JOURNAL OF SUSTAINABLE MINING 14 (2015) 203–210

HOSTED BY

ELSEVIER

Available online at www.sciencedirect.com

ScienceDirect

journal homepage: http://www.elsevier.com/locate/jsm

JOURNAL OF SUSTAINABLE MINING

Forecasting European thermal coal spot prices

Alicja Krzemień [a,*], *Pedro Riesgo Fernández* [b,1], *Ana Suárez Sánchez* [b,1], *Fernando Sánchez Lasheras* [c,2]

[a] *Central Mining Institute, Plac Gwarków 1, 40-166, Katowice, Poland*

[b] *Oviedo School of Mining, Energy and Materials Engineering, University of Oviedo, Independencia 13, 33004, Oviedo, Spain*

[c] *Department of Construction and Manufacturing Engineering, University of Oviedo, 33204, Gijón, Spain*

ARTICLE INFO

Article history:
Received 13 November 2015
Received in revised form
11 March 2016
Accepted 7 April 2016
Available online 20 April 2016

Keywords:
Thermal coal
Price forecasting
Time series analysis
Coal price drivers
Neural networks
Autoregressive model

ABSTRACT

This paper presents a one-year forecast of European thermal coal spot prices by means of time series analysis, using data from IHS McCloskey NW Europe Steam Coal marker (MCIS). The main purpose was to achieve a good fit for the data using a quick and feasible method and to establish the transformations that better suit this marker, together with an affordable way for its validation.

Time series models were selected because the data showed an autocorrelation systematic pattern and also because the number of variables that influence European coal prices is very large, so forecasting coal prices as a dependent variable makes necessary to previously forecast the explanatory variables.

A second-order Autoregressive process AR(2) was selected based on the autocorrelation and the partial autocorrelation function.

In order to determine if the results obtained are a good fit for the data, the possible drivers that move the European thermal coal spot prices were taken into account, establishing a hypothesis in which they were divided into four categories: (1) energy side drivers, that directly relates coal prices with other energy commodities like oil and natural gas; (2) demand side drivers, that relates coal prices both with the Western World economy and with emerging economies like China, in connection with the demand for electricity in these economies; (3) commodity currency drivers, that have an influence for holders of different commodity currencies in countries that export or import coal; and (4) supply side drivers, involving the production costs, transportation, etc.

Finally, in order to analyse the time series model performance a Generalized Regression Neural Network (GRNN) was used and its performance compared against the whole AR(2) process. Empirical results obtained confirmed that there is no statistically significant

* *Corresponding author*. Tel.: +48 322592556; fax: +48 322596533.
E-mail addresses: akrzemien@gig.eu (A. Krzemień), priesgo@uniovi.es (P. Riesgo Fernández), suarezana@uniovi.es (A. Suárez Sánchez), sanchezfernando@uniovi.es (F. Sánchez Lasheras).
Peer review under responsibility of Central Mining Institute in Katowice.
[1] Tel.: +34 985104284; fax: +34 985104242.
[2] Tel.: +34 984 833 135; fax: +34 985 565 386.
http://dx.doi.org/10.1016/j.jsm.2016.04.002

difference between both methods. The GRNN analysis also allowed pointing out the main drivers that move the European Thermal Coal Spot prices: crude oil, USD/CNY change and supply side drivers.

1. Introduction

"Does energy production have to be based on fossil fuels?" "Will coal continue to play an important role in the energy mix?" "How much do we need coal to provide security of supply in our electricity network?" These questions are essential for the future planning of coal production and consumption within the European Union.

According to the International Energy Agency (2015a) the share of electricity from fossil fuels has not varied much since 1985, after the major introduction of nuclear capacity. The electricity generation mix in the Organization for Economic Co-operation and Development (OECD) in 2014 remained dominated by fossil fuels (59%), mainly coal and gas, 32% and 24%, respectively.

Although Patzek and Croft (2010) forecasted the peak of coal production from existing coalfields as quite imminent, expecting a fall by 50% within the next 20 years, and Mohr and Evans (2009) forecasted something similar on an energy production basis (between 2011 and 2047), it is indubitable that coal will remain an important part of the world economy during many years.

In January 2014 the European Commission published the policy framework for climate and energy in the period from 2020 to 2030 (European Commission, 2014). Its main concern was the reduction of greenhouse emissions while considering at the same time the need for a competitive and secure energy supply within the EU.

This need for a secure energy supply has changed favourably the economic arguments for coal. Nevertheless, coal industry and coal-fired power generation within Europe are pushed by several factors, which are not independent of each other:

- Worldwide coal prices are low due to overproduction: without climate policy low coal prices would drive electricity production from natural gas to coal (Van Ruijven & van Vuuren, 2009), but this is not the scenario;
- A new variable is affecting the energy markets: the EU emission trading scheme, which started in 2005, setting caps for CO_2 emissions from power plants that can be increased only by the acquisition of emission allowances;
- Regulatory pressure to reduce greenhouse gas emissions due to new air pollution limits will come into force in 2016;
- If the damage costs that result from fossil fuels combustion are internalised into the electricity price, some renewable technologies may be financially competitive in comparison with electricity generation from coal (Owen, 2006); and,
- Coal production will lose state aids by 2018 in the European Union and money-losing mines will have to close after that.

