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AURELIA RYBAK[1], ALEKSANDRA RYBAK[2]

The impact of selected factors and access to mineral resources on the development of wind energy in Poland

Introduction

Decarbonization resulting from the implementation of the European Green Deal requires the introduction of extensive changes in the Polish energy mix. Currently, the basis of the energy generation structure in Poland is hard coal and lignite, which in 2022 was used to generate 71% of the consumed electricity (BP 2023). In 2022, the potential of generating capacity of this type was approximately 7,000 MW, and the annual production of wind energy oscillated around 8 GWh. This is just over 10% of the annual energy demand in Poland. The Polish Energy Policy assumes that by 2040, approximately 50% of electricity in Poland will be obtained from renewable energy sources (PEP 2040). These will be primarily wind and solar energy. In 2023, the installed capacity of onshore wind farms

✉ Corresponding Author: Aurelia Rybak; e-mail: aurelia.rybak@polsl.pl

[1] Silesian University of Technology, Gliwice, Poland; ORCID iD: 0000-0002-5945-7991; e-mail: aurelia.rybak@polsl.pl

[2] Silesian University of Technology, Gliwice, Poland; ORCID iD: 0000-0003-3752-2155; e-mail: aleksandra.rybak@polsl.pl

in Poland was 8.6 GW. The policy assumes the further development of wind energy from not only onshore but also offshore farms. By 2030, their installed capacity is to reach about 6 GW, and by 2040 it is to reach 11 GW. Therefore, by 2040, the capacity of Polish wind farms will most likely double. Poland's energy policy until 2040 assumes also that the role of hard coal in the economy will gradually decrease. Reducing the emission intensity of the energy sector will be possible through, among other means, the expansion of wind energy and the implementation of offshore wind energy. Renewable energy sources will take over an increasingly important role in the national energy mix. By 2030, it is to be at least 32% of the gross final energy consumption. This development will mainly be based on photovoltaics and wind farms. Onshore wind farms will continue to be developed. Additionally, PEP2040 assumes the development of offshore farms. This is mainly due to the productivity of these installations and the fact that they eliminate problems with social acceptance, which is often an obstacle in the case of onshore farms. Electricity production from offshore farms will have the largest share in total production from renewable energy sources. This is also consistent with the goals of the European Green Deal, which makes the development of offshore farms a strategic project of Poland's Energy Policy (PEP2040). Therefore, in order to replace coal, it will be necessary to significantly expand the potential of wind energy in Poland. Such an intensive evolution of the energy system will depend on many factors that will have positive or negative impacts on the pace of wind energy development. These include, among other factors, climatic and economic conditions, social moods, legal actors, and above all, the availability of critical raw materials on global markets that are necessary for the construction of wind farms. The Act of May 20, 2016 on investments in wind farms, and, above all, the 10 H rule contained therein, which determines the minimum distance of wind turbines from residential buildings, has resulted in the inhibition of the development of wind energy in Poland. In 2023, an amendment to the Wind Farm Act was introduced, where the distance guidelines were relaxed. This is a step towards the implementation of the PEP2040 assumptions, which may accelerate the development of onshore energy in Poland. The presented research focused only on quantitative factors. The following hypothesis was put forward: factors shaping the pace of the potential development of wind energy generation in Poland would allow the fulfillment of the assumptions of the Polish energy policy. Therefore, the presented research analyzes a set of factors that may potentially affect the development of wind energy in Poland. First, the focus was on critical raw materials, but factors that were included in the economic, ecological, and technological categories were also taken into account. The authors examined the impact of the factors adopted for the analysis on the volume of wind energy production in Poland. The statistical significance of the factors was verified using the ARMAX model, which was also used to build a forecast of the energy production volume in the selected time horizon.

1. Literature review

Wind energy is an inexhaustible source of energy, which in the light of rising electricity prices is an increasingly attractive solution (EON 2023). Energy production in wind farms is also free from pollutant emissions and greenhouse gases such as CO_2 (Yousefi et al. 2019; Forbes and Zampelii 2019). CO_2 emissions are one of the basic problems that significantly accelerated the decisions of the European Union and its member states concerning the need to introduce changes in energy mixes. In the literature, many publications on wind energy forecasting can be found (Gil et al. 2010). Usually, these are short-term analyses. Very few researchers have attempted to introduce Gray's forecasting method, which was designed for system analysis characterized by insufficient information. An empirical study based on real data obtained from a wind farm located in Penghu, Taiwan, demonstrated the effectiveness of the GM-based forecasting mechanism. It has also been applied to wind forecasting problems at different time intervals (Huang et al. 2011). Short-term wind speed forecasting using spectral analysis was also used. Experimental results show that trimming daily, weekly, monthly, and yearly patterns in the measurements significantly increases the accuracy of the estimates. The proposed framework is based on data detrending, covariance factorization using a recently developed subspace method, and prediction concepts using a single- and/or multi-step-ahead Kalman filter (Akcay and Filik 2017). The authors demonstrated that SVR is an effective method for predicting wind energy production based solely on wind measurements from windmills, especially without further meteorological data and weather forecasts (Kramer and Gieske 2011). Machine learning was used for the short-term forecasting of wind energy generation. The results showed that the algorithm proposed by the authors has a 10% lower RMSE value compared to other models (Shabbier et al. 2019). Long-term forecasts were also made using linear and nonlinear models. Various regression models were developed using, inter alia, electricity consumption and gross domestic product (GDP). Statistical tests were used to check the validity of the proposed models. It was indicated that the developed models are consistent with official forecasts (Bianco et al. 2009; Ha et al. 2019). The trends in the share of renewable energy in final energy consumption were analyzed using data for the EU. Empirical estimates of the share of renewable energy made using ARIMA models showed an increasing trend (Mehedintu et al. 2018). The authors used economic and sociological factors as input. In forecasting the volume of wind energy production, neural networks were also used to forecast the wind speed on the horizon of six months (Azad et al. 2014). However, the problem with forecasts based on meteorological data is that they can only reach the forecast horizon of the meteorological model at most. The literature also presents forecasts with a one-year time horizon using Bayesian modelling and Markov chain Monte Carlo (MCMC). The data presented in the literature show that forecasting the volume of wind energy production is complicated due to the nature of the phenomenon. A satisfactory forecast is obtained by dividing the problem into several periods with different beta distribution parameters. As a result of this, accurate forecast can be obtained (Mesa-Jimenez et al. 2023).

REE demand scenarios resulting from the demand for wind energy have been presented in the literature. It was examined whether the supply of REE on a global scale is able to meet the needs of the developing offshore wind energy (Kalvig and Machacek 2018; Imholte at al. 2018). The demand and prices of materials and metals were also forecasted to avoid future problems with the availability of these materials. In this study, lithium and cobalt, as well as neodymium, praseodymium and dysprosium were considered to be critical materials (Verma et al. 2022).

The authors of the presented research, in turn, wanted to create a long-term forecast of the volume of the production of wind energy in the horizon of two years, which would take into account the demand for critical metals necessary during the construction of wind farms. Therefore, information on the amount of demand for copper, nickel, boron, manganese and REE (rare earth metals) was introduced into the model.

2. Critical metals characteristics

The critical metals necessary in the wind turbine manufacturing process are briefly presented below.

Rare earth metals

Rare earth metals are yttrium, scandium, and a group of seventeen elements from the lanthanide group (Tao et al. 2022, Rybak and Rybak 2021). Access to rare earth elements will determine the success of the energy transformation of countries around the world in the future. Because REE will have a key impact on the development of the energy sector, as well as on the development of emission-free technologies, they are called vitamins of the new industry (Balaram 2019). This also applies to wind turbines (Ballinger et al. 2020). REE resources are located mainly in China, as well as the USA, Brazil, India and Australia (Jaroni et al. 2019). Since there are no REE deposits within the geographical area of the EU that would enable meeting the demand of member states, they are considered critical raw materials (COM 2023). REEs such as neodymium, dysprosium, praseodymium, and terbium are essential to the production of wind turbines. Poland does not have its own REE deposits of which exploitation could be profitable. However, an alternative native source of elements in this case may be fly ash generated in the coal combustion process (Blissett and Rowson 2012).

