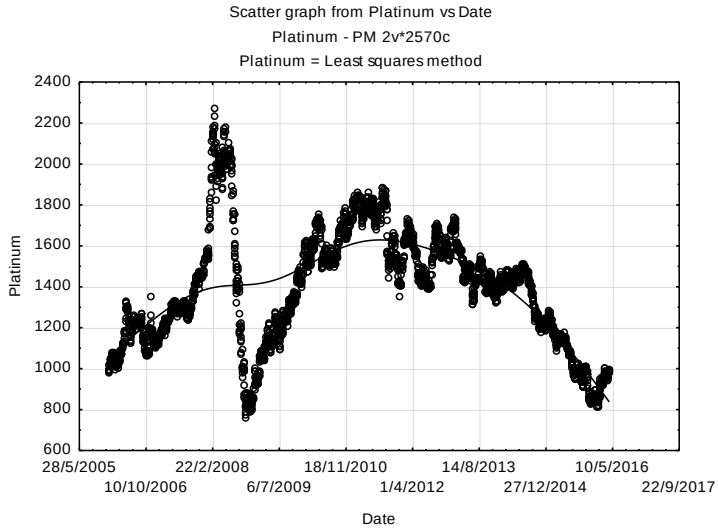

Figure 7 – Platinum price scatter graph fitted by regression curve – function of the least squares method by distance weighing
Source: Own

Figure 8 shows fitting with the function obtained by means of the least squares method by negative-exponential smoothing.

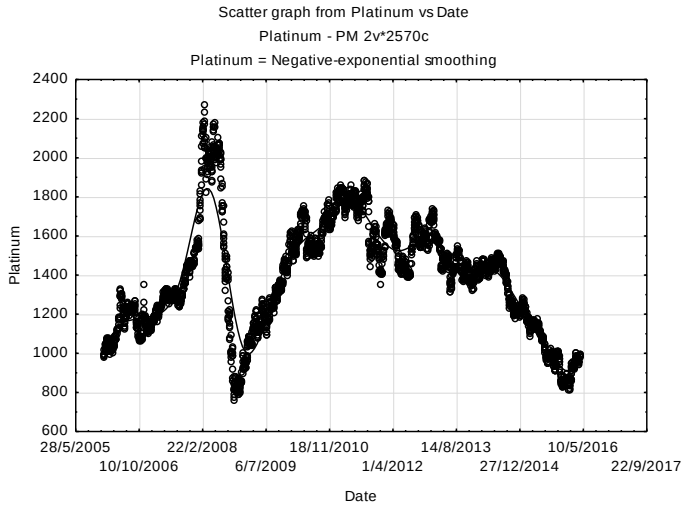

Figure 8 – Platinum price scatter graph fitted by regression line – function of the least squares method by negative-exponential smoothing
Source: Own

The correlation coefficient thus indicates the insignificant statistical dependence of the target variable on the development over time. Based on the evaluation of the results carried out only by the visual comparing of the development of the London Fix Price PM and the shape of the regression curve, taking into consideration the simple linear regression, it may be stated the curve fitted by the spline function is closest to the actual development of the platinum price. Another quite suitable one is the curve obtained using the least squares method by negative –

exponential smoothing. Other curves are unable to copy the basic development of the platinum price to the same extent as the spline function and negative – exponential smoothing. It is the curve obtained using the least squares method by negative – exponential smoothing that roughly follows the platinum price, which only slightly diverges from the actual price development and depicts the global extremes of this development. In contrast, the curve obtained by the spline function tracks not only the global extremes of the London Fix Price PM development, but also the local extremes of this development. With a view to a possible prediction of the London Fix Price, this function appears to be effective, but still somewhat inaccurate.

Neural structures

Based on the defined methodology, in total 1,000 artificial neural networks were generated. Out of these, 5 networks showing the best parameters were retained.

The most suitable networks are only multilayer perceptron networks with one hidden layer, where there is only one variable in the input layer, namely time. The neural networks in the hidden layer contain 6-19 neurons. The output layer logically contains only one neuron and one output variable – London Fix Price. The artificial neural structures differ also by the type of the used activation functions in the hidden layer. The output activation function with the retained neural structures is always logistic.

What is interesting is the training, testing and validation performance. Generally, we are looking for a network with ideally the same performance in all data sets (it is necessary to repeat that the data were randomly divided into the data sets). For the above mentioned networks, the performance is almost the same, which is a very positive result. The error should be as small as possible (unfortunately, the training, testing and validation error is relatively big).

