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Forecasting of Wind Speed and Power for Poland Using Prominent Variants of FFNN Tuned Through MHPSO-BAAC-x

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Abstract
One of the significant contributors to global warming is electricity production based on conventional fossil fuels, which exert a considerable environmental burden. This dependency can be mitigated through the increased utilization of Renewable Energy Resources (RERs), which offer both environmental and economic advantages. However, one of the main challenges associated with RERs, particularly wind energy, is their frequent installation at locations remote from load centers, which poses difficulties in efficient energy transmission. In this study, wind speed and power have been forecasted using three types of artificial neural networks: Feedforward Neural Network (FFNN), Cascaded Forward Neural Network (CFNN), and improved Feedforward Neural Network (id-FFN). The dataset used in this work was obtained from the Global Wind Atlas and covers the Silesian Region of Poland for the year 2023. Data from January to June were used to train the neural networks using a modified version of the Metaheuristic Hybrid Particle Swarm Optimization with Bat Algorithm Acceleration Coefficients (MHPSO-BAAC-x). The trained models were then employed to predict wind speed and power for the period from July to December 2023. To assess the accuracy of the forecasts, the following statistical error metrics were applied: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE). The predicted values were subsequently compared with the actual data for the same period to evaluate the effectiveness of the models. The id-FFN model demonstrated the best performance, achieving values of 0.0262 m/s for MAE, 2.62% for MAPE, and 0.0152 m/s for RMSE, confirming its high precision and reliability. The obtained results suggest that the developed forecasting system has the potential to support future planning and integration of wind power stations into the national power system.

Keywords
Wind forecasting, wind energy; Bat algorithm (BA); cascaded forward neural network (CFNN); feedforward neural network (FFNN); hybrid PSO and BA (HPSOBA), Poland Wind Energy

Introduction

Wind and solar energy farms have gained considerable importance in Poland's energy mix. According to Poland's energy policy (PEP-2040), the utilization of RESs in the electricity generation sector will expand after 2025 ("Risks Related to Energy Policy of Poland Until 2040 (EPP 2040)", 2023). The contribution of RERs by 2030 in the power segment will be 32%, and this will increase to 40% by 2040. The government will support this mechanism in these ways, bringing safety to grid operation and economical electricity prices ("PSE Capital Group - Suntech S.A.", n.d.).

The productivity of offshore wind power plants is higher than onshore wind power plants (WPPs). In the Polish northern region, transmission grids are in progress. When they become fully functional, sufficient electricity from the offshore turbines can be extracted easily. In 2024/2025, energy from offshore wind farms will be included in the country's energy mix (Office, n.d.). In the future, there is the possibility that more wind plants will be built in the dedicated economic zone in the Baltic Sea of Poland. In 2030, the energy from these resources will reach up to 5.9 GW, and 11 GW in 2040. In RES, the largest share is from offshore wind farms in the total energy mix. So, from all these, the wind farm has greater potential. This will be a game changer for Poland in achieving its goals according to the targets given by the European Union ("Polskie Sieci Elektroenergetyczne – Integrated Impact Report – Homepage", n.d.).

The efficient integration of solar and wind into existing structures is a big challenge. The complexity is due to the nature of wind generators and less flexibility of the existing infrastructure. On the demand side, the unpredictability of these resources is the point of concern (Hirth et al., 2018). Many researchers worked on day-ahead energy demand forecasting, including the Artificial Neural Network combined with wavelet transformation. Various data-driven approaches such as Deep neural networks are reviewed in detail and are presented in (El-Hendawi and Wang, 2020; "Krajowe zapotrzebowanie na energię elektryczną w 2020 r. - RYNEK ENERGI ELEKTRYCZNEJ I GAZU", n.d.; Lannoye, 2015).

According to the World Energy Outlook report prepared by the International Energy Agency in 2023, the energy sector is changing for the green transition ("World Energy Outlook 2023 – Analysis", 2023). The EU follows the global objective of the Paris Agreement and has a vision of a clean and green planet with affordable energy available for everyone. The change in the economy, which is based on fossil fuels towards clean and renewable energy (RE) by 2030 is a global requirement with many EU countries emerging as leaders in this prospect ("2050 long-term strategy - European Commission", n.d.; "'Fit for 55': delivering the EU's 2030 Climate Target on the way to climate neutrality", n.d.; Casalicchio et al., 2022). The policy of cleaner power for all was implemented through the European Legislative Package (CEP) of the EU to achieve its climate and energy objectives. This package also gave two directives that define the REC and Citizen Energy Community (CEC) ("Clean energy for all Europeans package", n.d.).

According to IEA 2023, China is on top of renewable growth, and their government plans to bring the overall emissions to zero level by 2060. The growth of RERs in the EU is also very significant growth recently, as can be seen from the graph given below in Fig. 1.

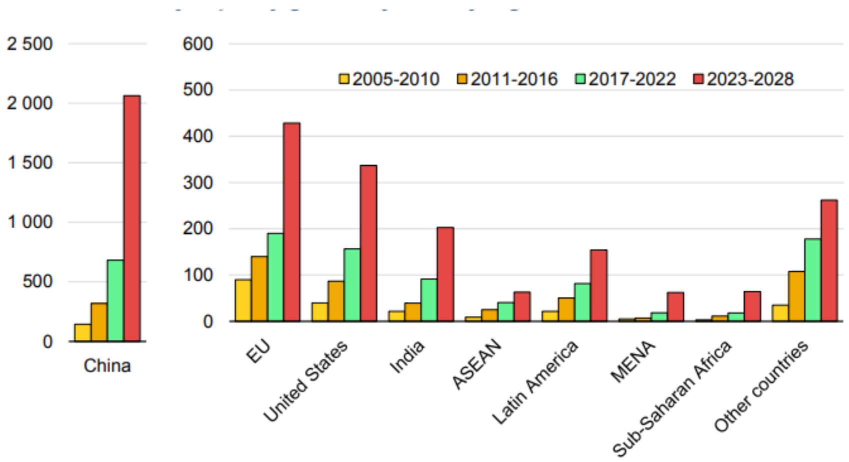


Fig. 1: Global contribution toward Renewable energy Resources ("Renewables will be world's top electricity source within three years, IEA data reveals - Carbon Brief", n.d.)

To shape the structure of the household budget, the cost of energy purchases plays a vital role, and this emphasizes finding an optimal solution through cheaper energy resources. Besides, the power demand is also rising, requiring an increased incorporation of RESs in power generation as it will provide a cleaner and cheaper solution to satisfy the energy demand. Developing countries like Poland, which are dependent on traditional methods of generating electricity, are facing problems related to conventional methods of power generation

(Menegaki and Tiwari, 2017; "Renewable Power Generation Costs in 2019", 2020, p. 2). Traditional methods are expensive, and they also cause many environmental problems.

