GOSPODARKA SUROWCAMI MINERALNYMI – MINERAL RESOURCES MANAGEMENT

2020 Volume 36 Issue 4 Pages 33–48

DOI: 10.24425/gsm.2020.133945

ANNA MANOWSKA[1]

Using the LSTM network to forecast the demand for hard coal

Introduction

Energy drives the world, it contributes directly to the development of the entire economy and the standard of living of societies. This development is possible only if the continuity of the energy supply and an acceptable price are maintained (Bluszcz 2018). To guarantee these goals, the Energy Union Strategy was developed in 2016, which aims to provide Europe and its citizens with affordable, secure and sustainable energy. This strategy is based on ensuring energy security, an integrated internal energy market, energy efficiency and reducing the economy's emissivity (Gawlik and Mokrzycki 2019). In 2019, all the acts of the 'Clean Energy for All Europeans' package were adopted and thus, the Energy Union was created. The energy goals adopted in the National Energy and Climate Plan for 2021–2030 (NECP) are as follows: at least 32.5% higher energy efficiency thanks to the reduction of energy consumption, at least 21–23% in the final gross energy consumption from renewable sources and a 7% reduction in GHG emissions in non-ETS sectors compared to 2005 levels,

✉ Corresponding Author: Anna Manowska; e-mail: Anna.Manowska@polsl.pl

[1] Silesian University of Technology Faculty of Mining, Safety Engineering and Industrial Automation, Gliwice, Poland; ORCID iD: 0000-0001-9300-215X; e-mail: Anna.Manowska@polsl.pl

and a 21% reduction in ETS sectors (Ministry of State Assets 2019). In Poland, electricity is mainly produced from coal, as shown in Figure 1.

In 2019, the share of coal in electricity production was 73.6% and it was the lowest since 1960, as shown in Figure 2.

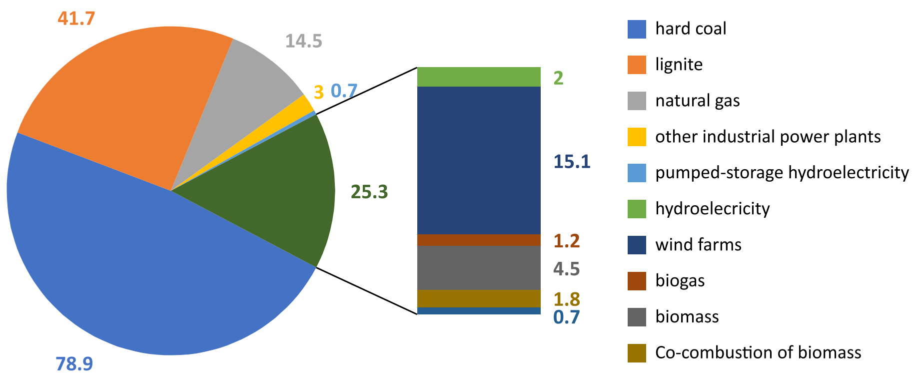

Fig. 1. Electricity production in 2019, TWh
Source: own study based on data (Forum energii 2020)

Rys. 1. Produkcja energii elektrycznej w 2019 roku, TWh

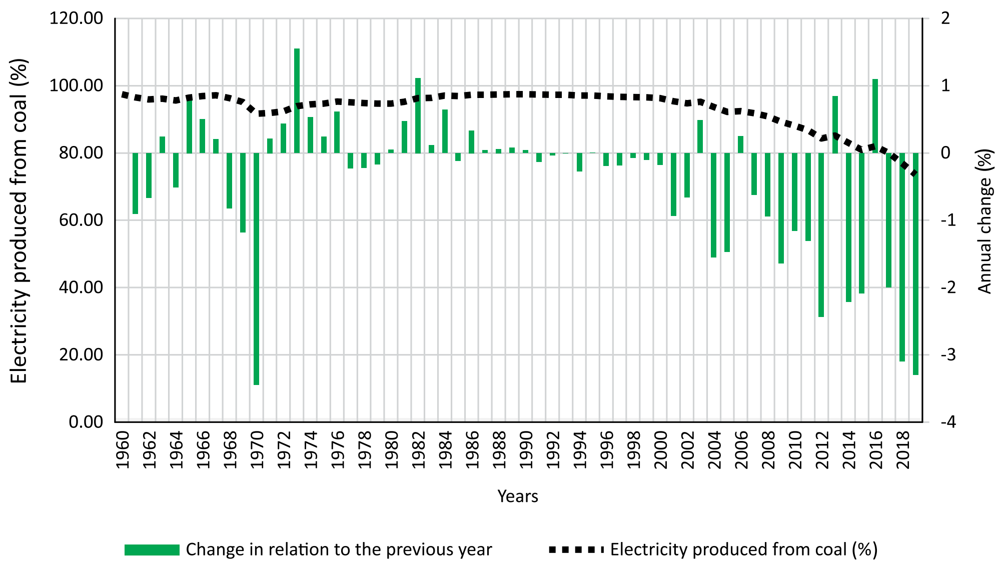

Fig. 2. Percentage share of electricity produced from coal
Source: own study based on data (Macrotrends 2020)

Rys. 2. Procentowy udział energii elektrycznej produkowanej z węgla

Initially, this share was 98%. A significant decrease occurred after 2000 due to an increase in the share of electricity production from natural gas and renewable energy sources. From that moment on, there has been a downward trend, but this share is still high, being above the level of 70%. In the case of hard coal, the demand from power plants and combined heat and power stations producing electricity accounts for about 50% of the total coal consumption in Poland (51.8% in 2017), while for lignite it is about 98% (Kaszyński and Kamiński 2020). Therefore, the analysis of the impact of climate and environmental regulations adopted in the NECP plan for the energy sector (introducing the BAT or COM standard (2018) 773) is of real and decisive importance for the assessment of the future demand for hard coal and lignite. The article proposes the use of deep learning techniques to forecast the demand for hard coal, which is a key raw material for electricity production.

