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Forecasting the Development of Offshore Wind Energy in Poland in the Context of the Energy Transformation and Sustainable Development Goals

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Abstract

This article presents the results of research on the potential development of offshore wind energy in Poland. Wind energy generated in offshore farms is intended to be the second pillar (alongside nuclear power) of Poland's energy transition, creating the foundation for a zero-emission energy system. The authors constructed a neural network that allowed them to forecast the development of the installed offshore energy capacity for Poland by 2030. For this purpose, the factors that have the greatest impact on the development of wind energy in Poland were identified. This knowledge will facilitate the development of state policy consistent with the Sustainable Development Goals (SDGs) and the European Green Deal. Since Poland currently does not have installed offshore wind energy capacity, Germany was used as a benchmark to train the model. The research results fill the identified gap: to date, forecasts of offshore development in Poland based on a model trained on German data have not been presented in the literature. The research results show that by 2030, Poland can achieve the goals set by the United Nations, the European Union, and the Polish Energy Policy 2040 (PEP2040). The PEP2040 assumes that Poland should have 5.9 GW of energy installed in offshore wind farms in the Baltic Sea by 2030. The forecast indicates that this will be approximately 5.3 GW, with the difference between these values remaining within the model's margin of error.

Keywords: offshore wind energy; LSTM model; SVR model; energy transition

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1. Introduction

The United Nations Agenda for Sustainable Development and the Sustainable Development Goals (SDGs), adopted in 2015, provide guidelines for member states on the path to developing stable economies that guarantee a prosperous life for their populations and eliminate all forms of poverty and inequality. However, in striving to achieve the SDGs, countries must consider a key aspect, which is climate protection. There are 17 SDGs, and one of them is Goal 7: Ensure access to affordable, reliable, sustainable and modern energy for all [1,2]. Achievement of Goal 7 is to be accomplished by increasing the share of renewable energy sources, developing clean energy infrastructure, and cooperating with

UN member states in order to exchange knowledge and technology. This goal is consistent with the energy transition guidelines in force in the EU. Transformation in the EU is being implemented through a number of acts, primarily the European Green Deal [3,4], the Fit for 55 package, including the Radio Equipment Directive (RED) [5,6], and the REPowerEU Plan [7]. These assume achievement of climate neutrality by 2050, reducing emissions by 55% by 2030, and increasing the share of renewable energy sources in EU countries' energy mixes to 45% by 2030. Wind energy is expected to play a key role in the energy transition process, replacing energy from fossil fuels, including those imported from the Russian Federation. Particular optimism is associated with offshore wind energy, where the EU is already a leader. Offshore wind farms are perceived as sustainable resources that do not generate public resistance. The development of offshore wind energy in the EU is expected to be further accelerated by focusing on developing transmission networks and simplifying the issuance of permits for their construction [8]. The Fit for 55 package presents offshore wind energy as a means of achieving the EU CO_2 emission reduction targets. The development of wind energy in the Baltic Sea will be of particular importance [9].

In Poland, the implementation of the SDGs and the energy transition is being carried out according to the documents mentioned above. The national document guiding the energy transition is the Polish Energy Policy until 2040 (PEP2040) [10,11]. This document also presents renewable energy as a key element of developing a low-emission economy, ensuring energy security, and thus fulfilling commitments to the EU and the United Nations. PEP2040 identifies solar and wind energy as the main sources of renewable energy. Wind energy is divided into two sectors: offshore wind and onshore wind. Onshore wind energy is expected to continue to grow in Poland, but it is assumed that this growth will be moderate. However, offshore wind farms are considered particularly important for the growth of renewable energy in Poland's energy generation structure due to the greater potential of strong and stable winds in the Baltic Sea [12]. Offshore energy also benefits from the favorable location, the limited public resistance, and the lack of problems with wind turbine proximity to buildings. In Poland, wind turbine proximity to buildings has been controversial, and the Distance Act and the 10H rule have significantly slowed the development of onshore energy since 2016.

Offshore wind energy is expected to be the second pillar (alongside nuclear energy) of Poland's energy transition, forming the basis for a zero-emission energy system. It is assumed that a key element of this transition is the building of an offshore wind farm capacity with an installed capacity of approximately 6 GW by 2030 and 11 GW by 2040 [10,13]. To confirm these assumptions, it is necessary to build a reliable mathematical model, but the literature on the subject lacks such studies. Therefore, in this article, the authors present a methodology to forecast the development of the installed offshore wind energy capacity by 2030. Research was carried out in the following steps:

- Determination of a set of explanatory variables that may influence the development of wind energy in Poland and data standardization.
- Verification of the set, selection of those variables whose statistically significant influence was confirmed using multiple regression.
- Selection of a benchmark for Poland. Since Poland currently has no installed capacity in offshore farms, it was necessary to select a set of data on which the forecasting model could be trained.
- Application of the support vector regression (SVR) machine learning model to forecast explanatory variables regarding Poland until 2030.
- Introduction of explanatory variables for the benchmark and Poland into the LSTM model.
- Construction of an LSTM model and training it on data from Germany.

- Introduction of a set of explanatory variables into the LSTM model and creation of a forecast for the installed capacity of Poland until 2030.
- Model verification, determination of error metrics, and analysis of model residuals.
- Creation of a forecast for the development of installed offshore energy capacity until 2030.

2. Literature Review

Poland began developing its installed wind energy capacity in 2001. By 2024, it had installed wind energy capacity on 1400 onshore farms [14]. Capacity growth in Poland was often slowed by legislative changes and modifications of wind energy financing programs [15]. Until 2016, the wind energy sector was developing dynamically, but there was no comprehensive renewable energy development strategy that precisely defined the grid development, connections, and farm locations. The primary mechanism to support the development of renewable energy was based on green certificates [16], whose price drops negatively affected the profitability of planned investments. In 2016, the Wind Energy Investment Act was introduced. It included very detailed and inflexible provisions regulating the distance of wind turbines from residential buildings [17]. This distance was to be at least ten times the height of the wind turbine. This led to a slowdown in the development of onshore wind farms in Poland. Those that were built were often approved before the aforementioned act came into force. Further impetus for the development of wind farms came from the amendment of the act in 2023 and the changes scheduled for 2025. The possibility of implementing investments was to be regulated by municipalities, which ultimately had the power to decide on their spatial development plans.