The performance of the individual data sets can be expressed in the form of the correlation coefficient. The values for the individual data sets by the specific neural networks are given in Table 2.

Network	Training platinum	Testing platinum	Validation platinum
1.MLP 1-4-1	0.997212	0.996530	0.997432
2.MLP 1-4-1	0.997210	0.996533	0.997435
3.MLP 1-8-1	0.997211	0.996532	0.997432
4.MLP 1-5-1	0.997206	0.996536	0.997434
5.MLP 1-10-1	0.997208	0.996531	0.997432

Table 2 – Correlation coefficients of individual data sets
Source: Own

The values in the table confirm that the performance of all retained neural structures is approximately the same. The slight differences do not affect the performance of the individual networks.

Figure 9 shows a graph describing the actual development of the London Fix Price. It can be seen from the graph that all neural networks predict the development of the London Fix Price PM similar. What is important is not the similarity of the predictions of the individual networks, but the similarity (or degree of conformity) with the actual development of platinum price. Even in this respect, it can be stated that the retained neural networks appear very interesting at first sight. They respect the global extremes of the curve evaluating the development of platinum price and tend to capture the local extremes of this curve.

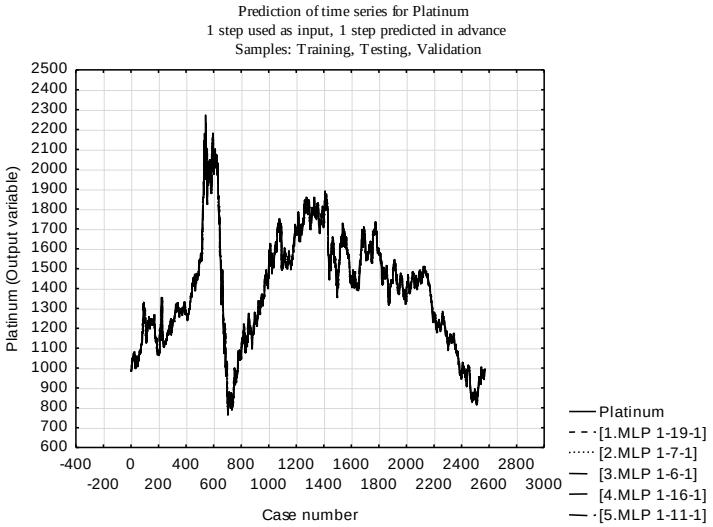

Figure 9 – Line graph: development of platinum price predicted by neural networks in comparison with the reference period
Source: Own

Conclusion

Each prediction is given by a certain degree of probability according to which it comes true. When we need to predict the future development of any variable, we try to estimate the future development of this variable on the basis of the previous data as precisely as possible. Despite the fact that the model shall include most factors influencing the target variable, there is always certain simplification of reality. We always have to work with a certain degree of probability that the predicted scenario will come true. In the case of linear regression as well as regression by means of neural networks, the simplification, sometimes very significant, occurs. This contribution considers only two variables – input (time) and output (London Fix Price). The contribution does not take into consideration other input variables, which undoubtedly influence the final platinum price (the development of national economy, political situation, legal environment, market barriers etc.). Despite, or maybe because of the fact there are a number of factors influencing the platinum price, the investigator has to consider whether working with time series does not simplify the development of the target variable too much or whether other variables are so insignificant that the input variable (time) and output variable (London Fix Price) are sufficient. Taking into consideration the impossibility to predict extraordinary situations and their influence on the platinum price, the simplification and creating relatively simply model is convenient and the result is useful. The platinum price can be fixed based on the statistical, causal and intuitive methods. This

contribution dealt with comparing statistical methods, which showed only a possible frame for predicting the platinum price development. What is important is to work with the information on a possible future development of economic, politic and legal environment. As indicated above, the prediction of these values is relatively complicated. However, if we were able to predict this development, we would be able to incorporate it into the platinum price. In this case, however, the evaluator – economist – is also important. Based on their experience and knowledge, they are able to correct the price set using statistical methods and specify it based on the causal links.

The objective of the contribution was to carry out the regression analysis of the platinum price development on the New York stock exchange by means of neural networks and linear regression. The aim was also to compare both methods and to choose the method more suitable for the possible prediction of future development of platinum price on the New York stock exchange. As for the linear regression, the most suitable one appeared to be the curve obtained by means of the spline function. Regression by means of neural networks helped to generate five most important neural structures, all of which can be used. Taken from the correlation coefficient point of view, for the performance only neural networks can be used, between which there is no significant difference. It would be interesting for example to analyse residuals, which would help to identify the most suitable neural network from the five retained ones.

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