1. Methods

Most of the existing studies on the analysis of the demand for hard coal in Poland investigated the impact of coal on the environment, coal mining technology and the relationship between coal and GDP or substitute energy carriers (Gawlik and Mokrzycki 2014; Rybak and Manowska 2019; Manowska 2018). The research was conducted with the use of regression techniques and time series forecasting. In all these studies, models with very high fitting parameters were obtained, however, at present there is a problem related to the small size of the data set, and in such a case these methods fail (Hyndman and Kostenko 2007). The mining sector is undergoing a transformation process, which significantly reduces the set of input data for modeling. There are no studies in national literature on the use of deep learning methods which can be applied to forecast small time sequences.

In world literature (Tae-Young and Sung-Bae 2019; Anđelković and Bajatović 2020; Li et al. 2018), these techniques have been used to forecast the consumption of fossil resources, as well as the demand for primary and final energy. The analyzed variables are realizations of classical non-linear time series models and strongly depend on statistical assumptions. This, in turn, reduces their predictive abilities, especially when these assumptions are also the realization of non-linear functions. Artificial neural networks (ANN) deal with this problem. The techniques try to imitate the behavior of variables through neurons, which are assumed to be non-linear (Gers 1999). Artificial neural networks are based on data that have a self-adaptive function. This adaptive ability makes them suitable for the analysis of problems in which the data is incomplete or its number is insufficient (Hyndman and Kostenko 2007).

Taking the fact that ANN allows for approximation of almost all non-linear processes into account, they are suitable for forecasting sales, demand or consumption. Long Short-Term Memory (LSTM) neural networks were used to forecast demand for hard coal. The architecture of these networks is recursive and is used in deep learning methods. Unlike standard recursive networks, the LSTM network has a feedback loop, which allows it to process not only individual data points, but also entire sequences. LSTM networks are a special type of Recurrent Neural Network (RNN), capable of learning long-term relationships. They were introduced by Hochreiter and Schmidhuber in 1997 (Hochreiter and Schmidhuber 1997), and then refined and popularized by many people in subsequent studies (Saksornchai et al. 2005; Felix et al. 2015; Ahmad and Chen 2018; Manowska 2020). They work extremely well with long-term dependency problems. Remembering information for long periods is their default behavior, and not something that needs to be learned.

The architecture of the LSTM network is as follows:

- the network contains special units called memory blocks in a recurrent hidden layer,
- memory blocks contain memory cells only with the connections that store the state of the network and units called gates to control the flow of information,
- each memory block in the original architecture contains an input and output gate,
- the input gate controls the flow of input activations to the memory cell,
- the exit gate controls the exit flow of cell activation to the rest of the network.

A forget gate is added in the memory block (Hochreiter and Schmidhuber 1997).

When designing the network, deciding which input data will be entered into the neuron, whether to remember the results of the calculations made in the previous step and when the input data will be forwarded to the next time stamp, as shown in Figure 3 are all required.

The functions shown in Figure 3 are defined as follows (Hochreiter and Schmidhuber 1997; Manowska 2020):

$$f_t = \sigma\left(w_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{1}$$

$$i_t = \sigma\left(w_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{2}$$

$$\widetilde{C}_t = \tanh\left(w_c \cdot [h_{t-1}, x_t] + b_c\right) \tag{3}$$

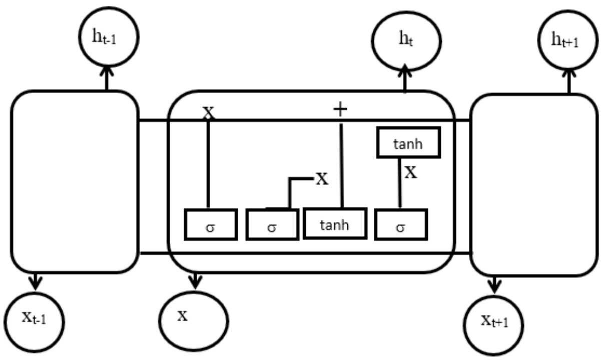

Fig. 3. Structure of the long short-term memory
Source: (Manowska 2020)

Rys. 3. Struktura komórki sieci neuronowej LSTM

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C_t} \tag{4}$$

$$o_t = \sigma\left(w_o \cdot \left[h_{t-1}, x_t\right] + b_o\right) \tag{5}$$

$$h_t = o_t \cdot \tanh\left(C_t\right) \tag{6}$$

x_{t-1} and x_t – the previous and current input values, respectively,
h_{t-1} and h_t – the previous and current hidden gates, respectively,
C_{t-1} and C_t – the previous and current cell states, respectively,
w_f, w_i, w_c and w_o – the weight values connecting the input to each gate,
b_f, b_i, b_c and b_o – the bias values for each gate's calculation,
σ – sigmoid function,
tanh – hyperbolic tangent function.