The largest number of offshore wind farms in Poland are located in the West Pomeranian Voivodeship (2188 MW) and the Pomeranian Voivodeship (1326 MW) [18]. This is due to several factors, primarily favorable wind conditions. Therefore, coastal zones are classified as Zone I in the five-zone division of Poland and are defined as exceptionally favorable because the typical wind speeds are in the range of 10–25 km/h. These speeds guarantee high turbine productivity, while being safe for the equipment. Access to open spaces, sparsely populated areas, developed transmission grid, and the support of local authorities also support the development of wind energy. The problems that have so far slowed its development in Poland can be solved by building offshore wind farms. Poland is in a privileged position in this regard, as it has access to the Baltic Sea, which along with the North Sea, is expected to become the main location for wind energy production in the EU. The Baltic Sea enjoys favorable conditions, mainly higher wind speeds than on land, averaging around 10 m/s [19], a favorable wind direction, and a favorable average water depth of 42 m. Construction of the first offshore wind farm in Poland, Baltic Power, began in 2024 [20], and its commissioning is planned for 2026. Ultimately, it is expected to deliver more than 1 GW of energy from 100 turbines. Subsequent projects to be implemented in the coming years include Baltic I, II, and III. Their combined capacity is expected to be 3 GW, with the first turbines scheduled to be commissioned in 2027. The first stage of the Baltica project is also scheduled to be completed the same year. Ultimately, the farm is expected to have a capacity of 2.5 GW by 2030 [21].

Knowledge about the future development of offshore wind energy will be crucial for shaping Poland's energy mix. Determining the expected installed capacity in the coming years will allow effective planning of the country's energy strategy. This strategy must consider the ability to ensure energy security while also addressing the EU climate goals and sustainable development guidelines. A credible offshore wind farm development plan will help potential investors in making their strategic decisions about participating in the projects. Such strategic decisions require reliable data on which to base decisions with long-term consequences. Local governments must also be adequately prepared to allow the construction of offshore wind farms in line with their established strategies. This requires appropriate spatial planning, the designation of areas for potential investors, the preparation of ports, and the training of officials to support the management of the energy transition. The development of wind energy in the Baltic Sea will also require access to qualified personnel, who will first provide the foundation for the construction of potential investments and ensure the maintenance and repair of the most trouble-free infrastructure. The presence of such specialists in the labor market also requires planning, educational institutions preparing appropriate study and vocational training profiles, and research centers preparing them to carry out work on wind technology. Educating the public, especially local communities, in areas where technology is to be implemented is also invaluable. Citizens must be aware of both the potential threats and the consequences of wind farm construction and the benefits they will bring. The more such positive outcomes of introducing offshore wind farms into the energy mix can be demonstrated to citizens, the less resistance they will have to such a change. The main advantages include affordable clean energy, reduced emissions of substances harmful to human health and the environment, energy security in terms of access to energy when needed, in the required quantity and at an acceptable price, and the tax impact of wind companies on municipal budgets and new jobs. The disadvantages that local communities may perceive in using offshore wind farms are significantly limited compared to onshore wind farms. The farms are far enough from the coastline (usually 30 km) that they do not disturb the landscape, and the community will not be affected by the turbine noise. However, it is important to remember that resistance in this case can arise from ignorance, so public education will play a key role.

All these activities, however, require knowledge acquired well in advance, which will allow the preparation of financial resources, land, infrastructure, specialists, and a positive public attitude toward the implementation of offshore wind farms. To build forecasts for offshore wind farms in Poland, it is necessary to use a benchmark. This will enable training of the forecasting model on data from the model country and then generation of predictions using explanatory variables specific to Poland. Germany was chosen as the representative country that would serve as a reference point for Poland. Germany has followed a long path in implementing renewable energy sources, which began in the late 1980s. In 1991, their development was accelerated by the Stromeinspeisungsgesetz, which aimed to support and promote the development of renewable energy sources [22]. Then, in 2000, the German parliament established a plan to change the energy mix, from which nuclear energy was to be phased out and replaced by renewable energy. The Erneuerbare-Energien-Gesetz Act (EEG) introduced additional support mechanisms for renewable energy, including wind energy. It was amended several times. The 2014 version modified the subsidy mechanism for renewable sources, but wind energy, especially offshore wind energy, remained a priority in the energy development support mechanism [23]. In 2017, WindSeeG [24] came into force, regulating the development of offshore installations until 2045. Its immediate goal is to increase the share of offshore energy in three stages: 30 GW by 2030, 40 GW by 2035, and 70 GW by 2045. Power lines are to be developed simultaneously with farms, requiring coordination of the permitting process, installation planning, and commissioning. All legal actions taken have been translated into concrete achievements. The first offshore wind farm in Germany was built in the North Sea and launched in 2010. It consisted of 12 turbines with a total capacity of 60 MW. Currently, Germany leads the EU in the development of offshore wind energy, with 32 farms [25], consisting of more than 1000 turbines in the North Sea, with a total capacity of 7.4 GW. The annual growth in the generation capacity is over 20%. The first German Baltic Sea wind farm, Baltic 1, was built in 2011, and currently there are six farms with a capacity of 1.5 GW. By 2024, 34% of offshore wind farms in the EU were installed in Germany [26,27]. Germany's energy strategy assumes that offshore wind farms are to be one of the pillars of the energy transition, and it should be remembered that by 2030, 80% of Germany's energy is to come from renewable sources. Therefore, Germany was assumed to represent the most adequate model for offshore wind energy development in Poland, and therefore, data from this country can be used to train a forecasting model. Numerous studies have been conducted on forecasting wind energy production [28] and installed wind energy capacity [29]. Wind energy has been forecasted in many ways, including long-term forecasts [30], annual forecasts [31], immediate–short-term forecasts with a horizon of up to 8 h, and short-term forecasts, where forecasts are prepared for a single day [32]. Forecasts can also be divided according to the methodology used, including deterministic, which considers weather data such as atmospheric pressure, temperature, and wind speed [33]. Statistical and mixed models are also used. The statistical approach is based on historical data; for example, the volume of energy production without taking into account weather data [34]. Various mathematical models have been used to forecast wind energy, including simple models, such as linear and nonlinear regression models [35–37], ARIMA models [38], Kalman filter [39], ARCH [40], and fuzzy logic [41], and machine learning models, such as the SVM model [42] and neural networks in various forms [43]; for example, multi-layer perceptron (MLP) [44], back propagation neural network (BPNN) [45], generalized regression neural network, deep neural network DNN [46], convolutional neural network [47], deep belief network (DBN) [48] and the long short-term memory (LSTM) model [49,50], which is a recurrent neural network model developed in 1997 during one of the booms in artificial intelligence development. It is one of the deep learning models.