The article (Manowska, 2021) presented a legal mechanism resulting from the recently accepted climate strategy, the New Green Deal, and the situations for the development of RESs in the process of energy transition. The features of chosen energy balances of countries are also presented, which may constitute a knowledge base on the diversity of the Member States in terms of energy resources used, levels of independence and self-sufficiency of raw materials, as well as the levels of current electricity prices. Based on the available statistical data, the Eurostat database presents forecasts of the levels of RES-based power usage in the 2030 time horizon for selected countries and according to the main types of RESs like solar, biofuel, geothermal, hydro, and wind. The statistical analyses presented in the article are important tools for building a development strategy for the process of integrating energy markets within the European Union.

Poland currently spends EUR 20 billion to neutralize carbon emissions, which is a big financial burden on the economy, increasing the cost of electricity per kW. Implementation of RER as a solution to overcome it is emphasized. In 2021, China was the biggest producer of wind energy at 64%, and in the EU, Denmark topped the list with a 49.7% share of wind production in the total energy mix (Ochoa et al., 2019; Valodka and Valodkienė, 2015).

The production of wind energy was 6.35 GW in 2020, and its share in 2022 exceeded 9.3% to 11%. Poland's share in the Baltic Sea is 12% in the economic zone, according to the Wind Europe Report, with a power capability of 17.2 GW. According to Poland Energy Policy 2040, there is a permanent rise in the share of wind energy, and the country has also set a target for offshore WPPs to have the capability to produce power up to 5.9 GW in 2030 ("Energy Policy of Poland until 2040 (EPP2040) - Ministry of Climate and Environment - Gov.pl website", n.d.; Koć, 2022).

Electricity production in Poland is still largely based on solid fuels such as hard coal and lignite. The power system, based on traditional technologies, is becoming less and less efficient, and its continued maintenance in its current shape raises several environmental and economic challenges. It requires gradual modernization and transformation towards low-carbon sources, in line with the European climate and energy policy assumptions.

The reform of the Polish energy policy, in line with m.in provisions of the European Association Agreement of 1991 and the European Energy Charter, focuses on ensuring energy security, stable supplies, and affordable energy prices while reducing greenhouse gas emissions. In this context, the development of precise analytical and forecasting tools supporting energy planning processes is particularly important.

Manowska's (2020a) work indicates that effective forecasting of electricity demand and production from renewable energy sources is an important element of the energy transition. At the same time, the approach proposed by Du et al. (2019), based on hybrid predictive models, confirms that integrating advanced data processing methods with modern algorithms can significantly improve the quality of energy forecasts.

With reference to the above concepts, this work focuses on developing a model for forecasting wind speed and power for the Silesian Voivodeship. It uses three artificial neural network architectures: a classic feedforward network (FFNN), a cascade neural network (CFNN), and an improved id-FFN network. These models were trained using the proprietary MHPSO-BAAC-x optimization algorithm, combining elements of swarm optimization with the Bat Algorithm acceleration mechanism.

Figure 2 shows a simplified flowchart of the designed forecasting system, which forms the basis of the research approach. The model is based on the processing of meteorological data from the first half of 2023 to forecast wind speed and power for the second half of the same year. This process is carried out using three types of artificial neural networks: FFNN, CFNN, and id-FFN, which have been trained using the developed MHPSO-BAAC-x optimization algorithm.

The goal of the analysis is to compare the effectiveness of each model in the context of forecast accuracy, assessed using indicators such as Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE). All models were tested with the same input data and uniform network parameters to ensure optimal comparison of results. The best results were obtained for the id-FFN model, confirming its high efficiency in forecasting wind resources.

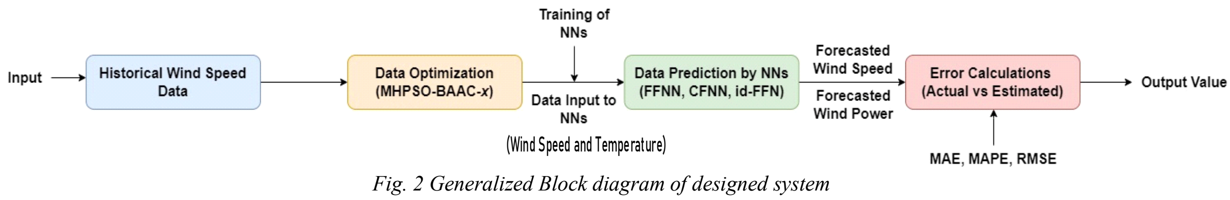


Fig. 2 Generalized Block diagram of designed system

The aim of the study is to increase the accuracy of wind resource forecasting as an element supporting the development of low-carbon energy in Poland, in particular through better planning of the power system operation and potential integration of large wind installations with the national energy market.

Literature Review

A comprehensive literature review is essential to identify current trends, limitations, and wind energy forecasting techniques innovations. In recent years, growing interest in integrating renewable energy has spurred the development of various data-driven approaches, including machine learning and deep learning models, to improve the accuracy and robustness of wind speed and power forecasts. The following section presents a selection of studies that have significantly contributed to the field, highlighting methodological advances and comparative evaluations of different modeling strategies.

An important element of the analysis is a study conducted by Hassan et al. (2025), which focuses on long-term forecasting of electricity production trends in Poland. In this work, the SARIMA (Seasonal Autoregressive Integrated Moving Average) model was used to estimate future trends in using conventional and renewable energy sources. The study aimed to assess how the share of Renewable Energy Sources (RES) is expected to change in the national energy mix by 2030, with a gradual reduction in the use of fossil fuels. The model was trained using a 70:30 split of the data—70% of the dataset was used for training and 30% for testing. The accuracy of the forecasting was assessed using the Mean Absolute Percentage Error (MAPE), which reached 4.48%. The results indicate the usefulness of the SARIMA model for analyzing long-term energy trends and confirm the direction of changes in the Polish energy policy aimed at reducing carbon dioxide emissions and increasing the share of RES.