The selection of independent variables will be performed using a principal components analysis (PCA). It is one of the oldest multivariate methods, which takes into account the observations described by many variables that are most often correlated with each other. This analysis is performed in order to extract the key information hidden in the data, reduce the size of the data and simplify their description. The analysis produces a set of new uncorrelated (orthogonal) dimensions called principal components, which are linear combinations of the base variables. The new components are described by the relationship (StatSoft 2020):

$$z_i = a_{i1}y_1 + a_{i2}y_2 + \ldots + a_{ip}y_p \tag{7}$$

z_i – i-th component, $i \in \{1, \ldots, p\}$,
$a_{i1}, \ldots, a_{ip}$ – real numbers, coefficients of a linear combination,
$y_1, \ldots, y_p$ – base variables on which the analysis is performed,
p – the number of base variables.

The components arise as a result of the initial rotation of the coordinate system, performed in such a way that the successive components are mainly characterized by less and less variability. The components obtained in this way are used when creating dependency models based on orthogonal variables, instead of strongly correlated independent variables.

In this paper, two widely used performance metrics are adopted i.e.: mean absolute error (MAE) & root mean square error (RMSE) to assess the prediction accuracy of the proposed methods (Zielaś at al. 2003):

$$MAE = \frac{1}{n} \cdot \sum_{i=1}^{n}\left(\left|y_i - \hat{y}_i\right|\right) \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2} \tag{9}$$

y_i – identifies the actual value for sample i,
$\hat{y}_i$ – identifies the predicted value for sample i,
n – is the testing data.

1.1. Coal mining and sales on the domestic market

Poland's hard coal deposits are found in the southern part of Poland. Hard coal mining is currently carried out in two of them: Upper Silesian Coal Basin (GZW) and in the Lublin Coal Basin (LZW). The industrial resources of mines, determined in the deposit development projects, amounted to 3 605.45 million Mg at the end of 2018 and were higher than in the previous year by 404 574 thousand Mg (Polish Geological Institute 2019). Changes in industrial resources are related to new projects of deposits development. In 2018, projects were designed for as many as 17 deposits, which in the case of seven deposits resulted in an increase in industrial resources, despite the conducted extraction with a total value of 549,521 thousand Mg. The industrial resources are now defined according to the duration of individual concessions and the current resource base is shown in Table 1.

Table 1. Hard coal deposits (million Mg), as of 12/31/2018

Tabela 1. Złoża węgla kamiennego [mln Mg], stan na 31.12.2018

Resources	Number	Balance resources	Off-balance resources	Industrial resources
Developed active plants (type 31–33 and 34–37)	45	22,307.91	3,775.19	2,912.95
Undeveloped active plants (type 31–33 and 34–37)	64	33,792.48	6,822.03	418.19
Discontinued operation (type 31–33 and 34–37)	52	5,335.84	1,476.74	274.31

Source: Polish Geological Institute 2019.

Coal extraction and sales on the domestic market are decreasing, which is shown in Figure 4.

Hard coal production in Poland in 2019 amounted to 61.6 thousand Mg and decreased by 2.8% compared to 2018. Total hard coal inventories in mines at the end of December 2019 amounted to 4617 thousand Mg. Compared to inventories at the end of 2018, it increased

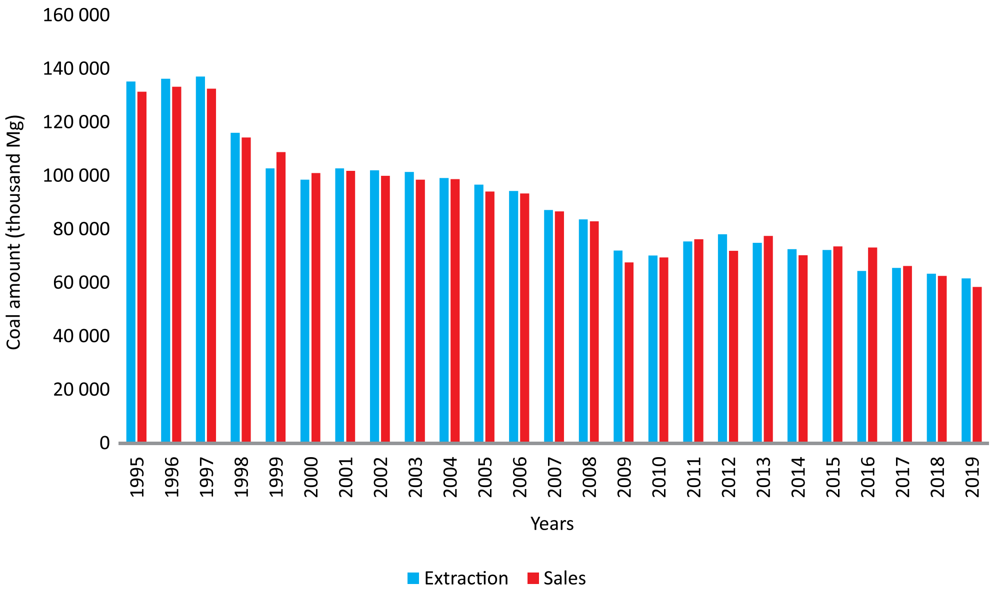

Fig 4. Coal extraction and sales on the domestic market
Source: own study based on: Industrial Development Agency 2020