Deep learning is a subset of machine learning. It uses neural networks modeled on the human brain, which allows these models to learn [51]. Deep learning models (DNNs) [52] mainly include recurrent neural networks (RNNs) [53], convolutional neural networks (CNNs) [54], and feedforward neural networks (FNNs) [55]. CNNs enable the analysis of temporal data, while RNNs analyze time series and sequential data [56]. FNN models are characterized by a simple structure. They are suitable for analyzing statistical data but not time series. FNNs can also be susceptible to overfitting, lack sequential memory, and face the vanishing gradient problem [57]. RNN models allow for the analysis of temporal dependencies and hidden state transfer [58]. They are flexible and can be applied to data with different sequences [59]. The main drawback of these models is the difficulty of capturing very-long-term dependencies, which has been addressed in the case of LSTM models, which require a large amount of memory and computational power when analyzing long sequences [60]. In the case of CNN models, their construction can be simplified due to weight sharing [61]. Trained on large datasets, they can be used to analyze new datasets with limited data (fine-tuning) [62]. However, CNN models require a large amount of labelled data to avoid overfitting [63]. Training a model with multiple layers also requires large amounts of memory and time [64]. The LSTM model is a special type of RNN. The model was built to eliminate the phenomenon of exploding and vanishing gradients, a fundamental problem for RNNs. A special mechanism of memory cells and LSTM gates allows the model to store information in multiple time steps, allowing it to represent long-term dependencies. These gates store only important data, so the model acts as a filter, eliminating random and momentary data variations. The LSTM model has been used successfully in various industries, including medicine [65], economics, finance [66], music [67], and even energy [68,69]. The model is extremely versatile, particularly when it comes to forecasting wind energy. It allows for forecasting hourly, daily, and weekly production, as well as the expansion of the installed capacity over a yearly horizon.

The literature offers numerous examples that compare the LSTM model with classical statistical models, such as the ARIMA model. The forecasts constructed using the LSTM model were found to achieve RSME errors up to 87% lower than those of the ARIMA model [70]. A comparison of the LSTM model with the artificial neural network (ANN) model also indicates its advantage, with the mean absolute percentage error (MAPE) errors being 15% lower [71,72].

Due to the abovementioned advantages, the authors used the LSTM model to forecast the installed capacity of offshore wind farms for the next 5 years, that is, until 2030.

The discussion on offshore energy in Poland conducted so far has focused mainly on social aspects [73], economic aspects [74], public opinion on offshore energy [75], wind energy production volumes in offshore farms [76], challenges for wind energy development in light of PEP2040 [77], legislative aspects [78], and, for example, the characteristics of competitiveness and uncertainty in the production of hydrogen from wind energy [79]. The modeling proposed by the authors was intended to fill a gap in the scientific literature on the forecasts of the installed wind energy capacity in Poland. The literature contains numerous studies on forecasting installed wind energy capacity, but there is a lack of research using transfer learning for Poland, that is, training a neural network model on data from a country with mature offshore infrastructure. The methods used in the current research are presented below.

3. Methods

The analysis utilized a Java program written by the authors, consisting of the following modules: multiple regression, LSTM, SVR model, and model validation and verification module. The deeplearning4j, Weka, and Apache libraries were used.

Before building the forecasting models, explanatory variables were selected. For this purpose, multiple regression was used, as described by the following formula:

$$z = \beta_0 + \beta_1 x_1 + \cdots + \beta_i x_i + \varepsilon \tag{1}$$

where:

β_i—regression coefficient,

ε—variable random,

x_i—explanatory variables.

The regression coefficients β_i indicate the direction and strength of the influence of the explanatory variable on the dependent variable. However, to verify the statistical significance of the parameters, it is necessary to conduct a Student's *t*-test, which verifies the following hypothesis:

$H_0 : \beta_i = 0$, which means that the x_i variable has no significant effect on the explained variable and the alternative hypothesis $H_1 : \beta_i \neq 0$, which means that the variable has a significant effect on the explained variable. The test statistic is described by the following formula [80]:

$$t_i = \frac{\hat{\beta}_i}{SE(\beta_i)} \tag{2}$$

where:

$\hat{\beta}_i$—estimator,

SE—standard error.

Based on the test statistic, a *p*-value is determined and compared with the significance level $\alpha = 0.05$. If p is greater than α, there is no basis for rejecting the null hypothesis, which means that the effect is insignificant.

Selected based on the β_i values, x_i were fed into an LSTM model [81]. The LSTM model is composed of cells (blocks) that process the input data. Each cell contains an input, output, and forget gate. The cells are connected recursively. A cell simultaneously processes the input signal and the output from the previous instant from the other connected cells. If the information is no longer useful in the forecasting process, it is removed by the forget gate:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{3}$$

The current signal and the previous output signal at time $t-1$ are multiplied by a weight matrix at the gate and added as bias. This result is processed by a sigmoid activation function. A computational result close to 0 results in the information being forgotten. A result close to or equal to 1 leads to the information being retained for further computation.