The European Commission (2013), forecasted the changing in Europe's energy mix till the 2030 scenario with a 30% reduction in solid fuels and an 80% increase in renewables (Table 1).

During the next years there will be a stable increase of renewables share into the energy mix. Nevertheless, their dominance will take decades to come according to BRG (2014).

Europe's domestic coal production plus hard coal imports during the first semester of 2015 were 2.7% lower than the previous year. The reduction in hard coal production was 3.6%, and the reduction in lignite production was 2.7%. Hard coal imports were reduced 1.7% (Euracoal, 2015).

Thus, main pressure is supported by hard coal production. Being Poland the biggest hard coal producer of the EU with a 68.3% share, it will be the country to suffer more from all the factors that push the coal industry and coal-fired power generation.

Therefore, it is really important to provide an effective forecasting of energy resources prices in the context of energy security as well as conducted energy policy and management of the energy industry in countries where coal is an energy main raw material and the primary energy source.

This paper presents a one-year forecast of European thermal coal spot prices by means of time series analysis, using data from IHS McCloskey NW Europe Steam Coal marker (MCIS). The main purpose was to achieve a good fit for the data using a quick and feasible method and to establish the transformations that better suit this marker, together with an affordable way for its validation.

Also, in order to analyze the time series model performance a Generalized Regression Neural Network (GRNN) was used and its performance compared against the whole process. Finally, this analysis also allowed pointing out the main drivers that move the European Thermal Coal Spot prices.

Table 1 – EU gross energy inland consumption. Source: (European Commission, 2013).

Source	2011	2030 (scenario)
Renewables	10%	18%
Solid fuels	17%	12%
Nuclear	14%	14%
Gas	24%	22%
Oil	35%	33%

2. Materials and methods

This paper uses data from IHS McCloskey NW Europe Steam Coal Marker (MCIS), a long-established coal price indicator for NW Europe that is quoted since January 1991. This indicator corresponds to steam coal spot prices in USD/t for 6000 kcal/kg and below 1% sulphur content, delivered with Cost, Insurance and Freight (CIF) to NW European ports: ARA (Antwerp, Rotterdam, and Amsterdam), France, Belgium, the North Sea, Ireland and the United Kingdom. Prices that are quoted on a Free On Board (FOB) basis are converted into CIF figures using freight rates from the London shipbroking community that provides service to the relevant delivery routes.

The MCIS index is published every Friday on a weekly basis. In order to undergo a one-year forecast, a monthly basis was selected, using for each month the MCIS value of the first Friday.

Another relevant index for Europe is the API 2, an average of Argus CIF ARA that reflects the ARA CIF coal price in USD/t, basis 6000 kcal/kg NAR (Net As Received), and the IHS McCloskey NW European Steam Coal Marker. Although the API 2 price is the primary price reference for physical and over-the-counter (OTC) coal contracts in Northwest Europe, as 90% of the world's coal derivatives are priced against the Argus/IHS McCloskey API 2 and API 4 indexes (API 4 is the benchmark for coal exported out of Richards Bay in South Africa), for this research the MCIS index was used due to data availability.

In order to be able to measure the proximity of the one-year prediction to its target, the European thermal coal spot prices according to MCIS from January 1998 to July 2015 (Fig. 1) were divided into two subsets. In first place, a training data subset was defined from January 1998 till July 2014 and, in second place, a validation data subset was defined with the data from August 2014 till July 2015.

The same approach was applied by Crespo Cuaresma, Hlouskova, Kossmeier, and Obersteiner (2004) who forecasted electricity spot-prices using data from the Leipzig Power Exchange by means of linear univariate time-series models. They divided the data set into an in-sample period and an out-of-sample period composed by the remaining observations which they used to assess the forecasting abilities of the different models.

Fig. 1 – The IHS McCloskey NW Europe Steam Coal marker (MCIS) from 01/1998 till 07/2015. (Data: Courtesy of CARBUNION).

Time series models were selected because the data showed an autocorrelation systematic pattern, and the number of variables that influence European coal prices is very large. Thus, forecasting coal prices as a dependent variable makes necessary to previously forecast the explanatory variables, a work that might be even more demanding than forecasting coal prices themselves (Behmiri & Manso, 2013).