Rys. 4. Wydobycie i sprzedaż węgla na rynku krajowym

by 2238 thousand Mg. Total sales of hard coal in 2019 amounted to 58436 thousand Mg and compared to 2018, it was lower by 4094 thousand Mg. During this period, there was a decrease in sales to the domestic market by 1094.8 thousand Mg, i.e. 1.9%. In 2018, there was an increase in sales to commercial and non-commercial heating plants by 14.7%, commercial energy sector by 4.0%, and other industrial customers by 3.3%. On the other hand, there was a decrease in sales to coking plants by 0.8%, the industrial energy sector by 15.6% and to other domestic customers by 27.1%. The export of high-quality coal also fell from 6,300 thousand Mg in 2017 to 3,900 thousand Mg in 2018 (–38%). Coal imports to Poland increased to 19,700 thousand Mg (+46.8%) in 2018 and was the highest ever. This coal came from Russia (+4,800 thousand Mg). Further unfavorable changes in the mining sector include the growing demand for imported coal to the energy sector. Other factors influencing the reduction of coal sales are mild winters, more electricity from wind turbines and electricity pricing policy.

1.2. Forecasting demand for hard coal

Hard coal is the key energy resource in Poland. It plays a relevant role in the Polish energy mix and provides more stable and safer energy, while accurate forecasting of the demand for this raw material allows for the adjustment of the industrial structure of the coal sector to achieve a coordinated development of coal resources consumption and environmental protection. The hard coal demand forecast also plays an important role in understanding the development direction and consumption trend.

Based on the presented assumptions, to build the theoretical model of demand for hard coal, the set of the following available data was used:

- petroleum consumption,
- natural gas consumption,
- RES consumption,
- CO_2 emission,
- coal export and import.

The available data from 1990–2018 were subjected to a detailed statistical analysis. When you look at the data scatter plot, you can see that the variables are correlated. This can be confirmed by creating a correlation matrix (Table 2).

Table 2. Correlation matrices for variables

Tabela 2. Macierze korelacji dla zmiennych

Variable	Oil	Natural gas	RES	Carbon Dioxide Emissions	Import	Export
Oil	1.00	0.95	0.80	–0.59	0.91	–0.90
Natural gas	0.95	1.00	0.90	–0.59	0.90	–0.92
RES	0.80	0.90	1.00	–0.45	0.82	–0.82
Carbon Dioxide Emissions	–0.60	–0.59	–0.45	1.00	–0.38	0.55
Import	0.91	0.90	0.82	–0.38	1.00	–0.88
Export	–0.90	–0.92	–0.82	0.55	–0.88	1.00

Source: own study.

Correlating variables is the basis for performing principal components analysis. The results of the analysis are shown in Figure 5 and Table 3.

As a result of the analysis, the number of obtained components was the same as the number of assumed variables. Therefore, it is possible to determine the optimal number of components − independent variables. In practice, it is difficult to determine a specific number of significant components, and yet it is very important for obtaining correct results because the eigenvalues of the components themselves contain information about the part of the variability included in a given component, and thus they are the source of data when defining the criterion of component significance. The number of components was determined using the Cattell criterion (scree plot), as shown in Figure 6.

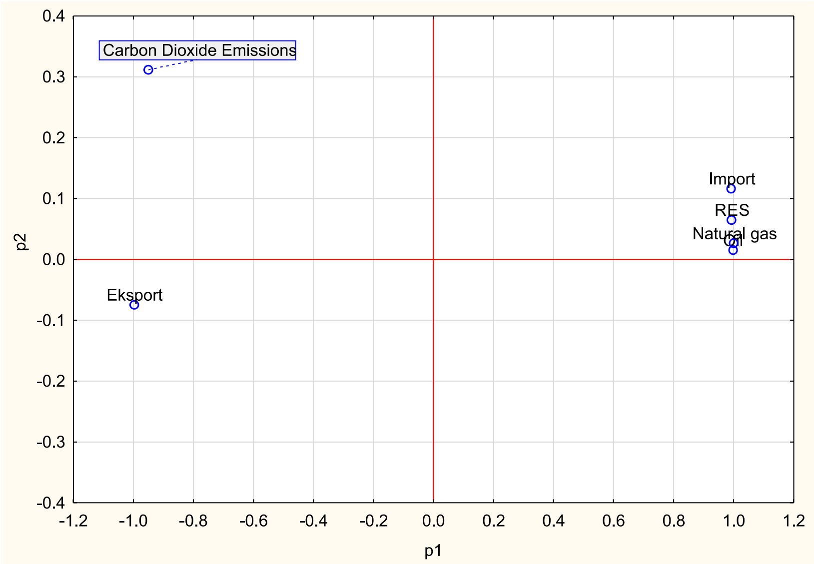

Fig. 5. The scatter plot of p1, p2 charges
Source: own study

Rys. 5. Wykres rozrzutu ładunków p1, p2

Table 3. Eigenvectors

Tabela 3. Wektory własne

Variable	Variable number	Component 1	Component 2
Oil	3	0.412410	0.043606
Natural gas	4	0.412819	0.076309
RES	5	0.410012	0.186817
Carbon Dioxide Emissions	6	–0.392422	0.894346
Import	7	0.409636	0.334984
Export	8	–0.411816	–0.212853

Source: own study.