Another important aspect highlighted in the literature is the environmental consequences of fossil fuel combustion and the challenges associated with increasing energy demand. Anwar et al. (2019) and Lashof and Ahuja (1990) have recorded a steady increase in atmospheric concentrations of carbon and sulfur oxides (COx and SOx), which significantly contribute to intensifying global warming. The main source of these emissions is the large-scale burning of fossil fuels to produce electricity. As West and Marland (2002) point out, continued population growth and the expansion of industrial and commercial infrastructure result in a continuous increase in energy consumption, which requires the use of additional thermal resources such as coal and natural gas. By the end of the twentieth century, atmospheric CO_2 concentrations had exceeded critical thresholds, with industry, transport, and energy making major contributions. In light of this, numerous studies highlight the urgent need for a transition to low-carbon and renewable energy sources (Wrigley, 2013; Zou et al., 2021). In this context, Graczyk et al. (2024) examined the impact of extreme weather on electricity consumption in Poland, focusing on the period from 2010 to 2022. Their study looked at changes in energy consumption during heat waves, as well as the impact of summer wind conditions on the performance of onshore wind farms. During the 2010 heatwave, electricity consumption increased by up to 4% on the hottest days. By 2019, this increase had reached 8%, exceeding the levels recorded during the 2015 heatwave. In addition, between 2016 and 2022, the average daily energy consumption on days with a temperature of 26°C was about 8% higher than on weekdays with an average temperature of 18°C. The authors concluded that the increasing frequency of heat events, combined with increased electricity demand, could adversely affect the stability of the power system.

To decrease global warming and CO_2 emissions, the recent Climate Change Conference of the Parties (COP28) held in Dubai, UAE, on December 13, 2023, increased the incorporation of renewables and energy efficiency pledges endorsed by 133 countries. European Union (EU), being a part of COP28, also pays a lot of attention to it. This commitment by EU member countries enhances the integration of RERs in the electrical power network and improves the progress in reducing greenhouse gas (GHG) emissions ("COP28 UAE - United Nations Climate Change Conference", n.d.).

The authors (Manowska et al., 2024) presented a paper for assessing the dynamics of energy renovation in the EU through a two-phase mechanism. The energy transformation dynamics matrix was used to categorize the European countries in the initial phase. Consequently, the actual examination of the dynamics of energy transformation was performed through a novel composite indicator. The outcomes identified that leaders in EU energy transformation were Austria, Denmark, France, Finland, Germany, Netherlands, Sweden, Spain, and Italy, while signifying the challenges faced by Bulgaria and Poland.

UN is *emphasizing the need to work towards decreasing GHG emissions in the energy sector while satisfying the growing power demand of the masses with the necessary consideration of energy affordability. For this purpose, they call upon governments to speed up their processes of transitioning away from fossil fuels and incorporating RERs. Besides, the implementation of wind and solar power must come to protect the environment, which is one of the top priorities. The use of RERs not only decreases CO2 emissions but also increases energy efficiency and conservation ("Report on the review of the report upon expiration of the additional period for fulfilling commitments for the second commitment period of the Kyoto Protocol of Finland submitted in 2023. Note by the expert review team | UNFCCC", n.d.).*

The authors (Robak et al., 2023) presented a detailed review of the commissioning of the onshore wind production in Poland. Several time horizons and the connection between wind-based power production and the demand of the Polish Power System (PPS) were considered. The outcomes indicated a high level of variation in wind-based generation throughout the year. Besides, the R2 (coefficient of determination) with a value of zero showed an absence of correlation between the power demand by PPS and wind-based generation. The authors also suggested designing and deploying an energy storage system to overcome the variability of wind-based production.

In European countries, Poland uses coal as the main source of electricity due to its large reserves available locally. According to the (Kardaś, n.d.), the emission of CO_2 per year is about 150 million tons in Poland for generating electricity, taking it to the second position in heat production among the IEA countries. To address this issue, Poland made its energy policy known as PEP 2040, and according to this policy, three basic pillars are defined: transition, an energy system with zero emission, and good air quality. This policy is made to achieve the target of EU countries while ensuring energy efficiency, economic development, and the optimal use of resources ("Energy Policy of Poland until 2040 (EPP2040) - Ministry of Climate and Environment - Gov.pl website", n.d.).

The authors (Piotrowski et al., 2021) in the paper presented a novel ensemble prediction method, "averaging ensemble based on hybrid methods without extreme forecasts". Forecasting results achieved through this technique showed lower RMSE values than those considered. LSTM emerged as the best single technique, with MLP taking second place, followed by SVR and KNNR linear regression (LR) models. The results also validated that the lagged values of estimated time series marginally enhanced the precision of prediction. The authors concluded that using large datasets and developing hybrid models show smaller error values.

Poland committed to succeeding a 23% contribution of RERs in the total energy pool. RERs are increasing day by day in Poland. The current statistics of 2023 from Polskie Sieci Elecktroenergetyczne (PSE) indicate that RERs, mainly wind and Photovoltaics, are increasing day by day. The production from PV in 2020 was 19 TWh, which has now increased to 30.4 TWh. Similarly, the production from wind farms was 6.6 GW in 2020, and currently, it has reached 9.18 GW. The PV system is in micro-installation ("Main page - PSE Raport", n.d.).

According to Poland Energy Policy 2040, it is planned that in 2030, the share of RESs in total use will be 23%. Wind and solar energy will account for more than 32% of the total energy consumption in this regard. The nuclear power plants are also installed and will be commissioned in 2033 with a 1-1.6 GW capacity. Till 2040, the requirement of heating by houses will be provided through net zero-emission sources. In 2030, the coal used for generating electricity must be less than 55% (Energetyki, n.d.).

The target for RES as a major contributor to electricity generation can only be achieved with the help of citizens, business enterprises, and communities (Liebe et al., 2017; Wood et al., 2020). For a greener future, a collectively comprehensive approach is needed from all the stakeholders, which will make the energy system better and more balanced. The energy production from renewable sources in 2017 was 29.9%. Due to geographical and weather conditions, wind energy is a useful resource among all available RESs in the EU. The ideal location for wind energy is the Northern and the Baltic Sea (Aasen and Vatn, 2018; Brożyna et al., 2019).

The European Union's "climate neutrality" initiative requires Member States to effectively manage energy. By this, we mean a resource-efficient and competitive economy in which there are no net greenhouse gas emissions and where economic growth is decoupled from resource consumption. The article analyzes the level of primary energy consumption in Poland. It was examined whether it will be possible to achieve a 23% decrease in energy consumption in 2030 compared to the base year, in accordance with the adopted assumptions about energy efficiency (Manowska, 2020b).

In the EU, onshore and offshore wind farms can be installed, but due to capital and operational costs, onshore wind farms are better than offshore turbines (Augutis et al., 2015; "Offshore wind in Europe - key trends and statistics 2020 | WindEurope", n.d.). The complexity and maintenance problems in marine environments increase the capital cost of offshore wind projects. Due to these issues, the onshore WPPs are more popular than the offshore systems and have a greater percentage in the energy landscape (Bañuelos-Ruedas et al., 2011). In 2021, wind energy production in different European Countries was as given in Fig. 3.