The methodology presented by García-Martos, Rodríguez, and Sánchez (2013), which was derived from the ARIMA methodology for the study of time series analysis developed initially by Box and Jenkins (1976), was used:

1. Checking variance stationarity in order to decide on using a logarithmic transformation.
2. Applying one difference (or in some particular cases, even two differences) when the mean is not constant over time, together with the selection of the most appropriate period for the deseasonalization.
3. After obtaining data stationarity, the adequate model should be selected together with its order based on the patterns presented by the autocorrelation Function (ACF) and the Partial autocorrelation Function (PACF). The ACF will give hints about the more suitable time series model and the PACF will allow identifying the order of the model.
4. Then the goodness of the fit with the selected model is estimated by means of Maximum Likelihood Estimation (Aldrich, 1997), Akaike Information Criterion (Sugiura, 1978) or Bayesian Information Criterion (Sawa, 1978), and tested against alternative models that may also be suitable.
5. Once the goodness of the model has been estimated, then the hypotheses assumed for the error term must be checked in the diagnostic checking stage. This can be done by applying the Ljung–Box test (Sánchez Lasheras, de Cos Juez, Suárez Sánchez, Krzemień, & Riesgo Fernández, 2015; Ljung & Box, 1978) to check the independence assumption, and the Kolmogorov–Smirnov test (Lilliefors, 1967) for testing the normality assumption. If the independence and normality assumptions are not rejected then the estimated model can be used to compute forecasts for the price. Otherwise, an alternative model should be estimated, going back to Steps 3, 4 and 5, subsequently.

@RISK 6, from Palisade Corporation (Ithaca, New York), was used for the simulation of the time series models.

The performance of the models obtained in this research was analysed by means of the Root Mean Square Error (RMSE) and Mean Percentage Absolute Error (MAPE). Both metrics help to determine if a particular fitted distribution is a good fit for the data.

The RMSE can be expressed as follows:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n}} \quad (1)$$

where: A_t is the actual value, F_t is the forecasted value and n is the number of forecasted values.

The equation of MAPE is:

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \quad (2)$$

Variables have the same meaning as in the equation above.

Also the results were evaluated by means of the Forecast Error (FE), using the formula (3).

$$\text{Forecast error(FE)} = \left[\frac{(\text{actual} - \text{predicted})}{\text{actual}}\right] \quad (3)$$

In order to make a comparative analysis of the time series model performance, Generalized Regression Neural Networks (GRNN) were selected, as they can be used as nonlinear regression models, generalizing the stationary and univariate models used in econometrics (Panella, Barcellona, & D'Ecclesia, 2012). GRNN are a kind of probabilistic neural networks that are often used for function approximation. They were put forward by Specht (1990, 1991) and covered in Masters (1995). They present clear advantages for our work as they can be trained fast and they do not require topology specifications such as the number of hidden layers and nodes.

NeuralTools 6, from Palisade Corporation (Ithaca, New York), was used for the training and validation of the GRNN.

Finally, StatTools6, from Palisade Corporation (Ithaca, New York), was used to develop the one-way ANOVA test (Lix, Keselman, & Keselman, 1996), together with other statistical calculations.

3. Time series analysis

The autocorrelation function (ACF) plot of the training data subset is presented in Fig. 2. Due to its shape it looks like the training data subset is non-stationary.

In order to confirm non-stationarity, a Dickey-Fuller test (Dickey & Fuller, 1979) was performed, and a p value of 0.0651 was obtained. So the training data subset is non-stationary.

Thus first it was necessary to find the appropriate transformations to the time series in order to produce stationarity.

A logarithmic transformation was applied to the price, $p = \log(P)$, in order to attain a more stable variance as in the work by Weron and Misiorek (2008). Moreover, Fernández Benitez (2003), in his study about coal power plants, stated that coal import prices have a cyclic behaviour with maximum and minimum values every two or three years. Under this consideration, first order and second order differencing deseasonalization and also additive deseasonalization were applied for different periods. The best result was given by the second order deseasonalization with a 24 months period.

The transformed training data subset was changed as presented in Fig. 3.

Fig. 4 shows the new autocorrelation function (ACF). Due to its alternating between positive and negative values, while decaying to zero, the indicated time series model should be the autoregressive (AR) one.

To identify the order of the autoregressive model, the partial autocorrelation plot was used (Fig. 5), showing that a second order autoregressive process AR(2) will be appropriate as the two first lag values are statistically significant.