The input gate allows information to be added to a state cell. The sigmoid function regulates the information, and the tanh function creates an output vector containing values between -1 and 1. The regulated values and the vector are multiplied, yielding only useful information in subsequent steps. The input gate is described by the following formula:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{4}$$

The output gate generates a vector of values using the tanh function. The sigmoid function filters the information, retaining what will be remembered. The results of the vector and function are then multiplied. The result obtained serves as an output and input for subsequent cells.

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

where:

$b_{o,i,f}$—bias with the forget gates,

$[h_{t-1}, x_t]$—the combination of the current input and the previous hidden state,

$W_{o,i,f}$—weight matrix associated with the forget gates,

σ—sigmoid activation function.

The cell state is updated according to the following equation:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C}_t \tag{6}$$

The data input into the LSTM model also had to be forecasted to enable forecasts of the installed capacity in Poland by 2030. For this purpose, the SVR model was used [82]. Figure 1 presents a block diagram of the forecasting process.

The model is designed to determine a function f(x) that is simple and well fitted to the processed data. The SVR model uses an insensitive loss function that allows the building of simple and noise-resistant regression functions [83]. The SVR model solves the following optimization problem [84,85]:

$$\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{7}$$

SVR model limitations:

$$y_i - \langle w, \phi(x_i)\rangle - b \le \varepsilon + \xi_i, \langle w, \phi(x_i)\rangle + b - y_i \le \varepsilon + \xi_i^*, \xi_i, \xi_i^* \ge 0,\ i = 1, \ldots, n. \tag{8}$$

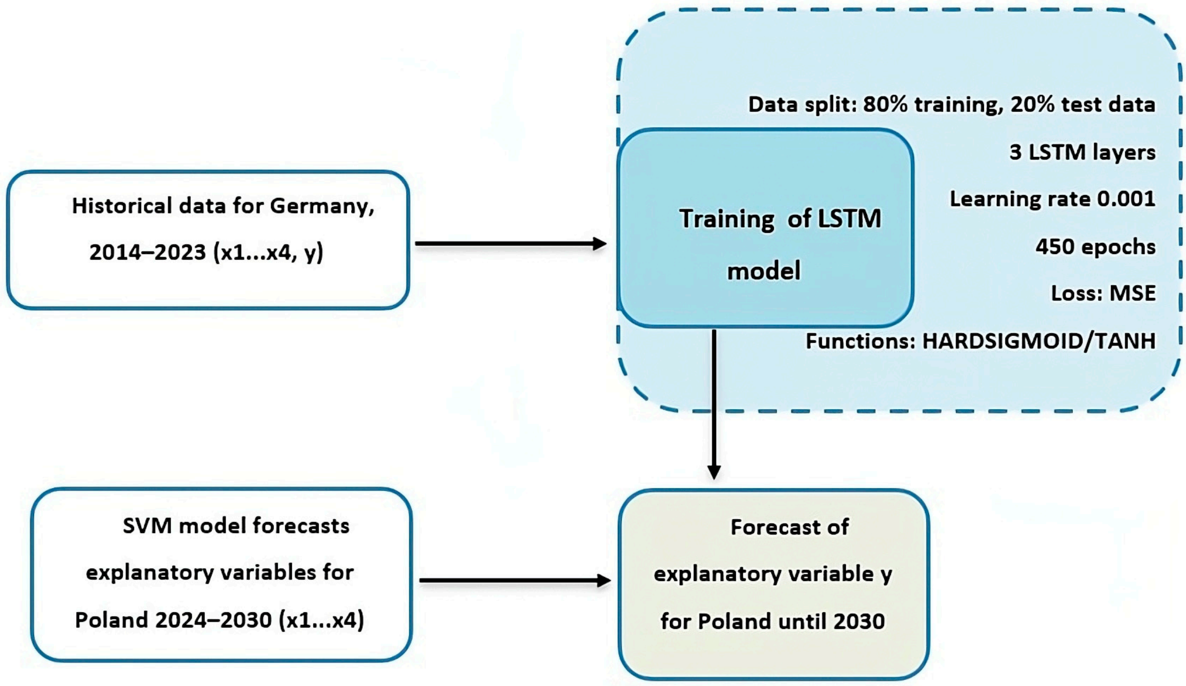

Figure 1. Block diagram of the forecasting process.

The regression function has the following form:

$$f x = w^T \phi x + b \tag{9}$$

where:

w—coefficient vector in the feature space,
ϕx—kernel function to map input x to a vector in the feature space,
b—intercept,
C—hyperparameter C,
T—transposition,
ξ_i, ξ_i^*—slack variables.

Mean error analysis was performed for the forecasts obtained by the models. The absolute error (MAE) [86], the root mean square error (RMSE) [87], and the MAPE [88] were determined according to the following formulas:

$$\text{MAE} = \frac{\sum_{i=1}^{n} |e_t|}{n} \tag{10}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} e_t^2}{n}} \tag{11}$$

$$\text{MAPE} = \frac{\sum_{i=1}^{n} |e_t / y_t|}{n} \tag{12}$$

where:

n—number of observations,
y_t—value of the dependent variable in period t,
e_t—error forecasts.