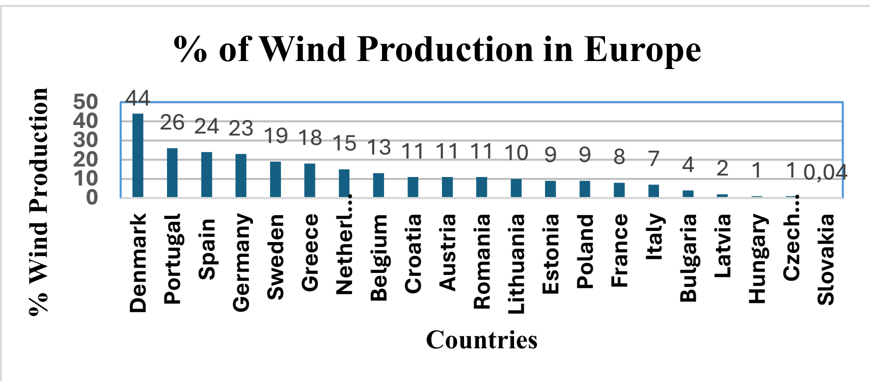


Fig. 3: Percentage of Wind Production in European Countries (Dawid, 2018; "Wind energy in Europe: 2022 Statistics and the outlook for 2023-2027 | WindEurope", n.d., pp. 2023–2027)

In Shahid et al. (2021), GA, the LSTM model, is used to take the speed of the wind as input, and an improvement in the accuracy of 30% was observed. A hybrid of GA and LSTM was used because it had the capability to learn automatically from the sequential data, while the GA was used to optimize the number of neurons and the pathway in the LSTM layer. The results were verified from the seven wind farms in Europe to check the validity of this algorithm.

IF, GRU, and LSTM were used in the reference (Kisvari et al., 2021), with IF filtering improving efficiency by up to 92%. This method was less sensitive to the noise in the SCADA System. Initially, the 12 attributes were examined in the forecasting model, including the wind speed at various elevations, the temperature of the generator, and the gearbox. The results showed a significant improvement in the accuracy and precision.

NN framework's hidden layer is used as an indirect link between the inputs and outputs, but in CFNN, it is used as a direct link, and short-term prediction was done with the help of bad data of numerical weather prediction (Xu et al., 2015).

Analysis was made on the dataset available that is relevant to Austria's electricity market. In this analysis, it was revealed that the performance of the Least Absolute Shrinkage Selector Operator (LASSO), Random Forest (RF), and Linear Regression (LR) models was inferior to the Decision Tree (DT) and MAE, MAPE, and RMSE were used to find the accuracy of the model. The MAE values for the DT model were as low as 2.08 and 2.20, respectively, for cases with and without considering the production from WPPs. With the help of integration from wind energy, the EU countries have been able to reduce the electricity cost (Kumar et al., 2023).

The final price to consumers is increased due to the transmission and balancing costs. There is a need to see wind energy development from another perspective, which will guarantee the continued development of wind-based generation systems. The results present a significant understanding to developers of wind energy systems, policymakers, and utility corporations to design energy models for a sustainable future (Dorrell and Lee, 2021). Table 1 presents the overview of the most recent techniques used for the precise estimation of Wind Speed and Power.

Table 1. Review of Prominent Techniques for Wind Speed and Power Forecasting

Reference	Technique	Mechanism	Strengths	Weaknesses
(Sun and Liu, 2024)	PSO-VMD-SE-ICEEMDAN	*1)* The Lasso technique is used to filter the features that significantly contribute to the wind speed data. *2)* CPSO optimized by introducing chaotic mapping determines the parameter pairs for VMD.	The precision of the estimated wind speed and power is higher due to the hybridized algorithm.	Computational time is very high as the data must pass through various calculations.
(Zhang and Yin, 2024)	Improved purely 2D CNN	*1)* Improved Unet-based ML technique, using residual learning to predict the spatial-temporal wind. ***2)*** Integrated with multi-head attention modulation using residual learning (Att-ResUnet)	A novel purely 2D CNN-based deep learning model with attention modulations is established for spatial-temporal wind speed forecasts in a relatively large-scale perspective.	Only historical wind characteristics were employed for future wind evolution forecasting in advance.
(Ammar and and Xydis, 2024)	Hybrid-forecasting model (includes pre-processing and DL techniques)	*1)* Data pre-processing for outlier handling. ***2)*** Utilization of DL technique for the estimation.	Ability to use the forecasting model on multiple locations regardless of location climate and geography.	The model's weights are not optimized.
(Jonkers et al., 2024)	Split Conformal Distribution Regression Forests (SCDRF)	The approach consists of a deep and dense convolutional neural network that is used as input for a grid of NWP variables.	Decreases the pinball loss function by 6.86%.	The technique appeared to have regional restrictions.

Mathematical Modeling

The dataset used in this research was acquired from the Global Wind Atlas and covers the Silesian Voivodeship in Poland for the year 2023, with a daily sampling interval. Each record contains the following meteorological variables:

- Wind speed [m/s],
- Air temperature [°C].

The dataset consists of 365 data points, which were divided into two sets:

- Training data: January–June 2023 (180 samples),
- Testing data: July–December 2023 (185 samples).

Prior to model training, the data underwent pre-processing, including:

- Removal of outliers based on the interquartile range (IQR),
- Linear interpolation for handling missing values,
- Min-max normalization to the [0, 1] interval.

The core objective of the model is to minimize the error between the predicted $v_{i,o}$, and observed $v_{i,t}$ wind speeds. This section summarizes the mathematical expressions with the consideration of optimization algorithms and NNs used to train the FF, CF, and id-FF neural networks. The subsections also present an elaboration of the MHPSO-BAAC-x technique because it is implemented to tune the NNs to assess the obtained predictions. The objective function used for the wind power and speed for the considered wind resource is given in (1),

$$Objective\ Function = \frac{1}{N}\sum_{i=1}^{N}\left(\left(v_{i,o}\right)-\left(v_{i,t}\right)\right)^2 \quad (1)$$

The observed velocity as the target and input indicate for the NNs are given as $v_{i,o}$ and $v_{i,t}$, respectively. Mathematically, FFNN, CFNN, and id-FFN are given in (2)-(4), respectively, and are taken from (Bebis and Georgiopoulos, 1994; "Feedforward Neural Networks - an overview | ScienceDirect Topics", n.d.; Warsito et al., 2018),

$$v_k = \sum_{i=1}^{N} W_{ki} X_i \quad (2)$$
$$y = \sum_{i=1}^{N} f^i \omega_i^i x_i + f^o\left(\sum_{j=1}^{k} \omega_j^o f_j^h\left(\sum_{i=1}^{N} \omega_{ji}^h x_i\right)\right) \quad (3)$$
$$y(t) = y_o + X(t)^T PL + S(X^T(t)Q) \quad (4)$$

y_0 is the output offset, $X(t)$ is a m-by-1 vector of inputs, P and Q are m-by-p and m-by-q projection matrices, respectively and a scalar. L is a p-by-1 vector of weights ("Multilayer feedforward neural network mapping function for nonlinear ARX models (requires Deep Learning Toolbox) - MATLAB", n.d.).