Copper

Copper in wind turbines is used in the generator located on the nacelle, in cables and wires, transformers, grounding, inverters and lightning protection and control systems (Carrara et al. 2020; Farina and Anctil 2022). Poland has its own copper deposits that will successfully cover the needs of the wind farm development process. Polish copper deposits are exploited by KGHM Polska Miedź. They constitute one of the largest deposits in the world and are extracted in three mines: Rudna, Lubin and Polkowice-Sieroszowice. KGHM's exploitable resources contain approximately 40 milligrams of copper (Geoportal 2021). In 2021, KGHM's production of payable copper amounted to 753.7 thousand Mg (KGHM 2021), which means a 7.5% increase compared to 2019. The growing demand for this raw material, which has been taking place since the beginning of the twentieth century, is currently due to the development of technological innovations, including those related to the development of renewable energy sources. It is estimated that the demand for copper and its prices will increase in the coming years as a result of the war in Ukraine as well as the demand caused by the green transformation and the need to ensure energy security in, among other places, the European Union and the United States (GS 2022).

Nickel

Nickel is used in many elements of wind turbines, mainly bearings, gears, shafts and hydraulic elements of nacelles, as well as in many other structural elements of wind turbines (Lee 2008; Carrara et al. 2020). In Poland, nickel is recovered in the processing of copper--silver ores from deposits of the Fore-Sudetic Monocline.

Boron

Boron is used to boronize the steel elements of wind turbines, such as gears. This makes them resistant to heat, abrasion and corrosion (Greco et al. 2011). Boron is also used in the permanent magnets of the turbine generator (Carrara et al. 2020). Boron compounds used in Poland are mainly imported from Italy and Germany (Witkowska-Kita et al. 2016).

Manganese

Small amounts of manganese are used as part of the steel components of turbines (USAID 2021). In Poland, manganese demand is mainly covered by imports from Brazil and Ukraine (Witkowska-Kita et al. 2016).

The explanatory variables selected by the authors were introduced into the ARMAX model. In addition, during the research, the authors took into account ecological, energy and economic factors, which were also introduced into the ARMAX model. The model and the WEKR 1.0 program are characterized in the Methods and Results chapters.

In Germany, copper and dysprosium have been identified as the most critical materials because they could cause supply bottlenecks while being fundamental to the functionality of wind turbines. It was determined that the demand for copper could require 0.2% of the currently known resources, and the demand for dysprosium could reach up to 0.6% of reserve levels. Both metals clearly exceed allocations for renewable energy technologies in Germany and will face strong competition from other sectors for raw materials (Shammugan et al. 2019).

Ren, Tan et al. noted that the annual demand for base metals for Chinese wind energy in 2050 will be as much as twelve times higher than in 2018, and the cumulative demand will be as much as twenty-three times higher. The cumulative copper and nickel demand of the wind power sector is 9–11.9 Mt and 2.1–2.8 Mt, respectively, accounting for 35–45.9% of the copper resources and 74–101% of the nickel resources in China. In terms of the demand for rare earths, the annual demand is projected to increase by more than eighteen times in 2050 compared to 2020, with cumulative demand for neodymium and dysprosium accounting for 1.6–3.3% and 1.4–2.8% of their reserves, respectively (Ren et al. 2021). Figure 1 presents global resources of selected REEs and the demand for them in the wind energy sector over the next thirty years. It is clearly visible that, especially in the case of Tb, where the demand related to wind energy will consume approximately 78% of resources by 2050, and Dy, where it will be 34%, the lack of access to new sources of REE will be a problem in the near future. It should also be noted that the demand for REE will increase in other sectors of the economy and not only in wind energy, which may lead to a complete lack of access to REE.

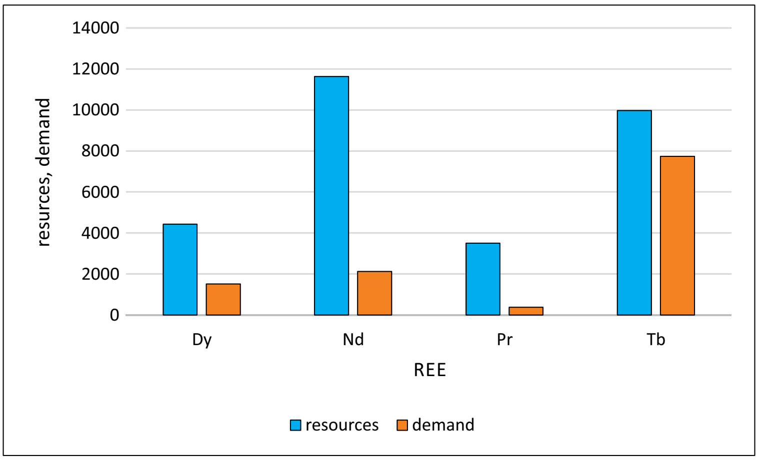

Fig. 1. Reserves and demand for REE within thirty years, own calculation based on (Alves Dias et al. 2020), Dy × 10^1 Mg, Nd × 10^2 Mg, Pr × 10^2 Mg, Tb Mg

Rys. 1. Zasoby i zapotrzebowanie na REE w ciągu 30 lat, Dy × 10^1 Mg, Nd × 10^2 Mg, Pr × 10^2 Mg, Tb Mg

Copper consumption per MW can be found in many publications. For example, in (Ardente et al. 2008; Crawford 2009) it ranges from 0.36 to 1 Mg/MW. In turn, it is approximately 0.7 Mg/MW. With the average assumption based on (Alves Dias et al. 2020) taking into account only Polish Cu resources, the annual demand for copper from wind farms was approximately 0.05% of production in 2022.

The literature also includes examples of determining the share of demand for metals in connection with the development of wind energy in 2020 in annual production (Li et al. 2022). For Cu, it was 0.1%, Ni 0.2% and Mn 0.0%. The authors performed a similar analysis for Poland, the results of which are presented in Figure 2. The results of research conducted for Poland are comparable. The only discrepancy occurs in the case of Nickel, because for

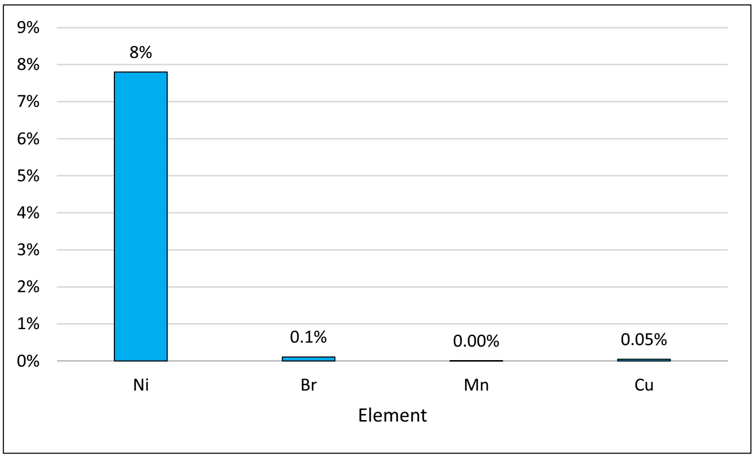

Fig. 2. Ratio of wind energy demand for Ni, Br, Mn, Cu to annual production in 2022

Rys. 2. Stosunek zapotrzebowania energetyki wiatrowej na Ni, Br, Mn, Cu do rocznej produkcji w roku 2022

Poland, only domestic production of the metal recovered during copper mining was taken into account.

3. Methods

The methodology according to which the research was performed is presented in Figure 3.