Nevertheless, confronting several time series processes that were used in order to try different fits of the data (Brownian motion with mean reversion, autoregressive moving average, autoregressive conditional heteroskedasticity and generalized autoregressive conditional heteroskedasticity), the second-order autoregressive process AR(2) was the one with a maximum likelihood estimates of the parameters according the Akaike Information Criterion (AIC). With the Bayesian Information Criterion (BIC) the ranking was different, but AR(2) was still the one with the lowest values,

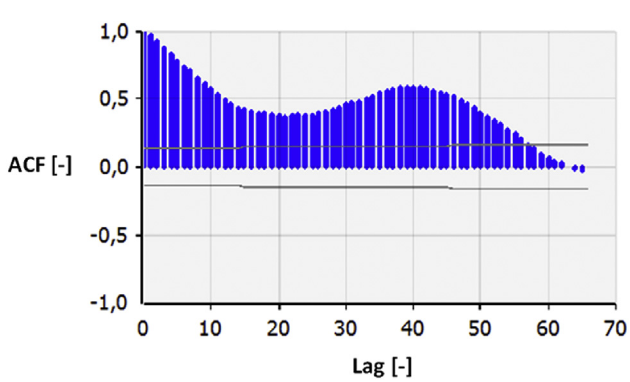

Fig. 2 – Autocorrelation function (ACF) of the training data subset.

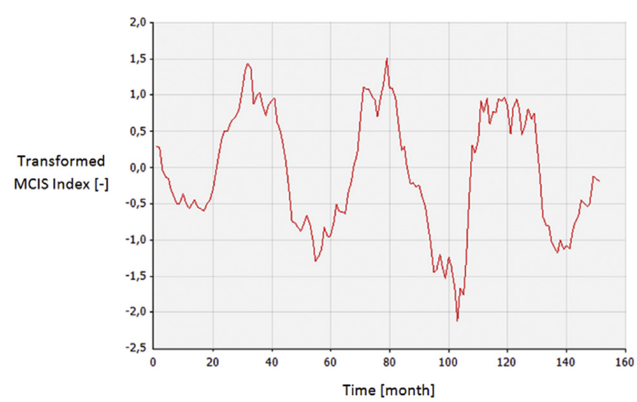

Fig. 3 – Transformed training data subset.

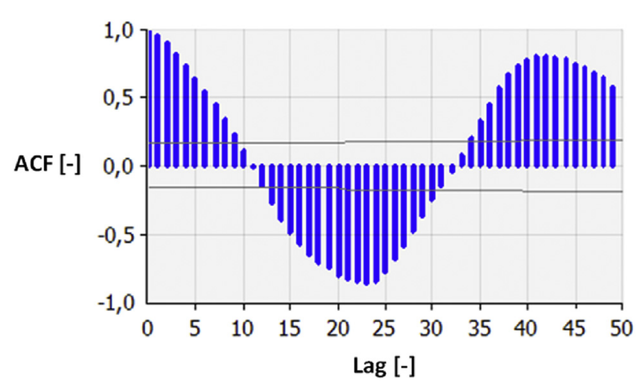

Fig. 4 – Autocorrelation function (ACF) of the training data subset after transformation.

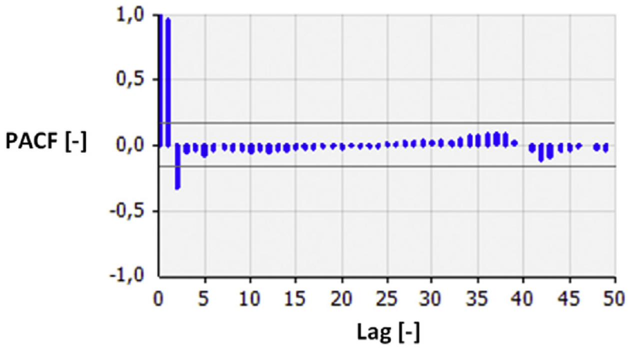

Fig. 5 – Partial autocorrelation function (PACF) of the training data subset after transformation.

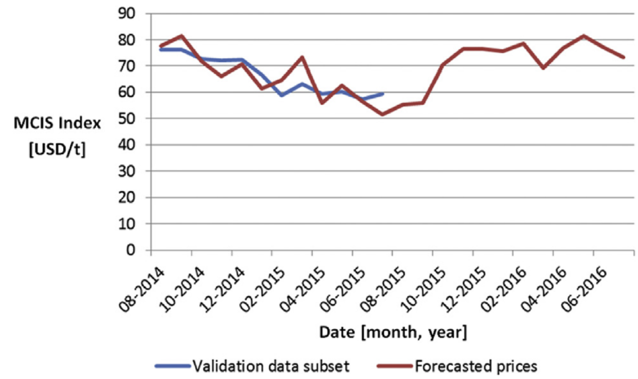

Fig. 6 – Time series forecasted prices versus validation data subset.

Table 2 – Akaike Information Criterion results and Bayesian Information Criterion results for different time series processes.

Process		AIC	BIC
Second-order autoregressive	AR(2)	−21.4288	−9.6336
First-order autoregressive moving average	ARMA(1,1)	−18.1037	−6.3085
Brownian motion with mean reversion	BMMR	−4.5513	7.2439
First-order autoregressive moving average	AR(1)	−3.0179	5.8707
Second-order moving average	MA(2)	119.3721	131.1672
First-order moving average	MA(1)	211.1737	211.1737
First-order autoregressive conditional heteroskedasticity	ARCH(1)	318.9009	327.7895
Generalized ARCH	GARCH(1,1)	320.9101	332.7053

something that explains the closest match between the training data subset and the time series process (Table 2).