The computation of forecasted power from wind through the estimated speed is performed using (5),

$$P = \left(\frac{1}{2}\right)\rho A C_p v^3 \quad (5)$$

where, ρ gives the air density (kg/m^3), C_p gives the performance coefficient, A gives the swept area of the wind turbines, and v designates the wind speed (Bañuelos-Ruedas et al., 2011).

MAE, MAPE, and RMSE are employed to verify the precision of the predicted values, and they are calculated using (6)-(8) taken from (Jiang et al., 2013),

$$MAE = \left(\frac{1}{n}\right)\sum_{i=1}^{N}\left|Ov_i - Pv_i\right| \quad (6)$$
$$MAPE = \left(\frac{1}{n}\right)\sum_{i=1}^{N}\left|\frac{Ov_i - Pv_i}{Ov_i}\right| \times 100 \quad (7)$$
$$RMSE = \left[\left(\frac{1}{n}\right)\sum_{i=1}^{N}\left(Ov_i - Pv_i\right)^2\right]^{\frac{1}{2}} \quad (8)$$

The total samples are represented by N, P_{vi}, and O_{vi} are predicted and original values for i^{th} data, respectively (Catalao et al., 2009; Houssein, 2017; Jiang et al., 2013; Liu et al., 2012; Monfared et al., 2009; Ren et al., 2014; Wang et al., 2015). The preceding section analyses the FF, CF, and idFF NNs considered to predict the power and speed of wind resources. The MHPSO-BAAC-*x* optimization algorithm employed to train the mentioned NNs is also briefly overviewed (Monfared et al., 2009).

Neural-Networks and Optimization Systems

This portion of the paper summarizes the NNs and the MHPSO-BAAC-x optimization algorithm. FFNN is an originally enhanced class of algorithm that involves neurons acting as the administering units and are designed in layers and each neuron in the layer relates to all the elements of the anterior layers. Data flows into the input layer and walks through the hidden layers to the output layer. In the usual manner, this NN operates as a categorizer and has no response in connecting layers, originating their name as FFNNs (Bebis and Georgiopoulos, 1994; "Feedforward Neural Networks - an overview | ScienceDirect Topics", n.d.).

When linking between the astuteness and multilayer network is established, then the structure has an explicit connection in the I/O layers shaped, and such a network is known as the CFNN (Warsito et al., 2018). The perceptron and the connection that is made in the I/O layers of CFNN is the following logic for direct relation. In contrast, for FFNN, a relationship is established between the I/O layers because of an indirect connection.

An id-FFN implements an NN-based operation as a nonlinear plotting object to assess nonlinearity in the ARX models. Such connectivity in the object allows the use of networks like DL Toolbox ("Multilayer feedforward neural network mapping function for nonlinear ARX models (requires Deep Learning Toolbox) - MATLAB", n.d.).

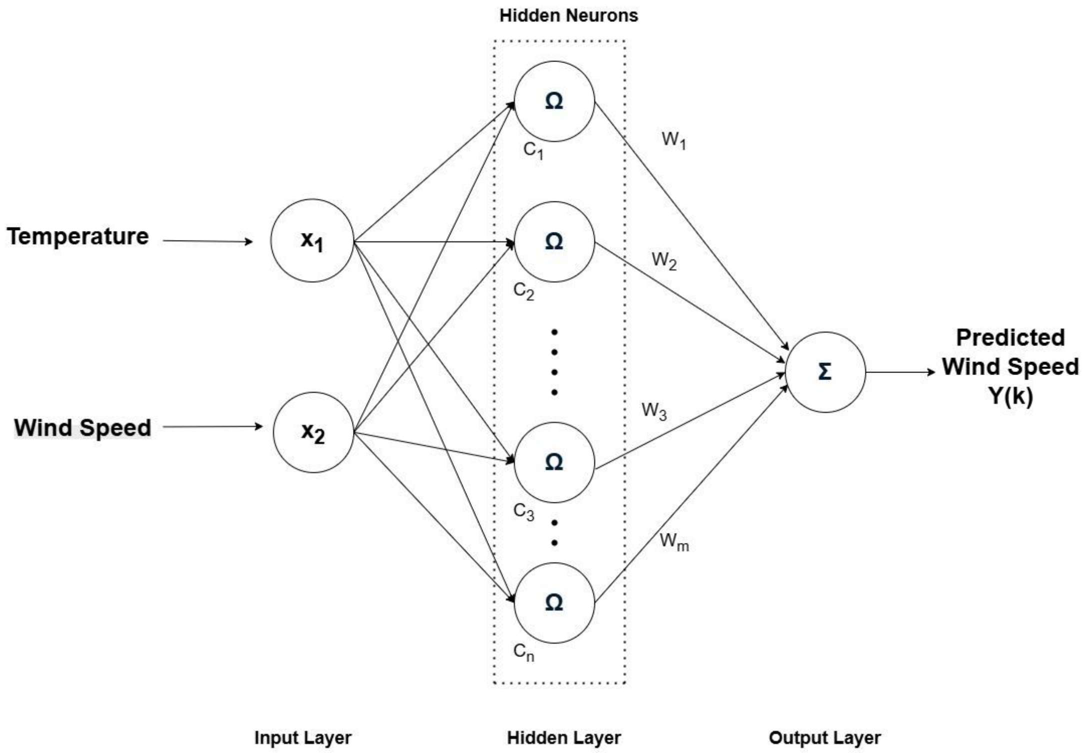


Fig. 4. Architecture of the id-FFN ("Multilayer feedforward neural network mapping function for nonlinear ARX models (requires Deep Learning Toolbox) - MATLAB", n.d.)