4. Results

The research began by compiling a set of statistical data on the explanatory variables. Factors that could influence the demand for wind energy were identified. These variables were determined through a literature analysis. Energy prices directly shape the break-even point for investments [89]. The levels of household income will shape their ability to accept the costs of energy transformation [90]. In turn, GDP levels influence the state's ability to invest in the development of renewable energy [91]. Decreasing the investment costs for wind energy increases the profitability of projects and stimulates the development of this sector. CAPEX is decreasing due to technological progress, which results in decreasing kWh costs [92]. Rare earth elements are a key factor influencing the development of wind technology, both financially and logistically. The limited resources of these critical metals can reduce turbine production volumes [93]. Energy efficiency stimulates innovation in the energy sector and increasing efficiency justifies investments in modern technologies [94]. Import dependence is a significant factor in the development of renewable energy. Countries are willing to invest in measures that reduce import dependence and increase energy security [95]. The growing consumption of primary and renewable energy determines the pace of renewable energy development [96]. The number of patents for renewable energy stimulates the development of renewable energy, and the development of renewable energy stimulates innovation [97]. Wind energy directly results in a reduction in greenhouse gas emissions [98]. Public spending on environmental protection favors the development of renewable energy and also indicates political priorities and the state's readiness for transformation, as well as the scale of state intervention in the development of wind energy [99]. The high percentage of households unable to heat their homes may indicate a social problem that inhibits investments in renewable energy and indicates a low willingness to bear the costs of energy transformation [100]. The share of renewable energy represents the effects of implementing the state's energy policy. The authors considered variables related to the energy system available in the Eurostat, IRENA, Strategic Metals Invest, and Energy Institute Statistical Review of World Energy databases. The initial set of indicators considered during the analysis included those listed in Table 1. The table also includes information on the data source and unit of measurement for each variable. The dataset was selected to eliminate missing values and includes annual data from 2014 to 2023. The set was constructed to reflect the fact that wind energy development is the result of an interaction of technological, economic, environmental, social and legal factors. Therefore, the authors ensured that the set included factors that represent each of these groups. Some factors can be classified into multiple categories, as they provide comprehensive information on the determinants of wind energy development. The group of economic factors includes energy prices, wind energy expeditions, income inequality level, GDP per capita, and rare earth prices. Technological factors are represented by energy efficiency, import dependence, primary energy consumption, wind power, and the number of patents. Environmental factors include mainly greenhouse gas emissions, national expenditure on environmental protection, and environmental taxes by economic activity—energy taxes. Social factors represent the inability to keep the home adequately warm and income inequality. Political factors that are difficult to capture quantitatively are represented by the share of renewable energy, national expenditure on environmental protection, environmental taxes by economic activity—energy taxes—and wind energy expenditures. The variables constitute a complementary set, complementing each other, thus providing a complete picture of the conditions for the development of wind energy.

In this set, the influence of the explanatory variables on the dependent variable was verified. Using a multiple regression model, the statistical significance of the mutual influence of the variables was examined. The linear regression model incorporated explanatory variables identified as potentially shaping the wind energy potential in Poland. The aim of the study was to verify this set of variables regardless of their intercorrelation. The study aimed solely at assessing the significance of the indicators for all the selected factors. However, to eliminate potential problems related to multicollinearity, weight standardization was applied. The residuals of the created model were verified. Their normal distribution was confirmed by the Kolmogorov–Smirnov test with a p-value of 0.14, and the lack of autocorrelation was confirmed by the Ljung–Box test with a p-value of 0.99. In turn, the lack of heteroscedasticity of the model was confirmed by the Breusch–Pagan test, where the p-value was 0.13.

Table 1. A set of factors taken into account when selecting explanatory variables, years 2014–2023.

Factor, Explanatory Variables x	Unit	Source
Energy prices	EUR/kWh	Eurostat [101]
Energy efficiency	Mtoe	Eurostat
Greenhouse gas emission, (x_1)	Mtoe	Eurostat
Inability to keep home adequately warm	%	Eurostat
Income inequality	Ratio	Eurostat
Share of renewable energy	%	Eurostat
National expenditures on environmental protection	% GDP	Eurostat
Environmental taxes by economic activity—energy taxes	Mil EUR	Eurostat
Primary energy consumption	Mtoe	Eurostat
Energy import dependency, (x_2)	%	Eurostat
Wind energy consumption, (x_3)	EJ	Energy Institute Statistical Review of World Energy [102]
GDP/capita	EUR	Eurostat
Patents, wind energy, (x_4)	number	IRENA [103]
Wind energy expenditures	Mil USD	IRENA
Installed wind energy capacity	GW	Eurostat
Nd, Dy, Pr, Tb prices	USD/kg	Strategic Metals Invest [104]

The β coefficients of the regression model were determined, thus indicating the number of units by which Y would change if X changed by one unit. The p-value was then estimated as a statistical measure of the probability of values similar to those observed, assuming (the null hypothesis) that the variable had no influence, i.e., $\beta = 0$. The results of the analysis are presented in Table 2.

Table 2. Results of the analysis of the statistical significance of the influence of the explanatory variables on the Y variable.

Variables	β	p-Value	Comment
x1 CO_2 emissions	0.000007	0.01	significant effect ($p < 0.05$), direction: positive
x2 Energy import	0.051007	0.05	significant effect ($p < 0.05$), direction: positive
x3 Energy demand	0.2831197	0.00	very significant effect ($p < 0.01$), direction: positive
x4 Patents	−0.00956	0.02	significant effect ($p < 0.05$), direction: negative

The coefficient of determination of the model was 0.99, while the standard deviation of the residuals (SEE) was 0.20.

Table 2 includes X variables that were shown to have a significant statistical impact on variable Y, so the set of 16 factors was reduced to 4 with significant ($p < 0.05$) and very significant ($p < 0.01$) impacts. This group includes the number of patents, the demand for wind energy, the import of energy, and CO_2 emissions. The selected data were entered into the next step into the LSTM model. The multifactor model allows for the explanation of specific causes of changes in demand and the tracking of how specific and most significant factors will influence the analyzed phenomenon. These are also factors that will be the subject of important discussions, which will be shaped in accordance with the EU energy and climate policy, particularly the volume of CO_2 emissions, energy demand, and import dependence. In turn, the number of wind-energy-related patents will also be a consequence of the EU support (or lack thereof) for this type of research. The dataset consisted of observations from 2014 to 2023, which is the complete available information for all the data included in the Eurostat databases.

Although there are differences in policy, industry structure, and transmission grid maturity, training the model on German data allows for the detection of universal patterns of dependencies between the explanatory variables and the dependent variable. The mechanisms of growth in the installed energy demand are similar in each country, occurring only on different scales. The model trained on German data provides a framework adapted to Polish conditions by introducing Polish explanatory variables.