The Ljung-Box statistic was used to check the adequacy of the model with an alfa level of 5%. The p value obtained for the Ljung-Box statistic was 0.9821, and therefore the null hypothesis that the residuals have no correlation cannot be rejected. Also, the normality was checked through the Kolmogorov–Smirnov test and confirmed with a p value of 0.9961.

Fig. 6 presents the time series prediction for a 24 months period, with the forecasted prices (24 months), and the validation data subset (12 first months).

From a visual perspective it can be observed that the forecasted prices are capable of modelling the validation data subset with quite a good detail, being able to reproduce the fluctuations of the original price curve with high detail.

The correlation coefficient of the validation data subset and those predicted with the second order autoregressive AR(2) process gave a value of 0.808. The RMSE obtained for the forecasted prices was of 5.16330462 while the MAPE was of 6.60%. Evaluating the results by means of the forecast error, an average value of 0.0009697 is obtained, with a minimum of −0.16244228 and a maximum of 0.1353705.

Sánchez Lasheras et al. (2015) used an autoregressive integrated moving average (ARIMA) model and two different kinds of artificial neural networks models (Elman and multilayer perceptron) in order to forecast the COMEX copper spot price for one month.

The RMSE and MAPE values obtained with our model are similar to the ones obtained by them with the ARIMA model and the Elman recurrent neural network, and higher than the values they obtained with the multilayer perceptron neural network.

Baumeister and Kilian (2012) while forecasting the real price of oil, determined that ARMA models were not as accurate as recursive vector autoregressive (VAR) models in the short run and that they lack directional accuracy. But for horizons ranging from 6 to 12 months they may produce lower mean squared prediction error (MSPE).

4. Neural networks analysis

In order to determine if the results obtained are a good fit for the data, a neural network analysis was also developed, taking into account the drivers that move the European thermal coal spot prices, to be able to accomplish a comparative analysis of the time series model performance.

Generalized Regression Neural Networks (GRNN) were selected and, trying to obtain better RMSE and MAPE values than the ones obtained with the second-order autoregressive process AR(2), each monthly value from the validation data subset was forecasted considering the values of the drivers including the month to be forecasted.

A hypothesis was established following Groen and Presenti (2010) that revisited the performance of commodity currency drivers together with supply and demand drivers across developed and developing countries in the forecasting of commodity prices. Moreover, Gargano and Timmermann (2014) found that commodity prices forecasting are closely linked to economic cycles, which can be represented by both supply and demand drivers. Commodity currency drivers will link supply and demand drivers from countries with different stages and rates of development. Thus, drivers were divided into four categories: (1) energy side drivers, that directly relates coal prices with other energy commodities like oil and natural gas; (2) demand side drivers, that relates coal prices both with the Western World economy and with emerging economies like China, in connection with the demand for electricity in these economies; (3) commodity currency drivers, that have an influence for holders of different commodity currencies in countries that export or import coal; and (4) supply side drivers, involving the production costs, transportation, etc.

Other drivers such as temperature events and institutional design issues, described in the work by Alberola, Chevallier, and Chèze (2008), were not considered because they are very uncertain and stochastic, with strong nonlinear features, bringing a high degree of complexity and difficulty in order to build a model (Feng, Zhao, Chen, Tian, & Wang, 2009).

The markers selected to represent the drivers within the different categories were the following ones:

1 For representing the energy side drivers two indexes, that reflect oil and natural gas prices, were selected: the ICE Brent Crude Oil Front Month Futures Index (quoted in USD per 10,000 mmBtu, this is, million British thermal units); and the Henry Hub Natural Gas Front Month Futures Index (quoted in USD per mmBtu), as front month contracts are generally the most liquid of futures contracts in addition to having the smallest spread between the futures price and the spot price on the underlying commodity. In fact, the weights used in the World Bank Energy Price Index are: coal (4.7%), crude oil (84.6%) and natural gas (10.8%) (The World Bank, 2015).
2 For representing the demand side drivers two stock market indexes were selected, one representing the western market and the other representing the eastern market: the NYSE Composite, that covers all common stock listed on the New York Stock Exchange, and the Shanghai Stock Exchange (SSE) Composite Index, a capitalization-weighted index that tracks the daily price performance of all A-shares and B-shares listed on the Shanghai Stock Exchange. NYSE was selected instead of Euro Stoxx 50 (STOXX50E), which may be a good representation of Europe's economy, due to the facts that the MCIS index is quoted in USD, and that the United States of America is the second major coal producer immediately after China (International Energy Agency, 2015b). In this way, the need to consider within the commodity currency drivers the exchange rate between EUR and USD was eliminated, simplifying our model.
3 As China is the major coal producer in the world with an estimated contribution of 46,7% in 2014 (International Energy Agency, 2015b), the exchange rate between USD and the renminbi (CNY), the official currency of the People's Republic of China, was used to reflect the commodity currency driver.
4 Finally, for reflecting the influence of the supply side drivers, the use of the Australian thermal coal price index was considered in first place (FOB piers, Newcastle/Port Kembla; 6300 kcal per kilogram, less than 0.8% sulphur and 13% ash). Nevertheless, it was checked that because of the higher degree of correlation between the two variables (0.899), even the Australian thermal coal itself was a better forecast than any other one. This is why finally supply side drivers were considered by introducing the very MCIS index with the following transformation: $x_t = x_{t-1}$. This is, production costs, transportation, etc., were represented by the historical data of the very European thermal coal spot prices, an arrangement quite typical within neural network analysis (Sánchez Lasheras et al., 2015).