Mathematically, id-FFN maps n inputs $X(t) = [x_1(t), x_2(t), \ldots, x_n(t)]^T$ with an output $y(t)$ that is considered as a scalar quantity, through a multilayer FFNN of static category. Some important considerations for the implementation of id-FFN are as follows,

- It is recommended that the unknown I/O dimensions be indicated by avoiding the default zero.
- When predicting a nonlinear ARX model, the system automatically decides about the size of the I/O network.
- Adjust the sizes manually by setting I/O limits to n-by-2 and 1-by-2 matrices, respectively, where n is the no. of nonlinear ARX model regressors, and the limits are set according to the output data and maximum to minimum values of regressors, respectively.

The considered modification, MHPSO-BAAC- χ, is designed by integrating the constriction factor "χ" in the standard HPSOBA optimization. A detailed description of the standard hybrid PSO and BA (HPSOBA) is provided by (Ellahi and Abbas, 2020). As described in the cited paper, the variable "α" controls both the social and cognitive components to accelerate the particles (Ellahi et al., 2021).

The calculations for the particle velocity are performed using (9)

$$v_{id}^{t+1} = \left(\omega v_{id}^{t} + \alpha\left((pbest_{id} - x_{id}^{t}) + (gbest_{gd} - x_{id}^{t})\right)\right) \times \chi \quad (9)$$

and the constriction factor can be calculated using (10)

$$\chi = \frac{2}{\left|2-\varphi-\sqrt{\varphi^2-4\varphi}\right|}, \ \langle 4.1 \le \varphi \le 4.2 \rangle \qquad (10)$$

The calculation for the parameters α and ω and the particle position can be taken from the equations given in (Ellahi and Abbas, 2020). The flow chart and the pseudocode of MHPSO-BAAC-x are presented in (Ellahi et al., 2021).

Description of System Model

The estimation model employs NNs to predict the wind resource and the power that can be extracted from it. The designed model uses an optimization technique for the training of considered NNs. The issue with using classical optimization techniques for NN tunning is that wind prediction is entirely a local phenomenon, as the environmental conditions of each region in the world are different. Consequently, the previous regional data, fed as input values, also vary for every region, so generalization is not possible. Nevertheless, the essential flexibility inherited by the NNs allows the system to be tuned and trained in accordance with the regional requirements.

The paper describes the prediction for the speed and power of wind resources achieved through the FF, CF, and idFF NNs trained by the novel MHPSO-BAAC-x optimization algorithm. The forecast efficiency is highly dependent on the historical data values used to train NNs. The size of the dataset is significant as small datasets may not be able to help achieve precise results, and large datasets may make the results generalized. The block diagram shows the working mechanism of the proposed model used to predict wind resources in Poland.

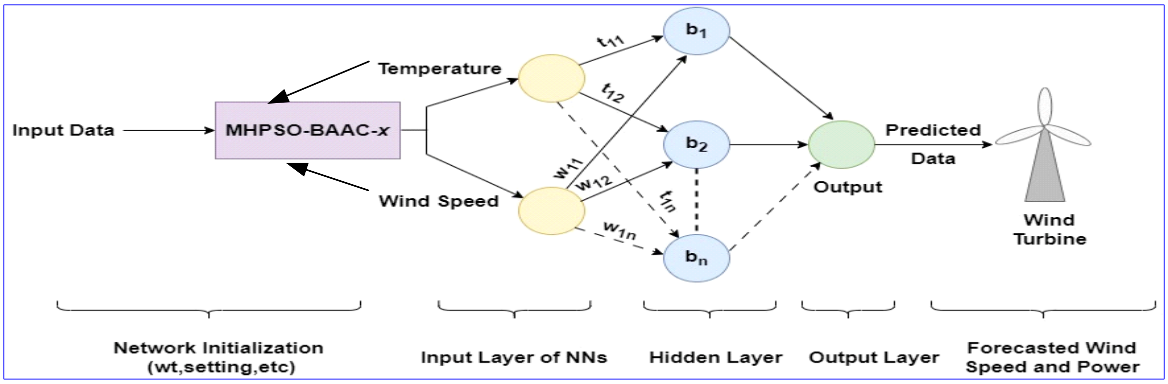


Fig. 5. Operational Diagram of Proposed Forecasting Model

The NNs consist of 350 neurons enlisted in parallel, and 180 recorded data values for the first six months of 2023 are used as input for the first layer. The MHPSO-BAAC-x trains the NNs, and they process the data from the input to the output layers of the mentioned NNs. The training of NNs is important to avoid the scenario of overfitting as it may obtain ambiguous results due to over-following of the input data by the generic NN-based system. This issue can be avoided by having a simplified and lesser number of input parameters. The correctness of the predicted output results can be tested through precision evaluation techniques like MAE, MAPE, and RMSE. The mathematical formulations of the mentioned precision testing schemes are presented in equations (6) to (8) of section 3 in this paper. Fig. 6 presents the flowchart of the working process of the designed mechanism for forecasting power and speed from wind resources.

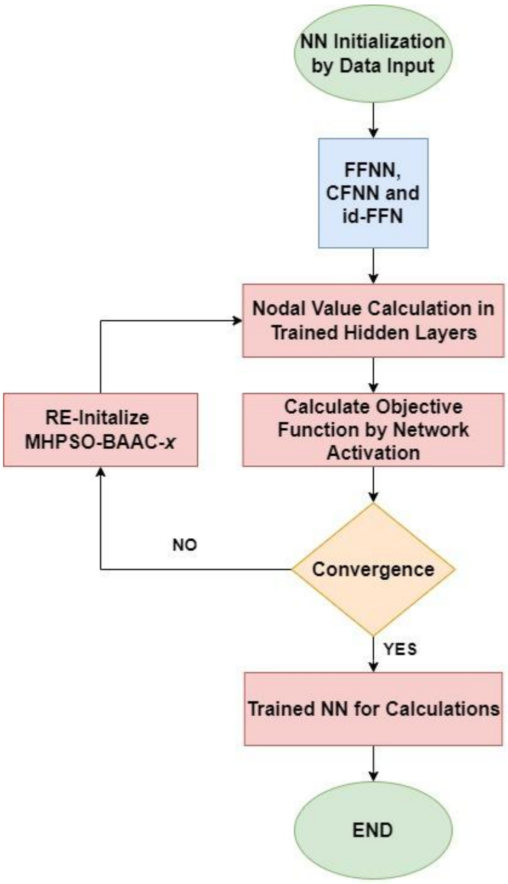


Fig. 6. Flow Chart of the working mechanism of the proposed model

The designed mechanism uses the 180 actual values of the second half of 2023 for computing the error in the actual and estimated values of the speed and power of wind resources. The pseudocode, representing the designed mechanism for the wind resource prediction using FFNN, CFNN, and id-FFN trained by the MHPSO-BAAC-*x,* is given in Table 2.