Step 1

The initial analysis took twenty-four factors into account selected on the basis of a literature review and classified into five categories:

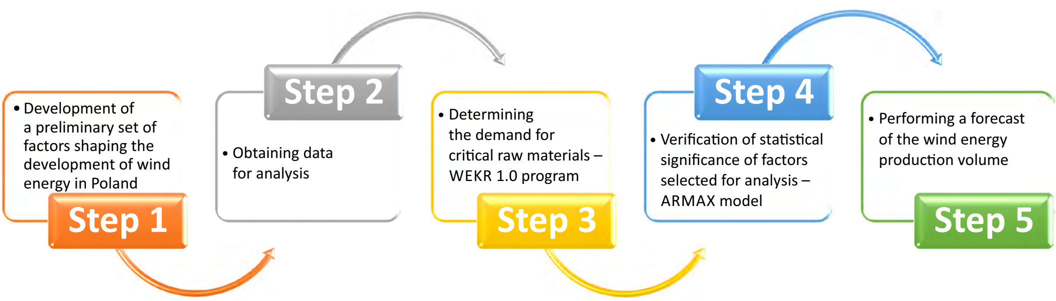

Fig. 3. Methodology of the presented research
Source: own elaboration

Rys. 3. Metodologia zastosowana w zaprezentowanych badaniach

- Technological factors:
  - annual installed capacity of wind energy, (MW);
  - number of patents.
- Energy factors:
  - wind energy production, (GWh) – dependent variable;
  - primary energy consumption, (GJ/capita);
  - gross available energy, (toe);
  - total energy supply, (toe);
  - final energy consumption, (toe);
  - renewables consumption, (EJ).
- Ecological factors:
  - CO_2 emission, (mil Mg).
- Economic factors:
  - real GDP per capita, (EUR/capita);
  - LCOE for onshore technology, (USD/kWh).
- Raw material factors:
  - Nd consumption, (kg/MW);
  - Pr consumption, (kg/MW);
  - Tb consumption, (kg/MW);
  - Dy consumption, (kg/MW);
  - annual REE production, (1000 Mg);
  - Ni consumption, (kg/MW);
  - Br consumption, (kg/MW);
  - Cu consumption, (kg/MW);
  - Mn consumption, (kg/MW);
  - annual domestic production of Cu (1000 Mg);
  - annual domestic production of Ni, (Mg);
  - annual world production of Mn, (1000 Mg);
  - annual world production of Br, (1000 Mg).

Step 2

In the second step, statistical data necessary to conduct the presented research was obtained. Table 1 presents sources of data acquisition.

Step 3

The consumption of individual raw materials was determined using the WEKR 1.0 program based on data from the report (Carrara et al. 2020). Figure 4 presents an algorithm, on the basis of which the programme determines the selected explanatory variables based on the example of nickel. The programme determines the number of wind energy MW that have been created in Poland since 1998. In the next step, it calculates how many kilograms of each metal were needed in a given year to generate the wind power generation capacity.

Table 1. Data acquisition sources

Tabela 1 Źródła pozyskania danych

Factor	Source
Installed power	Eurostat
Number of patents	IRENA
Energy factors	Eurostat
Ecological factors	Eurostat
Real GDP per capita, EUR/capita	Eurostat
LCOE for onshore technology, USD/kWh	IRENA
Cu, Ni, Mn, Br consumption	MEERI PAS, KGHM
Nd, Pr, Tb Dy consumption	MEERI PAS

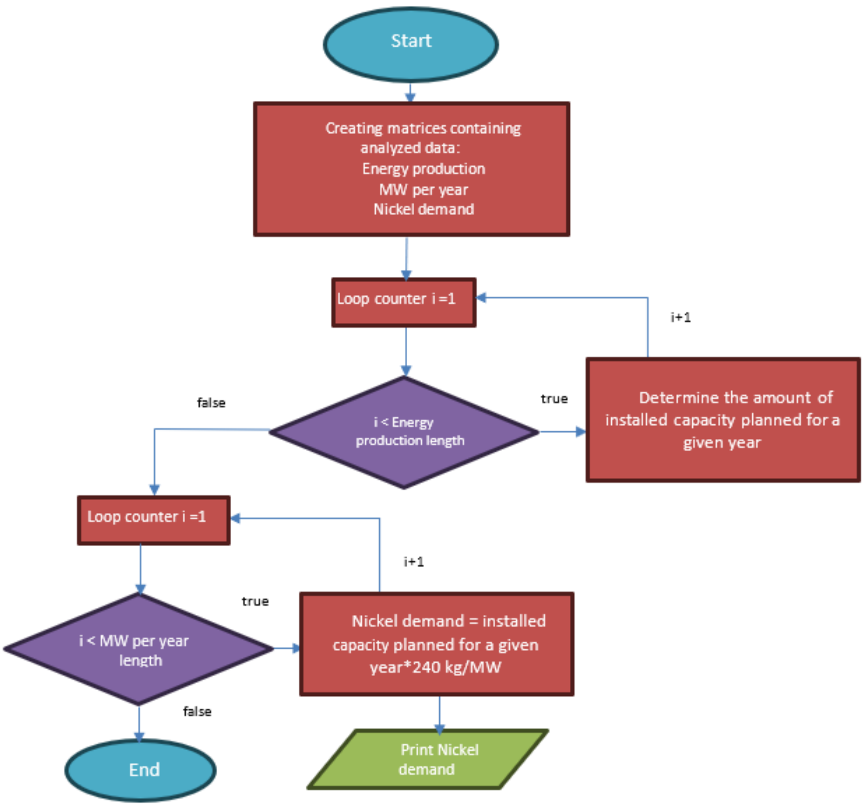

Fig. 4. The algorithm of the WEKR 1.0 program
Source: own elaboration

Rys. 4. Algorytm program WEKR 1.0

The input data to the algorithm are:

- The amount of energy production,
- The number of MW per year,
- The demand for REE, Cu, Ni, Br and Mn metals.

Input data is placed in arrays. The volume of MW built each year is determined. Additionally, the demand for a given metal is determined for each year. After determining this value for all observations of the time series, the program ends. The output data, i.e. the demand for nickel in accordance with the designated production capacity expected for a given year, is printed in the console and placed in a table, which then constitutes input data for the ARMAX model.

Steps 4 and 5

The Autoregressive Moving Average with Exogenous Input model (ARMAX) was used to forecast the volume of wind energy production in Poland. The model includes a moving average component and an autoregressive component. The ARMAX model enables the examination of the relationship between the explained variable and the explanatory variables. Optimization of the model parameters is performed by limiting the mean square error.

ARMAX is a discrete model of the input-output type used in the case of stochastic processes (Darbellay and Slama 2000; Hickey et al. 2012). The ARMAX model is described by the following equation:

$$y(t)=\sum_{i=1}^{n_a} a_i y(t-i)+\sum_{j=1}^{n_b} b_j u(t-j)+\sum_{k=1}^{n_c} c_k e(t-k)+e(t) \tag{1}$$

↳ $y(t)$ – output signal sequence,
t – time,
a_i, b_j, c_k – prediction coefficients,
$e(t)$ – white noise,
$u(t)$ – input signal string,
n – predictor order,
i, j, k – lag.

As a result of the use of the ARMAX model, it is also possible to determine the nature of the explanatory variable, i.e. to indicate whether it is:

- nominant, the character of which depends on its nominal value;
- stimulant, the increase of which has a positive effect on the dependent variable;
- destimulant, the decrease of which has a positive effect on the dependent variable (Shader et al. 2003).

In the case of a model with numerous explanatory variables, it should be verified that the multicollinearity phenomenon does not occur (Niu and Lee 2022). This is present when the variables are strongly correlated with each other. This may have a negative impact on the ARMAX model results. To verify whether there is multicollinearity in a selected set of variables, the VIF (variance inflation factor) can be used, which indicates how much the variance of the estimated model coefficient increased due to collinearity with the other explanatory variables. If the collinearity phenomenon occurs in the model, the variables do not carry information about the influence of the independent variable on the dependent variable. The VIF coefficient is determined according to the following formula (Belsley 1980; Miles 2014):

$$VIF_j = \frac{1}{\left(1 - R_j^2\right)} \tag{2}$$

↳ R_j^2 – determination coefficient.

Therefore, in the case of the occurrence of the multicollinearity phenomenon, it should be eliminated. This can be done in several ways. One of these is the transformation of the independent variables. This transformation consists of expressing the explanatory variables between which the collinearity occurred as a composite of these variables and expressing their mutual relation to each other. Another way is to modify the set of independent variables by eliminating those that cause the phenomenon of collinearity or by introducing additional explanatory variables (Wetherill 1986). However, this requires changing the research assumptions of the conducted and often verifying the hypotheses.

The stationarity of the time series was verified using the Dickey-Fuller (DF) test, which was first presented in 1979. The test checks the time series for the presence of a unit root. In this case, two hypotheses are put forward:

- H0: there is a unit root in the time series, $\delta = 0$;
- H1: the time series is stationary, $\delta < 0$.

The time series to be introduced into the ARMAX model should be stationary or should be reduced to a stationary form. Otherwise, the model may not be able to faithfully represent the fundamental data patterns and the results will be erroneous.

A stationary time series is characterized by a constant mean and autocorrelation over time. One way to bring a time series to a stationary form is to differentiate it.

The Dickey-Fuller test statistic for the existence of a unit root takes the form:

$$DF = \frac{\delta}{S(\delta)} \tag{3}$$

↳ δ – deterministic trend coefficient.