Using as the first data subset values from January 2004 till August 2014 (December 2003 till July 2014 in the case of $MCIS_{t-1}$), and forecasting the European thermal coal spot price month by month, the best results of the neural network by means of RMSD and MAPE were given by the combination of only three of the drivers: $MCIS_{t-1}$, Crude oil and USD/CNY exchange. The accuracy of the prediction gave a RMSE value of 4.5654 and a MAPE of 5.70%. Although this may look contradictory, Clark and West (2007) described that the mean squared prediction error (MSPE) from a parsimonious model will be smaller than that of a larger model due to the introduction of noise into the forecast.

Fig. 7 presents the neural network forecasted prices versus the validation data subset.

The relative variable impacts for the different forecasted months that indicate how much a variable influences the MCIS index were fluctuating in the different months, being $MCIS_{t-1}$ and the USD/CNY exchange the variables with the biggest impact on the forecast.

Evaluating the results of the forecast error an average value of -0.054261968 was obtained, with a minimum of -0.184730064 and a maximum of 0.016474187. These results are, as an average, worse than the ones obtained by the time series analysis. But they are quite logical, as the time series forecasted prices fluctuate around the validation data subset while the GRNN forecasted prices tended almost always over the validation data subset.

Finally, in order to detect if the differences between the two methods applied are statistically significant, a one-way Analysis of Variance (ANOVA) test was carried out at a 95% confidence level. The comparison of the AR(2) and the GRNN mean forecast errors was found to be non-significant ($p = 0{,}0643$), so in this specific case a one year forecast on a monthly basis using a GRNN does not improve significantly the results obtained by the time series analysis over the same twelve months.

5. Conclusions

According to the empirical results achieved it is possible to say that the performance of the Generalized Regression Neural Networks model on a monthly basis improves the one achieved by means of the time series analysis on a yearly basis when they are compared in terms of RMSE and MAPE.

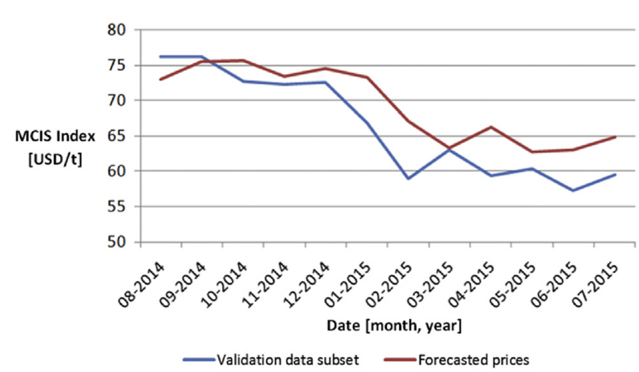

Fig. 7 – Neural network forecasted prices versus validation data subset.

Nevertheless, the differences between them are not statistically significant according to the ANOVA test.

In the case of the time series model, the forecasted prices are able to reproduce the fluctuations of the original price curve with high detail, while with the GRNN the forecasted prices tend almost always over the validation data subset, and they do not reproduce so well the fluctuations. This is why we can affirm that the time series analysis can be an adequate method when trying to forecast one-year prices evolution. Under this premise, European thermal coal spot price is expected at 70 USD/t by summer 2016.

Suárez Sánchez, Krzemień, Riesgo Fernández, Iglesias Rodríguez, Sánchez Lasheras, and de Cos Juez (2015) undergo a five year forecasting of tungsten prices through an auto-regressive integrated moving average (ARIMA) model and a feedforward artificial neural network model. In both cases the models returned the average of the time series from the twelve forecasted month.

When a self-exciting threshold auto regressive (SETAR) model was applied something similar happened but after a longer period of time (five years).