Table 2: Pseudocode for FFNN, CFNN, and id-FFN trained by MHPSO-BAAC-x

Algorithm: FFNN, CFNN, and id-FFN Trained Through MHPSO-BAAC-*x* Algorithm
Initialization of Neural Network (FFNN, CFNN, or id-FFN)
Initialize Nodes, bias, and weight
Defining the objective function
Feeding input from historical data values
The setting of Parameters, i.e., *npop*, maximum iterations, ω, *c*, *r* and *f* for MHPSO-BAAC-*x*
Setting the particle position and velocity
for *i*=1: *npop*
Position and Velocity initialization
Updating of personal best and *global best*
if optimal wind velocity >optimum velocity
optimal results = velocity;
end if
end for
Main Loop for MHPSO-BAAC-χ:
for *i*=1:*npop*
for iteration = 1 : *Maxit*
Calculation of α, ω and χ for MHPSO-BAAC-χ
Position and Velocity Updation
Updation of *personal best*:
if optimal velocity> velocity

position = optimal position;
velocity = optimal velocity;
output = optimal output;
Updating for *global best*
if optimum result of wind velocity > optimal velocity
Optimal velocity =optimum result;
end if
end if
end for
Optimal solution =Optimal Value;
Display (Iteration, Optimal Solution);
end for
Verify the precision of results using MAE, MAPE, and RMSE
Plotting of predicted wind power and speed

Results and Discussion

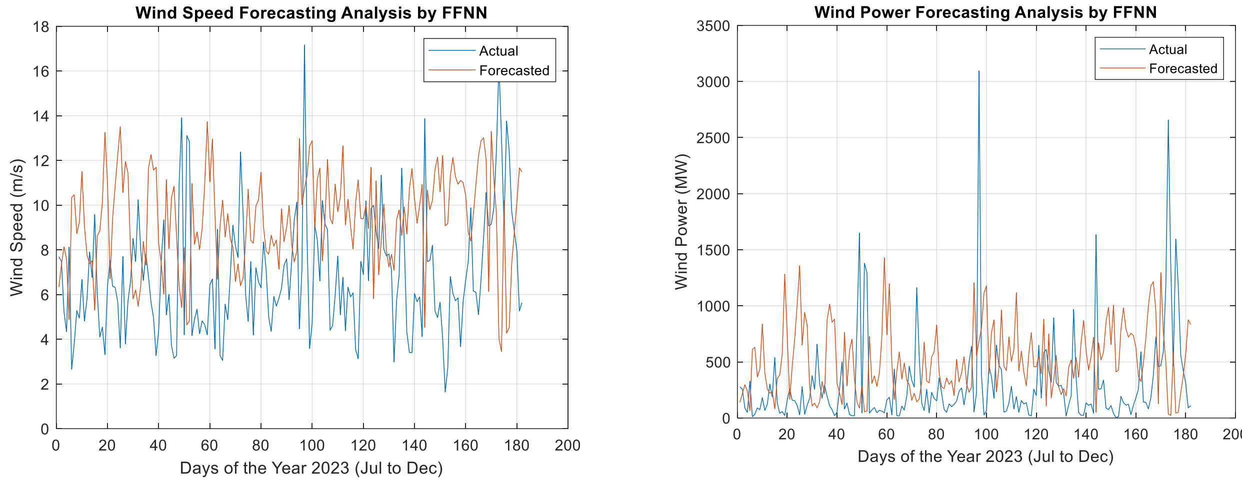
FFNN, CFNN, and id-FFN trained by the MHPSO-BAAC-*x* algorithms are implemented to predict wind power and speed. Poland has an extreme ability for electricity production using wind resources and needs a main shift towards the major power production by RERs as done by the developed countries in the EU ("Data collection survey on renewable energy development in Pakistan : final report. -", n.d.). Even though the country has a wonderful possibility for wind-based generation, Poland had previously mainly used TPPs to convince the demand for electricity. This restricted approach was mainly due to the intermittent nature of wind resources, which may create issues with the sustainability of RER-based power systems. This highlights the implementation of methods to make WPPs more trustworthy, specifically believing in improving the environment. This issue motivated to design and employ techniques for (Poland & its region for wind power generation). The values of the simulation parameters are specified in Table 3.

Table 3. Simulation Parameters of MHPSO-BAAC-x for the Designed System

Sr	*Parameters*	*Range*	*Value Used*
1	*Inertia Weight*	*[0–1]*	$\omega_{min} = 0.6$, $\omega_{max} = 0.8$
2	*Cognitive and Social co-efficient*	*[0–4]*	*2.5*
3	*C*	*[0-4]*	*2*
4	*Uniform random PDF*	*[0–1]*	*0.7*
5	*Frequency*	*[0–4]*	$fmin = 3.0$, $fmax = 3.5$
6	*Phi*	$[4.1 \leq \varphi \leq 4.2]$	$\varphi = 4.14$
7	*Population*	-	*100*
8	*Iteration*	-	*150*

The input consists of 180 values from January to June 2023, which are applied to forecast wind speed for the next six months, i.e., July to December. The remaining 180 values for 2023 are used to compare them with the forecasted results of the same period. Using these values, graphs for comparative wind speed and power are obtained that are presented in Fig.s 7, 8, and 9. The problem of over-fitting or under-fitting is restricted by a lower amount of required layers and input parameters. This approach of using lower numbers and simplified input parameters also assists in avoiding overfitting of targeted outputs.