ARMAX validation also consisted of the selection of models characterized by the lowest value of information criteria such as Schwarz (*BIC*), Hannnan-Quinn (*HQ*) and Akaike (Piłatowska 2010):

$$BIC = -2lnL\left(\hat{\theta}\right) + Kln\left(n\right) \tag{4}$$

$$HQ = -2lnL\left(\hat{\theta}\right) + 2Kln\left(lnn\right) \tag{5}$$

$$AIC = -2lnL\left(\hat{\theta}\right) + 2K \tag{6}$$

n – number of observations;
K – number of model parameters;
$L\left(\hat{\theta}\right)$ – the credibility function of the model corrected by the penalty function – the function of K.

Depending on the "penalty", the following models are considered appropriate:

- With a small penalty – a model with more parameters should be selected.
- With a large penalty – a sparingly parameterized model should be selected.

The next stage of validation was to determine model errors such as MAPE, RMSE, MAE, and Theil's Inequality Coefficient (Willmott and Matsuura 2005). The determination of several meters enables the selection of the appropriate model.

Mean absolute percentage error (MAPE) (Bliemel 1973; Farnum and Stanton 1989):

$$MAPE = \frac{\sum_{i=1}^{n} \left| e_t / y_t \right|}{n} \tag{7}$$

y_t – value of the dependent variable in period t,
e_t – prediction error.

Root mean square error (RMSE) (Safi and Zeroual 2002; Almorox et al. 2005):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} e_t^2}{n}} \tag{8}$$

Mean absolute error (MAE) (Chai and Draxler 2014):

$$MAE = \frac{\sum_{i=1}^{n} |e_t|}{n} \tag{9}$$

Theil's inequality coefficient (Kufel 2004):

$$U = \frac{RMSE}{\sqrt{\frac{1}{n}\sum_{i=1}^{n} |y_t^2|} + \sqrt{\frac{1}{n}\sum_{i=1}^{n} |\hat{y}_t^2|}} \tag{10}$$

↳ $\hat{y}_t$ – forecast of the dependent variable in period t.

The residuals of the selected model were also analyzed. It was verified whether the residuals are normally distributed and whether they show autocorrelation.

The Ljung box test (Burns 2002) was used to verify the autocorrelation of residuals:

$$Q = n(n+2)\sum_{k=1}^{h} \frac{\hat{\rho}_k^2}{n-k} \tag{11}$$

↳ $\hat{\rho}_k^2$ – sample autocorrelation at lag k,
h – number of lags tested.

The normality of the distribution of model residuals was confirmed using the Doornik-Hansen test (Domański and Szczepocki 2020):

$$DH = \left[Z\left(\sqrt{b_1}\right)\right]^2 + \left[z_2\right]^2 \tag{12}$$

↳ $Z\left(\sqrt{b_1}\right)$ – transformed sample skewness,
z_2 – Wilson-Hilferty transformation.

4. Results

During the determination of the ARMAX model, 39 function evaluations and 104 gradient evaluations were made. Standard errors of the parameters were based on a Hessian matrix.

The multicollinearity analysis of the variables showed that they are characterized by strong collinearity. This mainly concerned the demand for rare earth elements as well as nickel, boron, manganese and copper. When independent variables are correlated, it means that changes in one variable are related to changes in another variable. The amount of demand for metals is directly dependent on the amount of MW of wind energy generated each year, so they are correlated. In this case, the variables must be discarded or transformed. In the analyzed case, eliminating the explanatory variables was not an option so they had to be transformed (Kumari 2008). One way to do this is to sum the values of the variables and divide them by a common factor, which was necessary in the case of REE. The demand for individual REEs was summed and divided by the production per REE in a given year. The remaining variables were transformed separately. The demand for Cu, Mn, Ni and Br was divided by the production volume of these metals in a given year (Paul 2006), which was a sufficient measure. The multicollinearity phenomenon has been removed.

The multicollinearity testing was performed again. The obtained results are presented in Table 2.

According to the Belsley-Kuh-Welsch method, cond ≥ 30 means a strong almost linear correlation, while cond between 10 and 30 means a low correlation. Estimated parameters for which the variance is related to high status indicator values can always be considered to be problematic. In the tested case:

- The number of status indicators for cond ≥ 30 is 0.
- The number of status indicators for cond ≥ 10 is 1.

Values greater than 15 indicate a possible multicollinearity problem, while values greater than 30 should be expected to cause serious multicollinearity problems (IBM 2021). In the analyzed case, only one conditional index reaches a value greater than 10, which is equal to 13.79. This value is still lower than 15; therefore, the introduced modifications of the explanatory variables brought the intended result. Only in one case is there a low linear correlation, which did not affect the quality of the model.

The time series was analyzed for stationarity. For this purpose, the extended Dickey-Fuller test was performed. The null hypothesis was put forward that a zero root appears in the time series. The test confirmed the validity of the hypothesis. Therefore, it was necessary to differentiate the time series twice.

- First differentiation:
  model: $(1 - L)y = b0 + (a - 1) \times y(-1) + ... + e$
  the estimated value $(a - 1)$ is: –0.588709
  test statistic: tau_c (1) = –1.8106
  asymptotic p-value = 0.3758
  autocorrelation of first-order residuals: 0.021
- Double differentiation:
  model: $(1 - L)y = b0 + (a - 1) \times y(-1) + ... + e$
  the estimated value $(a - 1)$ is: –1.85095
  test statistic: tau_c (1) = –2.98582
  asymptotic p-value = 0.03625
  autocorrelation of first-order residuals: –0.030

The probability of $p < 0.05$ means that the time series was brought in a stationary form.

Table 2. Diagnostics of collinearity acc. Belsley-Kuh-Welsch (BKW 1980)

Tabela 2. Diagnostyka kolinearności według Belsleya-Kuh-Welscha

Lambda	Cond	Phi 1	Theta 1	Theta 2	REE ratio	REE production	Patents	Capacity	LCOE	GDP	E. consumption	CO_2 emission	Ni ratio	Br ratio	Cu ratio	Mn ratio
4.382	1.000	0.001	0.001	0.000	0.000	0.008	0.011	0.006	0.002	0.000	0.000	0.000	0.002	0.014	0.005	0.013
1.953	1.498	0.001	0.001	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1.225	1.891	0.000	0.000	0.000	0.020	0.000	0.000	0.000	0.000	0.017	0.008	0.108	0.000	0.001	0.000	0.001
1.148	1.953	0.000	0.000	0.000	0.105	0.000	0.000	0.000	0.000	0.078	0.004	0.000	0.000	0.000	0.000	0.000
1.132	1.968	0.000	0.000	0.000	0.013	0.000	0.000	0.000	0.000	0.047	0.133	0.001	0.000	0.000	0.000	0.000
1.027	2.066	0.012	0.012	0.000	0.013	0.001	0.001	0.000	0.005	0.011	0.014	0.006	0.180	0.001	0.000	0.001
1.002	2.091	0.250	0.250	0.000	0.001	0.000	0.000	0.000	0.160	0.003	0.004	0.002	0.024	0.000	0.000	0.000
0.986	2.108	0.726	0.726	0.000	0.001	0.000	0.001	0.000	0.062	0.002	0.002	0.001	0.001	0.001	0.001	0.001
0.812	2.323	0.001	0.001	0.000	0.006	0.002	0.003	0.001	0.003	0.005	0.005	0.006	0.005	0.003	0.319	0.004
0.411	3.265	0.001	0.001	0.000	0.004	0.011	0.017	0.005	0.003	0.004	0.004	0.005	0.004	0.068	0.002	0.788
0.344	3.567	0.000	0.000	0.000	0.007	0.062	0.117	0.000	0.003	0.006	0.005	0.007	0.006	0.758	0.004	0.006
0.255	4.147	0.005	0.005	0.000	0.006	0.031	0.610	0.182	0.009	0.007	0.007	0.008	0.005	0.052	0.000	0.000
0.226	4.400	0.001	0.001	0.000	0.001	0.511	0.108	0.196	0.003	0.001	0.002	0.001	0.001	0.031	0.121	0.001
0.072	7.826	0.000	0.000	0.340	0.140	0.072	0.019	0.142	0.129	0.138	0.137	0.144	0.134	0.025	0.542	0.048
0.023	13.794	0.001	0.001	0.639	0.682	0.301	0.112	0.467	0.621	0.681	0.675	0.711	0.638	0.046	0.005	0.136

phi – AR input argument; theta – MA input argument; cond – Belsley-Kuh-Welsch condition index; Lambda – eigenvalues of the inverse covariance matrix (the smallest is 0.0230326); REE, Mn, Ni, Br, Cu ratio – the ratio of demand to metal production.