The scree plot suggests that the optimal number of components should be 1 as it explains 97.7% of the variation. This group includes: consumption of natural gas, renewable energy sources and imports. Hard coal sales are statistically significantly correlated with all independent variables, as shown in Table 4.

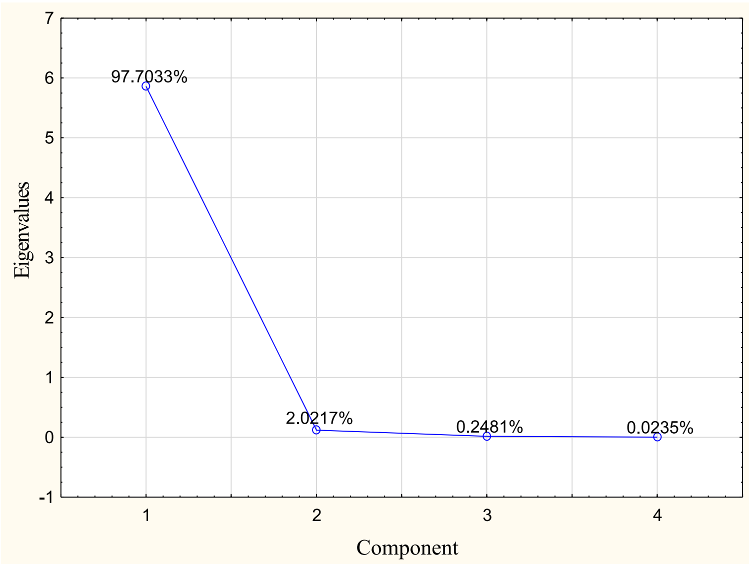

Fig. 6. Scree plot of eigenvalues
Source: own study

Rys. 6. Wykres osypiska wartości własnych

Table 4. Correlation matrix with the dependent variable

Tabela 4. Macierz korelacji ze zmienną objaśnianą

	Oil	Natural gas	RES	Carbon Dioxide Emissions	Import	Export
Coal sales	–0.92	–0.91	–0.79	0.57	–0.82	0.97

Source: own study.

Thus, the consumption of natural gas, renewable energy sources and imports were taken into account when forecasting the volume of hard coal sales. The forecasts were built with the use of the LSTM network, in accordance with the algorithm below, Figure 7.

The input data are entered into the LSTM network model in the *TensorFlow* environment. The theoretical values obtained from the model are analyzed according to the dependencies 1–6. Once a statistically significant match is achieved, ex post forecasts can be generated and then re-analyzed according to the dependencies 8–9. If the obtained values are within 5% of the statistical error, long-term forecasts of the demand for hard coal can be generated.

The model also takes the assumptions of the NECP regarding the demand for primary and final energy in accordance with the reference scenario and the energy and climate policy

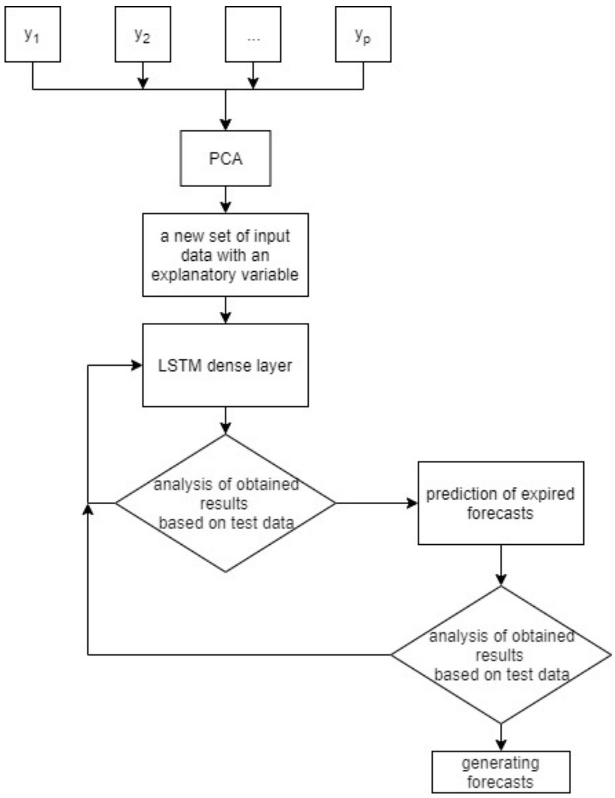

Fig. 7. Flow diagram of the model selection process
Source: own study

Rys. 7. Schemat blokowy procesu wyboru modelu

scenario (NECP) into account. In the reference scenario, the demand for primary and final energy increases by 17% compared to 2015. On the other hand, in the energy and climate policy scenario, there is a decrease in demand by 3% compared to 2015. The differences in these scenarios mean that the forecast of coal sales should be a numerical range.

The data was divided in two parts called training and test data in the ratio of 70:30. The comparison of theoretical and real values, the error distribution during network learning and network stability are shown in Figure 8.

The best results were obtained for the LSTM model (12,12,1). Table 5 summarizes the simulation parameters used in this study.

Based on the developed estimated models, it is possible to forecast the volume of hard coal sales with a confidence interval, because changes in the Polish energy sector require that the demand forecasts take into account assumptions NECP (Figure 9).