Thus, for a long-term forecasting, as in the case of having to estimate an average price in order to calculate the Net Present Value (NPV) within a feasibility study (a period normally estimated between five and ten years), time series analysis will give up to one year of quite reliable further information. From this point, the prices average or their tendency (if moderate) from the last stable period will be a reasonable assumption, as requested by the different standards for reporting of exploration results, mineral resources and reserves: the PERC code (Pan European Reserves and Resources Reporting Committee, 2013), and the JORC code (Joint Ore Reserves Committee, 2012).

Regarding the drivers that move the European thermal coal spot prices, only three of them were found as really representatives: crude oil prices, the exchange rate between USD and the renminbi (CNY) and, of course, the supply side drivers that involve production costs, transportation, etc.

It was quite a surprise that both the NYSE Composite and the Shanghai Stock Exchange Composite Index were not considered as significant by the GRNN. The explanation of this fact may be that crude oil prices and supply side drivers already reflect any economy fluctuation both in Western and Eastern economies. Moreover, the influence showed by the exchange rate between USD and the renminbi (CNY) can be explained by the statement of the International Energy Agency (2013): “In the end, it is all about China”, as China has an absolute dominance over the coal markets, being the growth engine of global coal demand. Since 2009, the development of European coal prices has been determined by the rise of coal imports to China and to Asia in general, accounting in 2014 for 72% of the world's trading volume (BRG, 2014).

Acknowledgements

The authors wish to thank CARBUNION (www.carbunion.com), the Spanish Federation of Coal Mining Companies, for their strong support that made the practical aspects of this research possible.

Post-doctoral Research Fellowship from Foundation “Luis Fernández Velasco” at the University of Oviedo (Spain) for the first author is highly appreciated.

REFERENCES

Alberola, E., Chevallier, J., & Chèze, B. (2008). Price drivers and structural breaks in European carbon prices 2005–2007. *Energy Policy, 36*(2), 787–797. http://doi.org/10.1016/j.enpol.2007.10.029.

Aldrich, J. (1997). R. A. Fisher and the making of maximum likelihood 1912–1922. *Statistical Science, 12*(3), 162–176. http://doi.org/10.1214/ss/1030037906.

Baumeister, C., & Kilian, L. (2012). Real-time forecasts of the real price of oil. *Journal of Business & Economic Statistics, 30*(2), 326–336. http://doi.org/10.1080/07350015.2011.648859.

Behmiri, N. B., & Manso, J. R. P. (2013). *Crude oil price forecasting techniques: a comprehensive review of literature*. Retrieved from https://caia.org/sites/default/files/3.RESEARCHREVIEW.pdf.

Box, G. E. P., & Jenkins, G. M. (1976). *Time series analysis. Forecasting and control*. San Francisco: Holden-Day.

BRG. (2014). *Energy study 2014. Reserves, resources and availability of Energy Resources (18)*. *Hannover, Germany*. Retrieved from http://www.bgr.bund.de/EN/Themen/Energie/Produkte/energy_study_2014_summary_en.html.

Clark, T. E., & West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics, 138*(1), 291–311. http://doi.org/10.1016/j.jeconom.2006.05.023.

Crespo Cuaresma, J., Hlouskova, J., Kossmeier, S., & Obersteiner, M. (2004). Forecasting electricity spot-prices using linear univariate time-series models. *Applied Energy, 77*(1), 87–106. http://dx.doi.org/10.1016/S0306-2619(03)00096-5.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit Root. *Journal of the American Statistical Association, 74*(366), 427–431. http://doi.org/10.2307/2286348.

Euracoal. (2015). *EURACOAL market report 2/2015*. Retrieved from http://euracoal.eu/library/coal-market-reports/.

European Commission. (2013). *Energy challenges and policy. Commission contribution to the European Council of 22 may 2013*.

European Commission. (2014). *Communication from the commission to the european parliament, the council, the european economic and social committee and the committee of the regions – A policy framework for climate and energy in the period from 2020 to 2030. COM(2014) 15 final. Brussels*.

Feng, Y. Z., Zhao, H. W., Chen, Y., Tian, L. Q., & Wang, P. (2009). Price forecasting algorithm for coal and electricity based on PSO and RBF neural network. In *2009 IEEE International Conference on Control and Automation, ICCA 2009* (pp. 1365–1369). http://doi.org/10.1109/ICCA.2009.5410509.

Fernández Benitez, J. A. (2003). *La tecnología de la energía en la generación de electricidad. Anexo Técnico III. Centrales de Carbón*. Madrid, Spain: Fundación COTEC.

García-Martos, C., Rodríguez, J., & Sánchez, M. J. (2013). Modelling and forecasting fossil fuels, CO_2 and electricity prices and their volatilities. *Applied Energy*, 101, 363–375. http://doi.org/10.1016/j.apenergy.2012.03.046.

Gargano, A., & Timmermann, A. (2014). Forecasting commodity price indexes using macroeconomic and financial predictors. *International Journal of Forecasting*, 30, 825–843. http://dx.doi.org/10.1016/j.ijforecast.2013.09.003.