All explanatory variables from the technological, economic, ecological, energy and raw material categories were introduced to the ARMAX model. Taking into account the optimal values of ex post error and information criteria, the ARAMX (1, 2, 2) model was finally selected. The values of the calculated indicators are presented in Table 3.

Table 3. The values of the calculated indicators

Tabela 3. Wartość wyznaczonych wskaźników

Index	Index value
Bayesian information criterion	318
Hannan Quinn information criterion	305
Akaike information criterion	303
MAE	207
RMS	252
MAPE, %	3
R2	0.99
Theil's coefficient, %	0.10

Source: own elaboration.

Explanatory variables were verified for statistical significance. Those that were identified as statistically insignificant were removed from the ARMAX model. Ultimately, twelve variables were used in the research. Their statistical significance was verified based on the value of the Student's t-statistic and the p value level. If $p \leq \alpha$, the null hypothesis of the variable significance should be rejected and the alternative hypothesis of the variable's significance should be accepted. If $p > \alpha$, there is no reason to reject the null hypothesis of non-significance. In all cases, the p value was lower than the assumed significance level alpha = 0.01 (***). The factors used in the construction of the ARMAX model are presented in Table 4.

In the last column of Table 4, the nature of the variable is specified. Four factors turned out to be destimulants, which means that their increase negatively affects the volume of wind energy production. These are:

- Increase in demand for REE, which means that REE deposits may be depleted faster than expected.
- A decline in REE production would inhibit the development of wind technology.
- CO_2 emissions, the increase of which would mean a slowdown in the development of wind energy.
- Mn/MW, the global consumption of which, unlike Cu, Br, and Ni, has been growing intensively over the last twenty years.

Table 4. ARMAX model parameters

Tabela 4. Parametry modelu ARMAX

Parameter	Parameter value	Standard error	Probability	Character of the variable
phi_1	−0.96	0.05	6.56e-089 ***	–
theta_1	−1.94	0.24	2.77e-016 ***	–
theta_2	0.99	0.22	7.47e-06 ***	–
REE/MW	–0.11	0.00	0.00 ***	destimulant
REE production, 1000 Mg	–18.30	0.03	0.00 ***	destimulant
Patents	20.97	0.03	0.00 ***	stimulant
Wind energy capacity (MW)	0.75	0.01	0.00 ***	stimulant
LCOE (USD/kWh)	76,418.7	35.82	0.00 ***	stimulant
Real GDP (EUR/capita)	1.31	0.00	0.00 ***	stimulant
Primary energy consumption (GJ/capita)	111.21	0.05	0.00 ***	stimulant
CO_2 emission (mil Mg)	–0.87	0.03	0.00 ***	destimulant
Ni/MW	210.18	0.09	0.00 ***	stimulant
br/MW	3,866,250,000	3,509,890.00	0.00 ***	stimulant
Cu/MW	14,915,700	8,148.58	0.00 ***	stimulant
Mn/MW	−1.33e+08	105,164	0.00 ***	destimulant

Source: own elaboration.

Using the ARMAX model, a wind energy forecast was then made for production until 2025, which is presented in Figure 5.

The forecast indicates that by 2025 a dynamic increase in wind energy production can be expected. Considering the influence of the explanatory variables on the volume of wind energy production, assuming that their development tendency does not change, this increase may even be 50% per year. The increase is a continuation of the trend that has been observed in the volume of wind energy production in recent years. Over a ten-year period, this production increased ten times. Because this is close to exponential growth, the model maintained this trend in the forecasts until 2025. Additionally, the growth was stimulated by explanatory variables, particularly GDP, metal consumption and LCOE. In the years 1990–2015, Poland was in second place among the EU countries in the ranking of the fastest developing countries. Over the last thirty years, Poland has achieved a GDP growth of 117% per capita (RNP 2023). PEP2040 assumes that offshore wind farms will be built in the coming years,

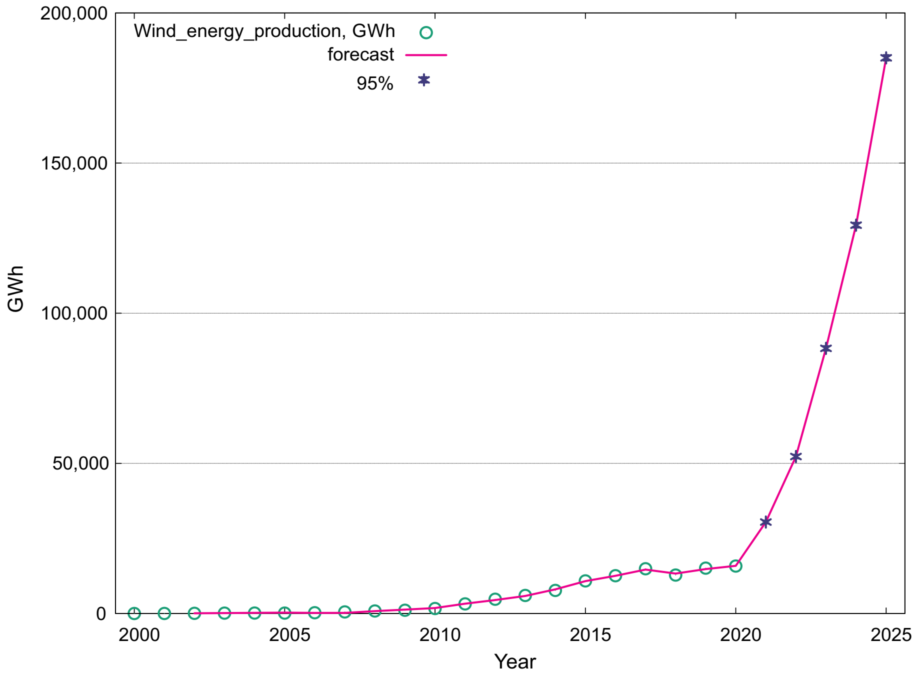

Fig. 5. ARMAX model results
Source: own elaboration

Rys. 5. Prognoza wykonana z użyciem modelu ARMAX

which provides an opportunity to maintain the trend of the increasing development of wind energy generation capacity.

It should be noted that all explanatory variables from the raw materials category were considered to be factors that have a significant impact on the volume of the production of wind energy. Copper and nickel can be obtained from deposits located in the geographical area of Poland. However, boron, manganese and, above all, REE are obtained by import. The most serious bottleneck in the green transformation of the energy systems of EU member states may be REEs. Most deposits of raw materials classified as REE are located in China, which accounts for approximately 60% of the total world production (Daigle and DeCarlo 2021), as well as the United States, Brazil, Australia, CIS countries and India (Jaroni et al. 2019). REE resources located in the EU do not even reach 0.5% of global resources; therefore, the European Union is forced to import REE. This constitutes a huge threat to the energy security of the EU, which in the future wants to base its energy mix on renewable energy sources. In the European Union, several scenarios for solving this problem are being considered. Actions have been taken to diversify the sources of REE (Kalvig and Machacek 2018). The USA will become a new source of REE in the future. They decided to increase REE extraction in order to strengthen their position on world markets, which they ceded to

China in the nineteen-eighties. Another solution may be obtaining REE from recycling and coal combustion waste (Rybak and Rybak 2021). As noted, fly ash produced from Polish coal is a rich source of REE. Additionally, this method of obtaining rare earth elements eliminates the need to exploit these raw materials and, at the same time, the associated negative impact of exploitation on the natural environment (Franus et al. 2015).

It should be remembered that factors related to social acceptance will have a huge impact on the development of wind energy in Poland. In general, wind energy is perceived as an excellent way to diversify Poland's energy mix and ensure energy security. Wind energy is perceived as accessible, free and zero-emission (Mroczek 2011). Problems with social acceptance appear at the local level when an investment is to be implemented in a specific selected location. As a result of the incorrect actions of companies erecting wind farms, turbines are associated with noise and limited visual values of the landscape (Łucki and Misiak 2011). It is necessary to undertake information and educational activities that will overcome social resistance to wind farms. Appropriate spatial planning is also important, which will enable the establishment of farms in places where they will not be in any way burdensome to the surrounding residential buildings. Another important factor is the state's policy towards renewable energy sources, in particular wind energy. The Wind Act of 2016 effectively limited investments related to wind energy. In 2023, the regulations regarding the distance of wind turbines from buildings were relaxed, but the very fact of legislative instability may affect the future investment decisions of energy companies and private investors.