Taking the current and predicted situation of hard coal on world markets, as well as the role of hard coal in satisfying the country's energy needs into account, the long-term

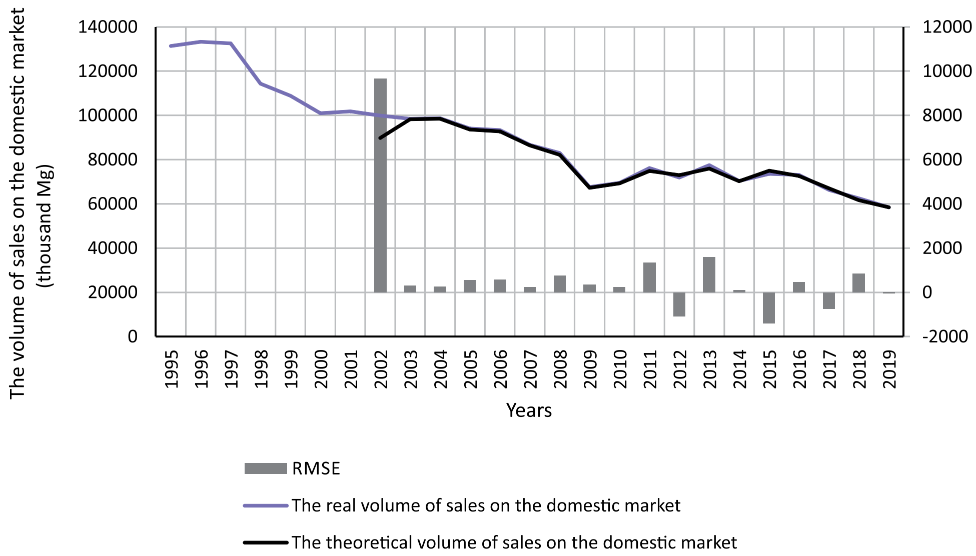

Fig. 8. The theoretical model of hard coal sales with network quality parameters
Source: own study

Rys. 8. Model teoretyczny sprzedaży węgla kamiennego wraz z parametrami jakościowymi sieci

Table 5. Simulation parameters

Tabela 5. Parametry symulacji

Layer (type)	Output Shape	Parameters
lstm_46 (LSTM)	(None, 20, 12)	672
lstm_47 (LSTM)	(None, 12)	1 200
dense_23 (Dense)	(None, 1)	13
Total parameters: 1 885		
Trainable parameters: 1 885		
Non-trainable parameters: 0		

Source: own elaboration.

hard coal sales forecast until 2030 has a downward trend, reaching 55,020 thousand Mg (decrease by 6% compared to 2019). This decrease is due to the increasing share of natural gas consumption, renewable energy sources and an increase in imports. These changes are also a consequence of the reduction of emissions, in accordance with the assumptions of the NECP, which should be understood as reducing or eliminating carbon dioxide emissions

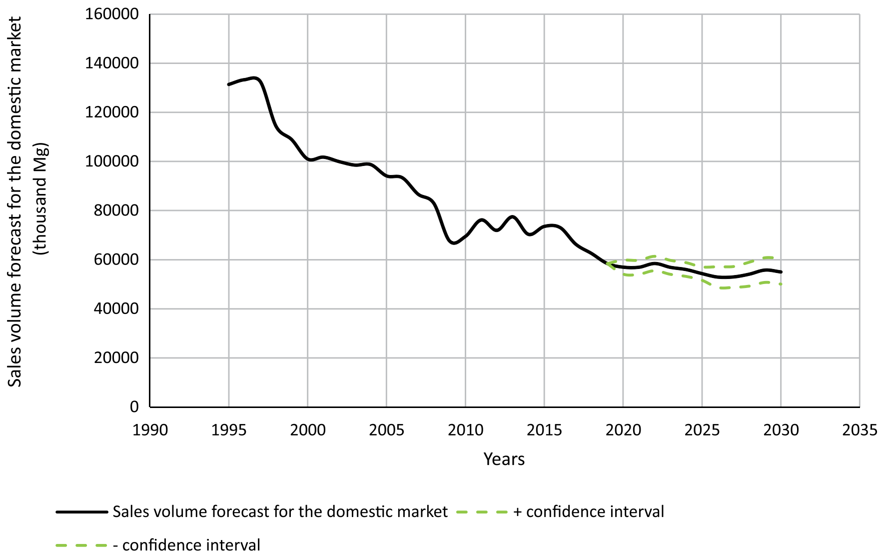

Fig. 9. Sales volume forecast for the domestic market to 2030
Source: own study

Rys. 9. Prognoza wielkości sprzedaży na rynku krajowym do 2030 roku

into the atmosphere as a result of the implementation of projects limiting or completely eliminating the combustion of solid fuels with high emission factors. In parallel to setting CO_2 reduction targets, Directive 2010/75/EU of the European Parliament and of the Council on industrial emissions, i.e. sulfur dioxide (SO_2) and nitrogen oxides (NO_X) and dusts (IED), was developed (Directive IED 2010). The IED Directive was adopted on November 24, 2010, and the base is the IPPC Directive. The IED Directive aims to achieve a high level of protection of human health and the environment as a whole by reducing harmful industrial emissions across the EU, in particular by applying the best available techniques (BAT).