The dataset for Germany was divided into two parts: 80% was placed in the training set and 20% in the test set. In the next step, an LSTM-based multilayer recurrent RNN network was built with four input variables. Statistical data for Germany enabled the model. The data was transformed into a time sequence format. The number of input variables was set to four, and the number of target variables was set to one. The first layer used a hard sigmoid activation function. This reduced computational complexity ensured stabilization of the hidden state in the first stages of training. The kernel weights connecting the input vector with the cell state were introduced. The weights were initialized using the SIGMOID_UNIFORM method, which ensured a stable initial distribution of the values for the activation functions used. The structure of the LSTM model is presented in Table 3.

Table 3. Structure of the LSTM model.

Layer	LSTM 1	LSTM 2	LSTM 3	Output
Entrance, features	4	32	32	16
Output, neurons	32	32	16	1
Activation	Hard sigmoid	Tanh	Tanh	Identity
Loss function				MSE

The model processed the input data sequentially since the analysis involved time series. To ensure an appropriate level of accuracy with a small sample size, a three-layer model was used. The ADAM optimizer with a learning rate of 0.001 was used to optimize the neural network. The optimizer is responsible for updating the weights and regulating how the LSTM model remembers information. The activation functions were the tanh and hard sigmoid, which fit well to the patterns contained in the analyzed time series. The mean squared error was used as the loss function. The weights were optimized by the ADAM optimizer to minimize the MSE prediction error. The model was trained for 450 epochs, during which the data were processed by the neural network, the loss function was calculated, and the calculations were terminated when the loss function stabilized and reached a minimum. The model used backpropagation, meaning that the network learned not only from errors at a given time point but also from previous steps. The number of time steps that the LSTM model simultaneously considered was set to 9.

The normality of the residuals of the model was confirmed by the Kolmogorov–Smirnov test, where the p-value was 0.21. In the Ljung–Box test, the p-value was 0.99, which excluded autocorrelation of the residuals. The model errors for the training set are presented in Table 4, and for the test set in Table 5.

Figure 2 presents the results of the model, the actual values, and the forecast made using the neural network.

Table 4. Error metrics of the built LSTM model: training set.

Error	Value	Standard Deviation
MSE	0.03	0.01
RMSE	0.18	0.01
MAE	0.14	0.02
MAPE, %	7.46	0.82

Table 5. Error metrics of the built LSTM model: test set.

Error	Value
MSE	0.68
RMSE	0.83
MAE	0.80
MAPE, %	10.11

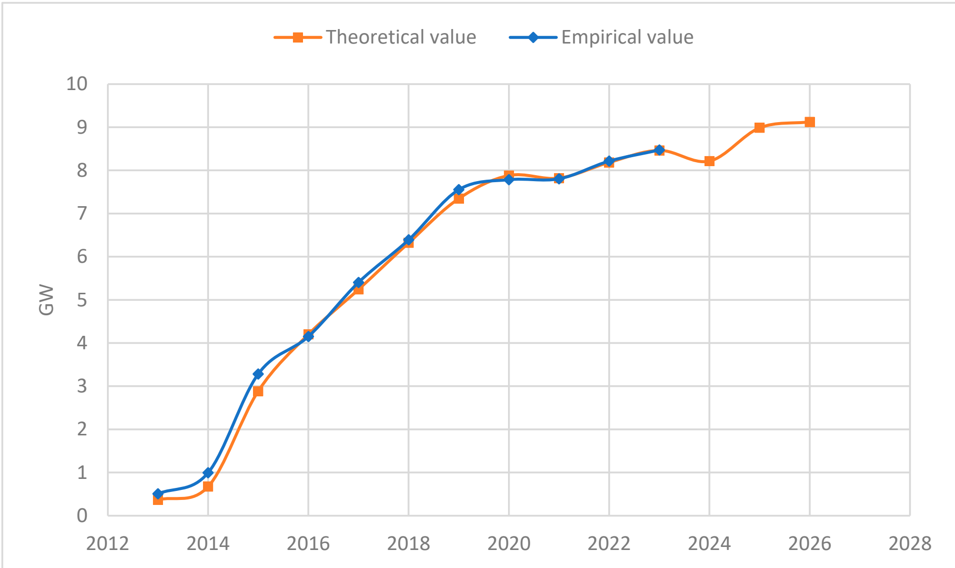

Figure 2. Actual values of installed wind energy capacity in Germany in 2013–2023 and theoretical values determined by the program.

The literature has determined that model MAPE of 16% can be considered acceptable [105]. Models with an MAPE below 10% have been defined as highly accurate, those in the range of 10–20% as good forecasts, 20–50% as acceptable, and those above 50% as inaccurate [106,107]. Of course, the level of acceptability ultimately depends on the industry to which the forecast applies and the expectations of the forecast recipient.

The error for the test set increased by 2% to 10%, which can still be considered very good model accuracy. It should be noted that the increase in the error could have been caused by the model's fit to the German data and indicate overfitting. However, it was not significant, and in addition, the test set (2022–2023) falls in years of strong market turbulence. The forecasts to 2030 were also treated using a non-deterministic scenario approach, which eliminated the problem of potential overfitting of the model to the data.

The MAPE of the model was less than 8%; therefore, it was considered sufficiently accurate and was used to forecast the installed offshore wind energy capacity in Poland by 2030. Analogous variables were used as input data, as in the case of Germany, but they were first forecasted to 2030 using the SVR model. The model used the SMOreg algorithm with an RBF kernel. The model's C parameter (complexity) was automatically selected using cross-validation from a range of 1–200. The model's gamma parameter, defining the range of influence of individual observations on the model, was set to 0.1, and its epsilon, defining the error tolerance, was set to 0.001. The cache size defaulted to 250,000 entries, providing the program with sufficient space for model estimation. The model parameters are listed in Table 6.

Table 6. SVR model hyperparameters.

Hyperparameters	Value
C	1–200, five-fold cross-validation
γ	0.1
ε	0.001
Tolerance	0.001
Cache size	250,000

Because no forecast can be considered 100% reliable, error metrics and scenarios were determined. Although the model demonstrated small errors, it should be noted that the quality of forecasts can be influenced by a number of factors, such as the length of the time series and the selection of explanatory variables. They can also be influenced by the quality of the data used, as well as external and macroeconomic factors, such as wars, inflation, and changes in commodity prices.