Conclusions

Wind energy in Poland currently covers only 10% of the electricity demand. To meet the assumptions of the Polish Energy Policy until 2040, it is necessary to take steps that will accelerate the dynamics of wind energy development in our country. To be effective, these actions must identify factors that will have a key impact on the building potential of the wind energy generation capacity. For this purpose, the authors built a set of variables that they considered potentially relevant in the context of this development. To confirm these assumptions, they used the ARMAX (1, 2, 2) model. As a result of this, it was possible to identify statistically significant explanatory variables, i.e. factors affecting the volume of wind energy production in Poland. Using the applied method, it was also possible to determine the nature of the impact of the individual variables on the volume of wind energy production. The forecast showed that if the development trends of the factors that affect wind energy do not change, it will be possible to meet the assumptions of PEP2040 regarding the dynamic development of wind farms in Poland and double the generation capacity by 2030. Analysis using the ARMAX model showed that access to raw materials such as REE, Cu, Ni, Br, and Mn will have a very significant impact on the development of wind energy in Poland. Each factor of the raw material category of raw materials that was introduced into the model was considered statistically significant at the significance level of $\alpha = 0.01$, i.e., at the lowest acceptable risk of error. Therefore, the raw material base will be of key importance to ensure access to wind energy at the level adopted in PEP2040. This is especially true for REE, which has limited global resources and most of its imports come from China. Therefore, REE-related variables turned out to be a destimulant. This means that the growing demand for REE may pose a threat to the further development of wind farms. The destimulant is also an explanatory variable that characterizes manganese consumption. In this case, the growing global demand may hamper the development of wind energy in Poland. It should be remembered that manganese is not mined in Poland, but is imported, which may pose a threat to the development of wind energy. Poland is not the only country that in the coming years will strive to diversify the sources of electricity and thus develop renewable energy in the form of wind energy. It will be a strategy implemented both in other EU countries and in other countries around the world. As a result, access to raw materials may become increasingly difficult, and their prices may increase. Due to the great importance of critical mineral resources for the further development of wind energy and ensuring Poland's energy security, it is advisable to look for new sources of obtaining them. In the case of most of the critical raw materials necessary for the production of wind technology, it is possible to recover them from mining waste and waste produced during the coal combustion process. This applies to rare earth elements, which can be recovered from fly ash and manganese, which, for example, in the Czech Republic will be recovered from flotation tailings.

The main limitation of the research is the inability to include qualitative data in the proposed solution. The next step of the research will be the use of fuzzy sets, which will allow the analysis to include information on public opinion about the impact of wind farms on the natural environment as well as to take into account the legal factors that greatly influence the pace of development of wind energy.

Symbols

ARMAX – Autoregressive Moving Average with Exogenous Input model,
VIF – Variance Inflation Factor,
MAPE – Mean Absolute Percentage Error,
PEP2040 – Polish Energy Policy until 2040,
REE – rare earth elements,
α – significance level,
$y(t)$ – output signal sequence,
t – time,
a_i, b_j, c_k – prediction coefficients,
$e(t)$ – white noise,
$u(t)$ – input signal string,
n – predictor order,
i, j, k – lag,

R_j^2	–	determination coefficient,
$\delta\delta$	–	deterministic trend coefficient,
DF	–	Dickey-Fuller test,
BIC	–	Schwarz information criterion,
HQ	–	Hannnan-Quinn information criterion,
AIC	–	Akaike information criterion,
K	–	number of model parameters,
$L(\hat{\theta})$	–	the credibility function of the model corrected by the penalty function,
e_t	–	prediction error,
$RMSE$	–	Root Mean Square Error,
MAE	–	Mean Absolute Error,
$\hat{y}_t$	–	forecast of the dependent variable in period t,
U	–	Theil's inequality Coefficient,
Q	–	Ljung Box test,
$\hat{\rho}_k^2$	–	sample autocorrelation at lag k,
h	–	number of lags tested,
DH	–	Doornik-Hansen test,
$Z\left(\sqrt{b_1}\right)$	–	transformed sample skewness,
z_2	–	Wilson-Hilferty transformation,
$LCOE$	–	levelized cost of electricity,
p-value	–	probability of obtaining the observed results.

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REFERENCES

Akçay, H. and Filik, T. 2017. Short-term wind speed forecasting by spectral analysis from long-term observations with missing values. *Applied energy* 191, pp. 653–662, DOI: 10.1016/j.apenergy.2017.01.063.

Almorox et al. 2005 – Almorox, J., Benito, M. and Fernandez, C.H. 2005. Estimation of monthly Angström -Prescott equation coefficients from measured daily data in Toledo, Spain. *Renewable Energy* 30(6), pp. 931–936.

Alves Dias et al. 2020 – Alves Dias, P., Bobba, S., Carrara, S. and Plazzotta, B. 2020. The role of rare earth elements in wind energy and electric mobility. DOI: 10.2760/303258.

Ardente et al. 2008 – Ardente, F., Beccali, M., Cellura, M. and Brano, V. L. 2008. Energy performances and life cycle assessment of an Italian wind farm. *Renewable and Sustainable Energy Reviews* 12(1), pp. 200–217, DOI: 10.1016/j.rser.2006.05.013.

Azad et al. 2014 – Azad, H.B., Mekhilef, S. and Ganapathy, V.G. 2014. Long-term wind speed forecasting and general pattern recognition using neural networks. *IEEE Transactions on Sustainable Energy* 5(2), pp. 546–553, DOI: 10.1109/TSTE.2014.2300150.

Balaram, V. 2019. Rare earth elements: A review of applications, occurrence, exploration, analysis, recycling, and environmental impact. *Geoscience Frontiers* 10(4), pp. 1285–1303, DOI: 10.1016/j.gsf.2018.12.005.

Ballinger et al. 2020 – Ballinger, B., Schmeda-Lopez, D., Kefford, B., Parkinson, B., Stringer, M., Greig, C. and Smart, S. 2020. The vulnerability of electric-vehicle and wind-turbine supply chains to the supply of rare-earth elements in a 2-degree scenario. *Sustainable Production and consumption* 22(1), pp. 68–76, DOI: 10.1016/j.spc.2020.02.005.

Belsley et al. 1980 – Belsley, D.A., Kuh, E. and Welsh R.E. 1980. *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*. New York: John Wiley and Sons, DOI: 10.1002/0471725153.

Bianco et al. 2009 – Bianco, V., Manca, O. and Nardini, S. 2009. Electricity consumption forecasting in Italy using linear regression models. *Energy* 34(9), pp. 1413–1421, DOI: 10.1016/j.energy.2009.06.034.

Bliemel, F. 1973. Theil's Forecast Accuracy Coefficient: A Clarification. *Journal of Marketing Research* 10(4), pp. 444–46.

Blissett, R. S. and Rowson N. A. 2012. A review of the multi-component utilization of coal fly ash. *Fuel* 97, pp. 1–23, DOI: 10.1016/j.fuel.2012.03.024.

BP 2023 – *BP Statistical Review of World Energy*. [Online:] https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html [Accessed: 2023-04-05].

Burns, P. 2002. Robustness of the Ljung -Box test and its rank equivalent. *Available at SSRN 443560*.

Carrara et al. 2020 – Carrara, S., Alves Dias, P., Plazzotta, B. and Pavel, C. 2020. *Raw materials demand for wind and solar PV technologies in the transition towards a decarbonised energy system.* EUR 30095 EN, Luxembourg: Publications Office of the European Union.

Chai, T. and Draxler, R.R. 2014. Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature. *Geoscientific Model Development* 7, pp. 1247–1250, DOI: 10.5194/gmd-7-1247-2014.

COM 2023 – [Online:] COM/2023/160 https://eurlex.europa.eu/legal content/EN/TXT/?uri = CELEX%3A52023PC0160 [Accessed: 2023-07-19].

Crawford, R.H. 2009. Life cycle energy and greenhouse emissions analysis of wind turbines and the effect of size on energy yield. *Renewable and Sustainable Energy Reviews* 13(9), pp. 2653–2660, DOI: 10.1016/j.rser.2009.07.008.