Groen, J. J., & Presenti, P. A. (2010). *Commodity prices, commodity currencies, and global economic developments*. Working Paper No.

15743. Cambridge, Massachusetts, USA: National Bureau of Economic Research http://www.nber.org/papers/w15743.pdf.
International Energy Agency. (2013). *Coal medium-term market report*. Retrieved from http://www.iea.org/publications/freepublications/publication/medium-term-coal-market-report-2013.html.
International Energy Agency. (2015a). *Energy balances of OECD countries 2015. IEA report*.
International Energy Agency. (2015b). *Key coal trends. IEA report*.
Joint Ore Reserves Committee. (2012). *The JORC code. The Australasian code for reporting of exploration results*. Australia: Mineral Resources and Ore Reserves. Retrieved from http://www.maneyonline.com/doi/abs/10.1179/aes.2001.110.3.121.
Lilliefors, H. W. (1967). On the Kolmogorov-Smirnov test for normality with mean and variance unknown. *Journal of the American Statistical Association, 62*(318), 399–402. http://doi.org/10.2307/2283970.
Lix, L. M., Keselman, J. C., & Keselman, H. J. (1996). Consequences of assumption violations revisited: a quantitative review of alternatives to the one-way analysis of variance F test. *Review of Educational Research, 66*(4), 579–619. http://doi.org/10.3102/00346543066004579.
Ljung, G. M., & Box, G. E. (1978). On a measure of lack of fit in time series models. *Biometrika, 65*(2), 297–303. http://doi.org/10.1093/biomet/65.2.297.
Masters, T. (1995). *Advanced algorithms for neural networks: A C++ sourcebook*. New York, USA: John Wiley & Sons, Inc.
Mohr, S. H., & Evans, G. M. (2009). Forecasting coal production until 2100. *Fuel*. http://doi.org/10.1016/j.fuel.2009.01.032.
Owen, A. D. (2006). Renewable energy: externality costs as market barriers. *Energy Policy, 34*(5), 632–642. http://doi.org/10.1016/j.enpol.2005.11.017.
Pan-European Reserves and Resources Reporting Committee. (2013). *PERC reporting standard. Pan-European standard for reporting of exploration results, mineral resources and reserves. Bruxelles, Belgium*.
Panella, M., Barcellona, F., & D'Ecclesia, R. L. (2012). Forecasting energy commodity prices using neural networks. *Advances in Decision Sciences, 2012*, 1–26. http://doi.org/10.1155/2012/289810.
Patzek, T. W., & Croft, G. D. (2010). A global coal production forecast with multi-Hubbert cycle analysis. *Energy, 35*(8), 3109–3122. http://doi.org/10.1016/j.energy.2010.02.009.
Sánchez Lasheras, F., de Cos Juez, F. J., Suárez Sánchez, A., Krzemień, A., & Riesgo Fernández, P. (2015). Forecasting the COMEX copper spot price by means of neural networks and ARIMA models. *Resources Policy, 45*, 37–43. http://doi.org/10.1016/j.resourpol.2015.03.004.
Sawa, T. (1978). Information criteria for discriminating among alternative regression models. *Econometrica: Journal of the Econometric Society*, 1273–1291. http://doi.org/10.2307/1913828.
Specht, D. F. (1990). Probabilistic neural networks. *Neural Networks, 3*(1), 109–118. http://doi.org/. http://dx.doi.org/10.1016/0893-6080(90)90049-Q.
Specht, D. F. (1991). A general regression neural network. *IEEE Transactions on Neural Networks, 2*(6), 568–576. http://doi.org/10.1109/72.97934.
Suárez Sánchez, A., Krzemień, A., Riesgo Fernández, P., Iglesias Rodríguez, F. J., Sánchez Lasheras, F., & de Cos Juez, F. J. (2015). Investment in new tungsten mining projects. *Resources Policy, 46*, 177–190. http://doi.org/10.1016/j.resourpol.2015.10.003.
Sugiura, N. (1978). Further analysis of the data by Akaike's information criterion of model fitting. *Suri-Kagaku (Mathematic Science), 153*, 12–18. http://dx.doi.org/10.1080/03610927808827599.
The World Bank. (2015). *World Bank commodity price data*. Retrieved August 25, 2015, from http://www.worldbank.org/.
Van Ruijven, B., & van Vuuren, D. P. (2009). Oil and natural gas prices and greenhouse gas emission mitigation. *Energy Policy, 37*(11), 4797–4808. http://doi.org/10.1016/j.enpol.2009.06.037.
Weron, R., & Misiorek, A. (2008). Forecasting spot electricity prices: a comparison of parametric and semiparametric time series models. *International Journal of Forecasting, 24*(4), 744–763. http://doi.org/10.1016/j.ijforecast.2008.08.004.