Conclusions

The use of native natural resources – hard coal and lignite – in the energy balance is a guarantee of Poland's energy security and stability to obtain an optimal mix structure open to the development of new technologies. The current ecological conditions, as reflected in the adopted legal acts of the European Union, require energy transformation of the Member States, including Poland. These changes, however, must proceed at a pace adjusted to the economic possibilities of individual economic systems, as the energy sector is an economic branch with high and capital-intensive investments. Reducing gas emissions and increasing the share of renewable energy sources are the transformations that determine the demand for hard coal in Poland. The article proposes a model for forecasting the demand for hard coal with a 95% confidence interval, which is based on long short-term memory (LSTM) artificial neural networks. In this model, explanatory variables were added. This model takes environmental regulations in the form of explanatory variables into account. The selection of variables was made using the principal components analysis. As a result of this analysis, variables were obtained that have a statistically significant impact on the transformation of the hard coal mining sector. This is the consumption of natural gas, renewable energy and imports. For these variables, alternative paths of changes were predicted based on the applicable legal acts. The long-term forecast indicates a gradual decline in hard coal sales, reaching the level of 55,020 thousand Mg in 2030.

The work was within in framework of statutory research 06/010/BK-20/0042.

REFERENCES

Ahmad, T. and Chen, H. 2018. Utility companies strategy for short-term energy demand forecasting using machine learning based models. *Sustainable Cities and Society* 39, pp. 401–417.

Anđelković, A.S. and Bajatović, D. 2020. Integration of weather forecast and artificial intelligence for a short-term city-scale natural gas consumption prediction. *Journal of Cleaner Production* 266, 122096.

Bluszcz, A. 2018. The emissivity and energy intensity in EU countries – consequences for the Polish economy. Conference proceedings Energy and clean technologies. Recycling, air pollution and climate change. STEF92 2018 Sofia, 18, 14.2, pp. 631–638.

Directive IED 2010. Directive (EU) 2010/75/EU of the European Parliament and of the Council of 24 November 2010 on industrial emissions (integrated pollution prevention and control).

Felix et al. 2015 – Felix, A., Jürgen, G., Schmidhuber, J. and Cummins F. 2015. Learning to Forget: Continual Prediction with LSTM. *Neural Computation* 12(10), pp. 2451–2471.

Forum energii 2020. *Energy transformation in Poland. 2020 edition* (*Transformacja energetyczna w Polsce. Edycja 2020*). [Online] https://forum-energii.eu/public/upload/articles/files/Transformacja%20energetyczna%20w%20Polsce.%20Edycja%202020(2).pdf [Accessed: 2020-07-21] (*in Polish*).

Li et al. 2018 – Li, J. Wang, R. Wang J. and Li, Y. 2018. Analysis and forecasting of the oil consumption in China based on combination models optimized by artificial intelligence algorithms. *Energy* 144, pp. 243–264.

Gawlik, L. and Mokrzycki, E. 2014. Scenarios of coal utilization in power engineering in Poland in the light of EU climate policy (*Scenariusze wykorzystania węgla w polskiej energetyce w świetle polityki klimatycznej Unii Europejskiej*). *Przegląd Górniczy* 70(5), pp. 1–8 (*in Polish*).

Gawlik, L. and Mokrzycki, E. 2019. Changes in the Structure of Electricity Generation in Poland in View of the EU Climate Package. *Energies* 12, 3323.

Gers, F.A. 1999. Learning to forget: Continual prediction with LSTM. *9th International Conference on Artificial Neural Networks: ICANN'99*, pp. 850–855.

Greff et al. 2015 − Greff, K., Srivastava, R.K., Koutník, J., Steunebrink, B.R. and Schmidhuber, J. 2015. LSTM: A Search Space Odyssey. *IEEE Transactions on Neural Networks and Learning Systems* 28(10), pp. 2222–2232.

Hochreiter, S. and Schmidhuber, J. 1997. Long short-term memory. *Neural Computation* 9(8), pp. 1735–1780.

Hyndman, R.J. and Kostenko, A.V. 2007. Minimum sample size requirements for seasonal forecasting models. *Foresight* 6, pp. 12−15.

Industrial Development Agency 2020. Polish Coal Market. [Online] https://polskirynekwegla.pl/raporty-dynamiczne [Accessed: 2020-08-01].

Kaszyński, P. and Kamiński, J. 2020. Coal Demand and Environmental Regulations: A Case Study of the Polish Power Sector. *Energies* 13, 1521.

Manowska, A. 2018. Use of autoregressive models to estimate a demand for hard coal. *18th International Multidisciplinary Scientific GeoConference. SGEM 2018, vol. 18, Ecology, economics, education and legislation. No. 5.3, Environmental economics, Sofia*, pp. 975–982.

Manowska, A. 2020. Analysis and Forecasting of the Primary Energy Consumption in Poland Using Deep Learning. *Inżynieria Mineralna – Journal of the Polish Mineral Engineering Society* 1(1), pp. 217–222.

Macrotrends 2020. *Poland Fossil Fuel Consumption 1960-2020*. [Online] https://www.macrotrends.net/countries/POL/poland/fossil-fuel-consumption [Accessed: 2020-08-05].