Daigle, B. and DeCarlo, S. 2021. *Rare Earths and the US Electronics Sector: Supply Chain Developments and Trends*. Office of Industries, US International Trade Commission.

Darbellay, G.A. and Slama, M. 2000. Forecasting the short-term demand for electricity: Do neural networks stand a better chance? *International Journal of Forecasting* 16(1), pp. 71–83.

Domański, C. and Szczepocki, P. 2020. Comparison of selected tests for univariate normality based on measures of moments. *Statistics in Transition new series* 21(5), pp. 151–178.

EON – [Online:] https://eon.pl/dla-biznesu/firmy-i-instytucje/baza-wiedzy/artykuly/energia-wiatrowa-czym-jest-i-jak-ja-wykorzystac [Accessed: 2023-07-20] (*in Polish*).

Farina, A. and Anctil, A. 2022. Material consumption and environmental impact of wind turbines in the USA and globally. *Resources, Conservation and Recycling* 176, 105938.

Farnum, N.R. and Stanton, W. 1989. *Quantitative Forecasting Methods*. Boston: PWS-Kent Publishing Company.

Franus et al. 2015 – Franus, W., Wiatros-Motyka, M.M. and Wdowin, M. 2015. Coal fly ash as a resource for rare earth elements. *Environmental Science and Pollution Research* 22, pp. 9464-9474, DOI: 10.1007/s11356-015-4111-9.

Forbes, K.F. and Zampelli, E.M. 2019. Wind energy, the price of carbon allowances, and CO_2 emissions: Evidence from Ireland. *Energy Policy* 133, DOI: 10.1016/j.enpol.2019.07.007.

Geoportal 2023 – [Online:] http://geoportal.pgi.gov.pl/css/surowce/images/2021/bilans_2021.pdf [Accessed: 2023-11-10].

Gil et al. 2010 – Gil, A., De La Torre, M., Domínguez, T. and Rivas, R. 2010. *Influence of wind energy forecast in deterministic and probabilistic sizing of reserves*. [In:] *9th International Workshop on Large-Scale Integration of Wind Power Into Power Systems As Well As on Transmission Networks for Offshore Wind Power Plants*. Quebec, 18–19 October 2010.

Greco et al. 2011 – Greco, A., Mistry, K., Sista, V., Eryilmaz, O. and Erdemir, A. 2011. Friction and wear behavior of boron based surface treatment and nano-particle lubricant additives for wind turbine gearbox applications. *Wear* 271(9–10), pp. 1754–1760, DOI: 10.1016/j.wear.2010.11.060.

GS 2023 – [Online:] https://www.goldmansachs.com/intelligence/pages/gs-research/green-capex-greenflation-returns-and-opportunity/report.pdf [Accessed: 2023-11-10].

Ha et al. 2019 – Ha, S., Tae, S. and Kim, R. 2019. Energy demand forecast models for commercial buildings in South Korea. *Energies* 12(12), DOI: 10.3390/en12122313.

Hickey et al. 2012 – Hickey, E., Loomis, D.G., and Mohammadi, H. 2012. Forecasting hourly electricity prices using ARMAX-GARCH models: An application to MISO hubs. *Energy Economics* 34(1), pp. 307–315, DOI: 10.1016/j.eneco.2011.11.011.

Huang et al. 2011 – Huang, C.Y., Liu, Y.W., Tzeng, W.C., and Wang, P.Y. 2011. *Short term wind speed predictions by using the gray prediction model based forecast method*. [In:] *IEEE Green Technologies Conference (IEEE-Green)* (pp. 1–5).

IBM 2023 – [Online:] https://www.ibm.com/docs/pl/spss-statistics/29.0.0?topic = sales-collinearity-diagnostics [Accessed: 2023-11-15].

Imholte et al. 2018 – Imholte, D.D., Nguyen, R.T., Vedantam, A., Brown, M., Iyer, A., Smith, B.J., Collins, J.W., Anderson, C.G. and O'Kelley, B. 2018. An assessment of US rare earth availability for supporting US wind energy growth targets. *Energy Policy* 113, pp. 294–305, DOI: 10.1016/j.enpol.2017.11.001.

Jaroni et al. 2019 – Jaroni, M.S., Bernd, F. and Peter, L. 2019. Economical feasibility of rare earth mining outside China. *Minerals* 9(10), DOI: 10.3390/min9100576.

Kalvig, P. and Machacek, E. 2018. Examining the rare-earth elements (REE) supply–demand balance for future global wind power scenarios. *GEUS Bulletin* 41, pp. 87–90, DOI: 10.34194/geusb.v41.4350.

Kamani, D. and Ardehali, M.M. 2023. Long-term forecast of electrical energy consumption with considerations for solar and wind energy sources. *Energy* 268, DOI: 10.1016/j.energy.2023.126617.

KGHM 2021 – [Online:] https://kghm.com/pl/wstepne-wyniki-produkcyjne-i-sprzedazowe-grupy-kghm-polska-miedz-sa-za-grudzien-2021-r [Accessed: 2023-11-11].

Kramer, O., and Gieseke, F. 2011. *Short-term wind energy forecasting using support vector regression*. [In:] *Soft computing models in industrial and environmental applications. 6th International Conference SOCO 2011*. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 271–280.

Kufel, T. 2004. *Econometrics. Solving problems using the Gretl program* (*Ekonometria. Rozwiązywanie problemów z wykorzystaniem programu GRETL*). Warszawa: PWN (*in Polish*).

Kumari, S.S. 2008. Multicollinearity: Estimation and elimination. *Journal of Contemporary research in Management* 3(1), pp. 87–95.

Lee, C.K. 2008. Corrosion and wear-corrosion resistance properties of electroless Ni-P coatings on GFRP composite in wind turbine blades. *Surface and Coatings Technology* 202(19), pp. 4868–4874, DOI: 10.1016/j.surfcoat.2008.04.079.

Li et al. 2022– Li, C., Mogollón, J. M., Tukker, A., Dong, J., von Terzi, D., Zhang, C. and Steubing, B. 2022. Future material requirements for global sustainable offshore wind energy development. *Renewable and Sustainable Energy Reviews* 164, DOI: 10.1016/j.rser.2022.112603.

Mehedintu et al. 2018 – Mehedintu, A., Sterpu, M. and Soava, G. 2018. Estimation and forecasts for the share of renewable energy consumption in final energy consumption by 2020 in the European Union. *Sustainability* 10(5), DOI: 10.3390/su10051515.

Mesa-Jiménez et al. 2023 – Mesa-Jiménez, J.J., Tzianoumis, A.L., Stokes, L., Yang, Q., and Livina, V.N. 2023. Long-term wind and solar energy generation forecasts, and optimization of Power Purchase Agreements. *Energy Reports* 9(2), pp. 292–302, DOI: 10.1016/j.egyr.2022.11.175.

Miles, J. 2014. *Tolerance and variance inflation factor*. DOI: 10.1002/9781118445112.STAT06593.

Niu, M. and Li, G. 2022. The Impact of Climate Change Risks on Residential Consumption in China: Evidence from ARMAX Modeling and Granger Causality Analysis. *International Journal of Environmental Research and Public Health* 19(19), DOI: 10.3390/ijerph191912088.

Paul, R.K. 2006. *Multicollinearity: Causes, effects, and remedies.* IASRI, New Delhi 1(1), pp. 58–65.

PEP 2040 – The Energy Policy of Poland until 2040. [Online:] https://www.gov.pl/web/klimat/polityka-energetyczna-polski [Accessed: 2023-0401].

Piłatowska, M. 2010. Information Criteria in Model Selection (*Kryteria informacyjne w wyborze modelu ekonometrycznego*). *Studies and Works of the Cracow University of Economics* 10, pp. 25–37. (*in Polish*).

Ren et al. 2021 – Ren, K., Tang, X., Wang, P., Willerström, J. and Höök, M. 2021. Bridging energy and metal sustainability: insights from China's wind power development up to 2050. *Energy* 227, DOI: 10.1016/j.energy.2021.120524.

RNP 2023. [Online:] https://zpp.net.pl/wpcontent/uploads/2023/07/14.07.2023-Raport-ZPP-1992-2022.-Najlepszy-czas-Polski.pdf [Accessed: 2023-04-10].