The MAPE of the explanatory variables did not exceed 20% (Table 7).

Table 7. SVR model MAPE.

Variable	MAPE, %
x_1	2
x_2	20
x_3	17
x_4	20

Figure 3 presents the forecast and scenarios for the installed offshore wind energy capacity in Poland by 2030. The forecast showed that in 2026, the installed capacity would amount to 0.36 GW, and in the last year of the forecast, it would be approximately 5.3 GW.

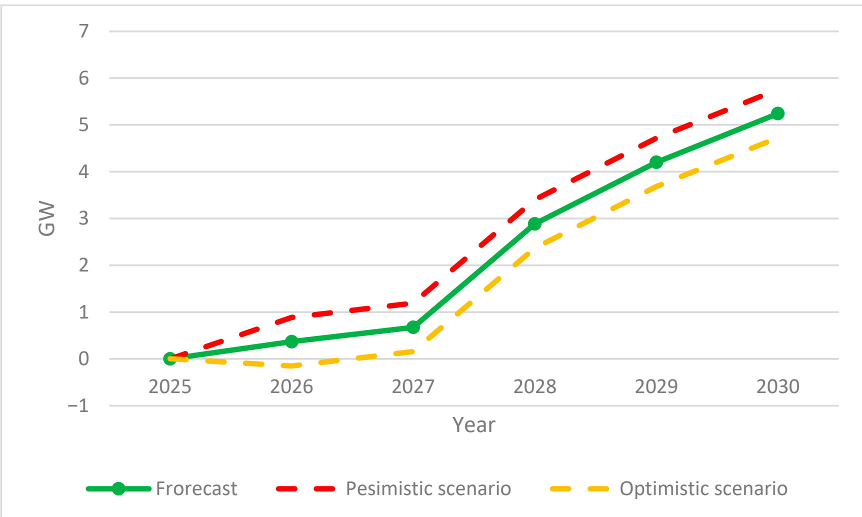

Figure 3. Installed offshore wind energy capacity in Poland, forecasts and scenarios for 2026–2030.

5. Discussion

The research results show that by 2030, Poland can achieve the goals set by the UN, the EU and PEP2040. A 95% confidence interval was constructed for the forecast. The forecast represents the baseline, i.e., the most probable scenario, the red series—the optimistic scenario, and the purple series—the pessimistic scenario. The confidence interval defines the range within which the forecast may change with a probability of 95%. According to the baseline scenario, intensive growth in installed offshore capacity begins after 2027, reaching 5.2 GW by 2030. This dynamic is consistent with the pace indicated by the historical data. However, it should also be considered that offshore capacity development may be influenced in the future by factors that are currently unpredictable. Therefore, the construction of the scenario allows for the consideration of factors that both stimulate and delay the development of offshore wind energy in Poland. The pessimistic scenario assumes that only up to 4.7 GW of installed capacity will be built by 2030. This could be due to unexpected administrative obstacles, grid constraints, or investment problems. The optimistic scenario, on the other hand, indicates that the installed capacity will grow very dynamically by 2030, reaching up to 6 GW. This scenario could be realized if planned projects are implemented on time, the grid infrastructure is rapidly developed, and the financing programs are facilitated by favorable legal regulations and efficient financing programs. Scenario analysis indicates that only the pessimistic scenario poses the risk of a significant discrepancy between the PEP2040 goals and the actual level of offshore energy development in Poland. The PEP2040 assumes that by 2030, Poland should have 5.9 GW of installed energy in offshore wind farms in the Baltic Sea. The forecast shows that it will be around 5.3 GW, and the difference between these values remains within the model's margin of error. This means, first, that the model is reliable and uses adequate explanatory variables. It also demonstrates the consistency of scientific forecasts and policy assumptions. Therefore, the wind energy policy was developed realistically and is based on rational goals, not only on political postulates. This consistent nature of the results can strengthen the decision-making process, as it provides confidence that the direction of offshore energy development is appropriate. Objective market analysis and alignment with state policy mean acceptable capital risk and enhance Poland's attractiveness as a suitable location for potential projects. Poland is working in accordance with the EU and the Sustainable Development Goals, taking steps to increase renewable energy in the energy mix, reduce CO_2 emissions and improve the country's energy security. Wind energy, especially offshore wind energy, will reduce dependence on fossil fuels and imported energy, which is a key pillar of the transformation. The development of offshore energy in Poland can contribute to the achievement of the SDGs, primarily Goal 7, but also Goal 8 (economic growth), by developing the renewable energy sector and creating new jobs. It will also contribute to the achievement of Goal 9. Renewable energy is a key sector, and innovations in turbine development are the basis for optimizing the operation of this technology. This will also contribute to the achievement of Goal 11, which aims to create sustainable cities and communities by reducing the negative impact of energy on the environment and human health, and, of course, Goal 13, which aims to promote climate action. The forecast also indicates that Poland is at the beginning of a long road to creating a potential similar to that of Germany. Macroeconomic factors indicate that Poland will be able to achieve the goals of Poland's energy policy. However, to materialize these forecasts, Poland must implement a number of actions. To learn from the mistakes of others, it is beneficial to examine the actions of Germany, which has been striving since the 1990s to develop renewable energy sources that can support its energy needs. Germany has established a statutory framework to support renewable energy sources, which has guaranteed investors' long-term profitability of investments. Above all, a stable and predictable law consistent with energy policy is essential. Frequent regulatory changes have effectively limited the development of onshore wind energy in Poland in the past. Investors must operate within a stable regulatory and financial system that provides them with investment predictability for at least the next

20 years. The development of transmission grids in parallel to offshore energy was also crucial in Germany. In Poland, the transmission grid already constitutes a bottleneck in the process of developing renewable energy. It is essential to develop installation ports and service bases, for example, in Świnoujście, for investments in the Baltic Sea. Germany has also established an extremely stable financial system that supports the development of wind energy. Poland lacks such long-term support mechanisms. Poland also lacks cooperation between science and industry, R&D infrastructure for offshore energy, and a network of companies that form the supply chain from technology manufacturers to grid operators. Therefore, Poland will be building its first offshore wind farms more than a decade later than Germany, which had its first wind farm in the North Sea in 2010, and its average annual installed capacity growth between 2013 and 2024 was 20%. According to the forecast, Poland would need to achieve a slightly faster growth rate of approximately 22% annually to reach 5 GW of installed capacity in 5 years. To achieve this, a sustained investment pace is essential.