Ministry of State Assets 2019. *National Energy and Climate Plan for 2021–2030. Assumptions, Goals and Policies Project – v. 3.1. 04/01/2019 (Ministerstwo Energii. Krajowy plan na rzecz energii i klimatu na lata 2021–2030. Założenia i cele oraz polityki i działania. Projekt – w. 3.1. 04.01.2019)*. [Online] https: //www.gov.pl/web/energia/projekt-krajowego-planu-na-rzecz-energii-i-klimatu-na-lata-2021-2030 [Accessed: 2020-07-20] (*in Polish*).

Polish Geological Institute 2019. National Research Institute: Balance of mineral resources in Poland as at December 31, 2018, Warsaw 2019. [Online] geoportal.pgi.gov.pl [Accessed: 2020-07-21].

Saksornchai et al. 2005 – Saksornchai, T., Lee, W.J., Methaprayoon, K., Liao, J.R. and Ross, R.J. 2005. Improve the unit commitment scheduling by using the neural-network-based short-term load forecasting. *IEEE Transactions on Industry Applications* 41(1), pp. 169–179.

StatSoft 2020. *Electronic Statistics Textbook*. [Online] https://www.statsoft.pl/textbook/stathome.html [Accessed: 2020-07-22].

Tae-Young, K. and Sung-Bae, Ch. 2019. Predicting residential energy consumption using CNN-LSTM neural networks. *Energy* 182, pp. 72−81.

Rybak, A. and Manowska, A. 2019. The forecast of coal sales taking the factors influencing the demand for hard coal into account. *Gospodarka Surowcami Mineralnymi – Mineral Resources Management* 35(1), pp. 129–140.

Zielaś et al. 2003 − Zielaś, A., Pawełek, B. and Wanat, S. 2003. *Economic forecasting, theory, examples, given* (*Prognozowanie ekonomiczne, teoria, przykłady, zadana*). Warszawa: PWN, 380 pp. (*in Polish*).

USING THE LSTM NETWORK TO FORECAST THE DEMAND FOR HARD COAL

Keywords

time series, principal components analysis, hard coal sales, LSTM artificial neural networks

Abstract

Securing the certainty of supplies of the necessary minimum energy in each country is a basic condition for the energy security of the state and its citizens. The concept of energy security combines several aspects at the same time, as it can be considered in terms of the availability of own energy resources, it concerns technical aspects related to technical infrastructure, as well as political aspects related to the management and diversification of energy supplies. Another aspect of the issue of energy security is the environmental perspective, which is now becoming a priority in the light of the adopted objectives of the European Union's energy policy. The restrictive requirements for reducing greenhouse gas emissions and increasing the required level of renewable energy sources in the energy balance of the Member States is becoming a challenge for economies that use fossil fuels to a large extent in the raw material structure, including Poland. Poland is the largest producer of hard coal in the European Union and hard coal is a strategic raw material as it satisfies about 50% of the country's energy demand. In this context, the main goal of the article was to determine the future sale of hard coal by 2030 in relation to environmental regulations introduced in the energy sector. For this purpose, a mathematical model with a 95% confidence interval was developed using artificial LSTM neural networks, which belong to deep learning machine learning techniques, which reflects the key relationships between hard coal mining and the assumptions adopted in the National Energy and Climate Plan for the years 2021–2030 (NECP).

WYKORZYSTANIE SIECI LSTM DO PROGNOZOWANIA ZAPOTRZEBOWANIA NA WĘGIEL KAMIENNY

Słowa kluczowe

szeregi czasowe, analiza składowych głównych, sztuczne sieci neuronowe LSTM, sprzedaż węgla kamiennego

Streszczenie

Zabezpieczenie pewności dostaw niezbędnego minimum energii w każdym kraju jest podstawowym warunkiem bezpieczeństwa energetycznego państwa i jego obywateli. Pojęcie bezpieczeństwa energetycznego łączy kilka aspektów jednocześnie, gdyż można je rozpatrywać na płaszczyźnie dostępności własnych surowców energetycznych; dotyczy aspektów technicznych związanych z infrastrukturą techniczną, a także aspektów politycznych, które związane są z zarządzaniem oraz dywersyfikacją dostaw surowców energetycznych. Kolejnym elementem zagadnienia bezpieczeństwa energetycznego jest perspektywa środowiskowa, która nabiera obecnie priorytetowej ważności w świetle przyjętych celów polityki energetycznej Unii Europejskiej. Restrykcyjne wymagania w zakresie redukcji poziomów emisji gazów cieplarnianych oraz wzrostu wymaganego poziomu odnawialnych źródeł energii w bilansie energetycznym krajów członkowskich stają się wyzwaniem dla gospodarek wykorzystujących w dużej mierze paliwa kopalne w strukturze surowcowej, do których należy również Polska. Polska jest największym producentem węgla kamiennego w Unii Europejskiej i jest to surowiec strategiczny, gdyż zaspokaja około 50% zapotrzebowania energetycznego kraju. W tym kontekście głównym celem artykułu było określenie przyszłej sprzedaży węgla kamiennego w perspektywie do 2030 roku, w odniesieniu do regulacji środowiskowych wprowadzanych w energetyce. W tym celu opracowano model matematyczny z 95-procentowym przedziałem ufności z wykorzystaniem sztucznych sieci neuronowych LSTM, które należą do technik uczenia maszynowego – *deep learning*, który odzwierciedla kluczowe relacje między górnictwem węgla kamiennego a przyjętymi założeniami w Krajowym planie na rzecz energii i klimatu na lata 2021–2030 (KPEiK).