Rybak, A. and Rybak, A.2021. Characteristics of some selected methods of rare earth elements recovery from coal fly ashes. *Metals* 11(1), DOI: 10.3390/met11010142.

Safi, S. and Zeroual, A. 2002. Prediction of global daily solar radiation using higher order statistics. *Renewable Energy* 27(4), pp. 647–666, DOI: 10.1016/S0960-1481(01)00153-7.

Schader et al. 2003 – Schader, M., Gaul, W.A. and Vichi, M. 2003. *Between Data Science and Applied Data Analysis.* Proceedings of the *26th Annual Conference of the Gesellschaft für Klassifikation*, Springer Berlin.

Shabbir et al. 2019 – Shabbir, N., AhmadiAhangar, R., Kütt, L., Iqbal, M.N. and Rosin, A. 2019. *Forecasting short term wind energy generation using machine learning*. [In:] *IEEE 60th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON)* (pp. 1–4). IEEE.

Shammugam et al. 2019 – Shammugam, S., Gervais, E., Schlegl, T. and Rathgeber, A. 2019. Raw metal needs and supply risks for the development of wind energy in Germany until 2050. *Journal of Cleaner Production* 221(9), pp. 738–752, DOI: 10.1016/j.jclepro.2019.02.223.

Tao et al. 2022 – Yue Tao, Lu Shen, Chong Feng, Rongyi Yang, Jianhua Qu, Hanxun Ju, Ying Zhang. 2022. Distribution of rare earth elements (REEs) and their roles in plant growth: A review. *Environmental Pollution* 298, DOI: 10.1016/j.envpol.2021.118540.

USAID 2021 – [Online:] https://www.land-links.org/wp-content/uploads/2021/11/USAID_GM_Manganese.pdf [Accessed: 2023-07-25].

Verma et al. 2022 – Verma, S., Paul, A.R. and Haque, N. 2022. Assessment of materials and rare earth metals demand for sustainable wind energy growth in India. *Minerals* 12(5), DOI: 10.3390/min12050647.

Wetherill et al. 1986 – Wetherill, G.B., Duncombe, P., Kenward, M., Köllerström, J., Paul, S.R., Vowden, B.J. and Vowden, B.J. 1986. Heteroscedasticity and serial correlation. *Regression Analysis with Applications*, pp. 199–214.

Willmott, C.J. and Matsuura, K. 2005. Advantages of the Mean Absolute Error (MAE) over the Root Mean Square Error (RMSE) in Assessing Average Model Performance. *Climate Research* 30(1) , pp. 79–82, DOI: 10.3354/cr030079.

Witkowska-Kita et al. 2016 – Witkowska-Kita, B., Blaschke, W., Biel, K. and Orlicka, A. 2016. Management of the Non-Energy Raw Materials in Poland; Critical, Strategic and Deficit Natural Resources (*Gospodarka surowcami nieenergetycznymi w Polsce – surowce mineralne krytyczne, strategiczne i deficytowe*). *Przegląd Górniczy* 72(3), pp. 76–84 (*in Polish*).

Yousefi et al. 2019 – Yousefi, H., Abbaspour, A. and Seraj, H. 2019. Worldwide development of wind energy and co2 emission reduction. *Environmental Energy and Economic Research* 3(1), pp. 1–9, DOI: 10.22097/EEER.2019.164295.1064.

THE IMPACT OF SELECTED FACTORS AND ACCESS TO MINERAL RESOURCES ON THE DEVELOPMENT OF WIND ENERGY IN POLAND

Keywords

wind energy, ARMAX model, forecasting, rare earth metals

Abstract

This article presents the results of research on the importance of access to critical raw materials for the development of wind energy in Poland. The authors have built a set of factors that can potentially influence this development. Twenty-four explanatory variables were taken into account, which were assigned to five categories. The amount of demand for mineral resources related to the development of wind technology was determined using a computer programwritten by the authors. The importance of individual factors was verified using the ARMAX model. As a result of this, it was possible to identify the explanatory variables that significantly affect the volume of wind energy production in Poland. The group of mineral resources includes critical metals that are necessary for the production of wind turbines. These are rare earth elements, copper, nickel, boron and manganese. The ARMAX model enables the examination of the relationship between the explained variable and the explanatory variables. Optimization of the model parameters was performed by limiting the mean square error. During the validation of the model, the VIF (variance inflation factor), Dickey-Fuller and Doornik-Hansen tests were used. The ARMAX validation also consisted of selecting the model characterized by the lowest value of information criteria and determining ex post errors, including the mean absolute percentage error (MAPE). In addition, the nature of individual independent variables was determined, i.e. whether they were stimulants, nominants, or destimulants. The forecast made it possible to verify the possibility of meeting the assumptions of the Polish Energy Policy until 2040. It showed that if the development trends of the factors that affect wind energy do not change, it would be possible to meet the assumptions of PEP2040 regarding the dynamic development of wind farms in Poland and double the generation capacity by 2030. Analysis using the ARMAX model showed that access to raw materials such as REE, Cu, Ni, Br and Mn would have a very significant impact on the development of wind energy in Poland. Each factor of the raw material category that was introduced into the model was considered statistically significant at the significance level of $\alpha = 0.01$, i.e. at the lowest acceptable risk of error. Therefore, the raw material base would be of key importance to ensure access to wind energy at the level adopted in PEP2040.

WPŁYW WYBRANYCH CZYNNIKÓW I DOSTĘPU DO SUROWCÓW MINERALNYCH NA ROZWÓJ ENERGETYKI WIATROWEJ W POLSCE

Słowa kluczowe

energia wiatrowa, model ARMAX, prognozowanie, metale ziem rzadkich

Streszczenie

W artykule zaprezentowano wyniki badań dotyczących znaczenia dostępu do surowców krytycznych dla rozwoju energetyki wiatrowej w Polsce. Autorzy zbudowali zbiór czynników, które potencjalnie mogą wpływać na ten rozwój. Pod uwagę wzięto 24 zmienne objaśniające, które przyporządkowano do pięciu kategorii. Wielkość zapotrzebowania na surowce mineralne w danym roku związane z rozbudową technologii wiatrowej wyznaczono z wykorzystaniem programu napisanego przez autorów. Znaczenie poszczególnych czynników zostało zweryfikowane z wykorzystaniem modelu ARMAX. Dzięki temu możliwe było wskazanie tych zmiennych objaśniających, które istotnie wpływają na wielkość produkcji energetyki wiatrowej w Polsce. Do grupy surowców mineralnych zaliczono metale krytyczne, które są niezbędne do wytwarzania turbin wiatrowych. Są to pierwiastki ziem rzadkich, miedź, nikiel, bor, mangan. Model ARMAX pozwala na zbadanie związku zmiennej objaśnianej ze zmiennymi objaśniającymi. Optymalizacja parametrów modelu była prowadzona na drodze ograniczania wielkości błędu średniokwadratowego. Podczas walidacji modelu posłużono się współczynnikiem VIF – variance inflation factor, testami Dickeya-Fullera oraz Doornika-Hansena. Walidacja ARMAX polegała także na wyborze modelu, których charakteryzuje najniższa wartość kryteriów informacyjnych oraz na wyznaczeniu błędów ex post między innymi błędu Mean Absolute Percentage Error (MAPE). Dodatkowo określono charakter poszczególnych zmiennych niezależnych, czyli ustalono czy są one stymulantami, nominantami, czy destymulantami. Wykonana prognoza umożliwiła zweryfikowanie możliwości spełnienia założeń Polityki Energetycznej Polski do 2040 roku. Prognoza wykazała, że jeśli nie zmienią się trendy rozwojowe czynników wpływających na energetykę wiatrową, możliwe będzie spełnienie założeń PEP2040 dotyczących dynamicznego rozwoju farm wiatrowych w Polsce i podwojenia mocy wytwórczych do 2030 roku. Analiza z wykorzystaniem modelu ARMAX pokazała, że dostęp do surowców takich jak REE, Cu, Ni, Br i Mn będzie miał bardzo istotny wpływ na rozwój energetyki wiatrowej w Polsce. Każdy czynnik kategorii surowców wprowadzony do modelu uznano za istotny statystycznie na poziomie istotności $\alpha = 0{,}01$, czyli przy najniższym akceptowalnym ryzyku popełnienia błędu. Dlatego baza surowcowa będzie kluczowa dla zapewnienia dostępu do energetyki wiatrowej na poziomie przyjętym w PEP2040.