Multiple regression analysis identified the factors with the greatest impact on the development of offshore energy in Poland. Of the 16 indicators considered, four factors proved to have a statistically significant impact, with the energy demand proving to be the strongest determinant. The growing demand from the economy and households requires an increased share of renewable energy sources in Poland's energy mix to ensure the country's energy security while simultaneously meeting the energy transition targets. Greenhouse gas emissions also positively impact offshore energy development. Regulatory pressure to reduce greenhouse gas emissions stimulates the development of low-emission technologies and encourages investment in domestic renewable sources. Another factor positively influencing offshore energy development is the level of dependence on energy imports. The higher the level of dependence, the more likely countries are to invest in renewable energy, which is intended to increase the energy system's independence from other countries and increase resilience to energy price fluctuations and geopolitical changes. The fourth identified factor is the number of patents. This correlation is negative, which may indicate barriers to the implementation of innovation in Poland. There are no strong mechanisms that support the transfer of technology to the industrial scale and the use of the research potential for developing wind energy.

6. Conclusions

The development of offshore wind energy in Poland has been significantly limited compared to Germany. This was due to regulatory, administrative, financial and infrastructural factors. The lack of a legal framework and offshore support systems was paramount. Concepts for the first farms in the Baltic Sea were developed as early as 2010, but it was not until the adoption of the PEP2040 Act in 2021 and the Act on the Promotion of Electricity Generation in Offshore Wind Farms that targets for offshore energy development were introduced and investors were encouraged. Development was also slowed by location permits, which were a multiyear process and were regulated by the 2020 amendment to the Maritime Areas Act. The lack of transmission infrastructure in the north of the country capable of transmitting several gigawatts of energy also posed a limitation. The first interconnector, which will deliver electricity to consumers inland, is the Choczewo–Żarnowiec line, which was approved in 2024. All these factors mean that Poland will begin using offshore energy more than a decade later than other European countries. The modeling carried out by the authors provides forecasts for the development of installed offshore wind energy capacity in Poland based on reliable artificial intelligence forecasting models. Combining the SVR and LSTM models allows for synergistic effects. The SVR model generates data for the LSTM model, which in turn provides a forecasting tool that enables the modeling of long-term dependencies while eliminating the problem of vanishing gradients. This combination enabled the generation of forecasts with a low MAPE of less than 8%. The forecasts indicate that by 2030, Poland could reach 5 GW of installed wind energy capacity, with the factors that will have the greatest impact on this development being the energy demand, greenhouse gas emissions, development of innovations in wind energy, and dependence on energy imports. This knowledge is crucial for effective support of energy policy. The strongest impact of the growing energy demand should signal to decision makers to prioritize investments in transmission networks and energy storage.

This knowledge also enables efficient resource utilization and allocation based on where they will yield the greatest benefits. Knowledge of the factors shaping offshore energy development also allows the development of state policy consistent with the SDGs and the European Green Deal. The research results fill an identified gap. To date, the scientific literature has not presented forecasts of offshore development in Poland based on a model trained on German data. The research provides a reference point for further analysis, particularly for a time horizon beyond 2030 and in the context of other renewable energy sources, including nuclear energy, which, along with renewable energy, is expected to make a significant contribution to the Polish energy mix. They can also be applied to research on the integration of renewable energy with energy storage, which will be essential to stabilizing the operation of the renewable-energy-based energy system. The forecasts obtained are important for shaping and estimating Poland's energy security. They allow the verification of whether Poland will be able to diversify its energy mix by 2030 to the extent necessary to cover the gap left by the gradual phase-out of coal with, among others, wind energy. This is a huge challenge, considering that currently, around 50% of electricity in Poland is generated from coal. Having a domestic energy source also means that the energy system is less vulnerable to external crises, which have been numerous in recent years as a result of the war in Ukraine.

The presented solution can also support monitoring and reporting of EU countries' progress in achieving energy transition goals or the SDGs. The results can be valuable for policymakers, suggesting practical and effective solutions to achieve a zero-emission economy, investors, energy grid operators, local governments, and the scientific community. The forecasts obtained provide essential information for planning energy transitions, creating plans with limited investment risk, planning further research directions, and educating the personnel necessary for wind energy generation. The analytical results provide the basis for assessing the profitability of planned projects, as well as potential profits, assessing supply chain capabilities, turbine supply, balancing, and developing energy system flexibility mechanisms. These are important aspects that require time to design correctly, and the forecasts developed will certainly enable planning well in advance. The method used also has its drawbacks. The lack of data for Poland regarding the installed offshore energy capacity meant that the model was trained on data from Germany. This was necessary, but it can generate limitations resulting from knowledge transfer. Although Germany provides the best possible benchmark due to geographical similarities, similar natural and wind conditions, technical requirements for turbines, energy demand, infrastructure connections, and implementation of EU policies, it is natural that differences between Poland and Germany also exist, limiting the model's applicability. Above all, Germany is already very advanced in terms of offshore energy development, while Poland is at the beginning of its journey to build a suitable offshore wind energy potential technologically, procedurally, regulatorily, and infrastructurally.

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Rybak), A.R. (Aleksandra Rybak) and S.D.K.; validation, A.R. (Aurelia Rybak) and A.R. (Aleksandra Rybak); visualization, A.R. (Aurelia Rybak) and S.D.K.; investigation, A.R. (Aurelia Rybak); funding acquisition, A.R. (Aurelia Rybak); methodology, A.R. (Aurelia Rybak) and A.R. (Aleksandra Rybak). All authors have read and agreed to the published version of the manuscript.

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