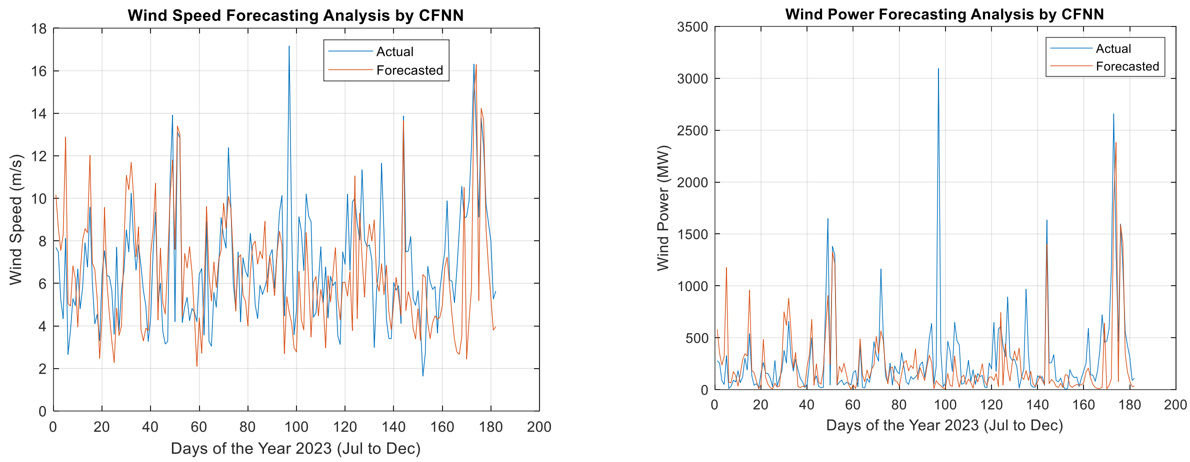
Fig.s 7 (a) and (b) compare the actual vs. estimated speed and power of wind resources when the FFNN is trained through the MHPSO-BAAC-x metaheuristic algorithm.



(a) Prediction of Wind Speed *(b) Prediction of Wind Power*

Fig. 7. Comparative Analysis Speed and Power of Wind Resource Forecasting through FFNN Trained by MHPSO-BAAC-x

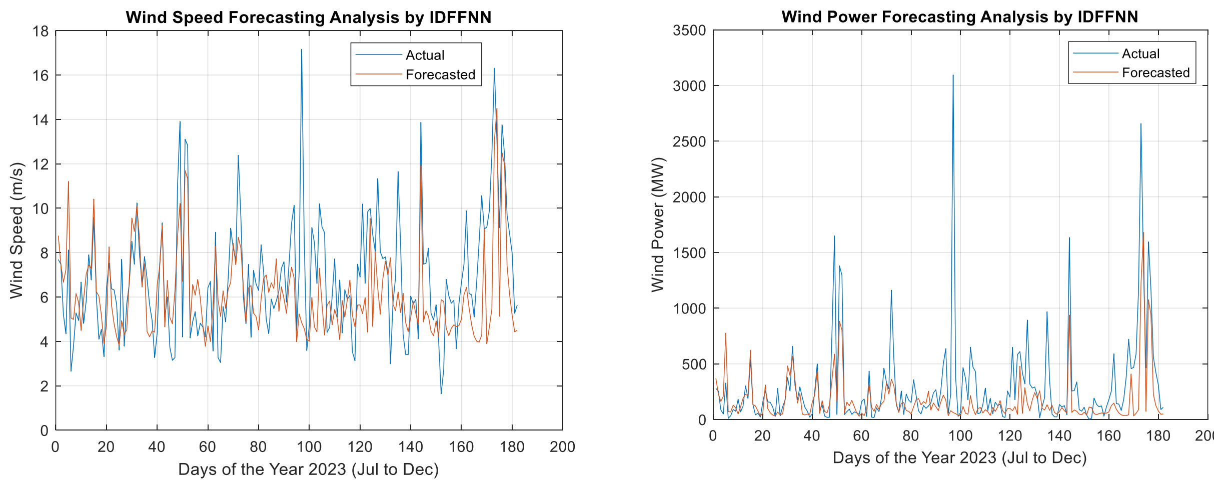
Fig.s 8 (a) and (b) compare the actual vs. estimated speed and power of wind resources when the MHPSO-BAAC-x metaheuristic algorithm is used to train CFNN.



(a) Prediction of Wind Speed *(b) Prediction of Wind Power*

Fig. 8. Comparative Analysis Speed and Power of Wind Resource Forecasting through CFNN Trained by MHPSO-BAAC-x

Fig.s 9 (a) and (b) compare the actual vs. estimated speed and power of wind resources when the id-FFN is trained through the MHPSO-BAAC-*x* metaheuristic algorithm.



(a) Prediction of Wind Speed *(b) Prediction of Wind Power*

Fig. 9. Comparative Analysis Speed and Power of Wind Resource Forecasting through id-FFN Trained by MHPSO-BAAC-x

From Fig.s 7(a) to 9(a), it is depicted that the id-FFN tuned by MHPSO-BAAC-*x* gives a better prediction result for wind speed as they are more mapped on the original values during the same period. The swept area of the turbine and the performance coefficient are set at 1, and Fig.s 7(b) to 9(b) present the graphs for the comparison of predicted and actual power from wind resources. As can be seen, these figures show a similar trend, and the id-FFN shows a closer mapping of the estimated wind power with the originally computed mean value.

Table 4 presents the MAE, MAPE, RMSE, and objective function computations for the considered FF, CF, and id-FF neural networks when trained through the MHPSO-BAAC-*x* optimization technique. The table also provides the mean of estimated wind power by each NN, the mean of overall actual wind power, and the time taken by each tuned NN to perform the assigned calculations.

Table 4. Average values of predicted wind speed, power, MAE, MAPE, RMSE, and objective function through the algorithm

NN's	Objective Function	Actual Power (MW)	Mean Forecasted Wind Power (MW)	MAE (m/s)	MAPE (%)	RMSE (m/s)	Elapsed Time (ms)
CFNN	5.0597	299.5827	298.3717	0.0121	0.0487	0.0122	615000
FFNN	5.0655	299.5827	304. 6806	0.0509	1.6732	0.0598	630117
ID-FFN	4.8591	299.5827	300.7795	0.0119	0.0398	0.0127	630865

Among the calculated objective functions from the considered NNs, id-FFN provides the best results, and the same trend is observed for the estimated wind power, computational time, and precision testing mechanisms, while the second-best performance is achieved by the algorithm when CFNN is used. Table 2 summarizes that both CFNN and id-FFN provide optimal results for wind power estimation with reasonable precision, in contrast to the FFNN. The values of the MAE, MAPE, RMSE, and objective function also validate the better performance achieved by the id-FFN as compared to FFNN and CFNN, as it is also evident from the comparative graphs presented in Fig.s 7, 8, and 9.

Conclusion

The study aimed to increase the accuracy of wind speed and power forecasts for the Silesian Voivodeship using meteorological data from 2023. Modeling was carried out using three neural network architectures: a classic feedforward network (FFNN), a cascade network (CFNN), and an improved version of the FFNN network (id-FFN). Each model was trained on data from the first half of the year (January-June) and then used to forecast values for the second half of the year (July-December).

Analysis of the results showed that the id-FFN model achieved the highest accuracy of the forecasts, obtaining the lowest values of error rates. The MAE for the id-FFN model was 0.0119 m/s for the wind speed forecast, while the value for CFNN was 0.0121 m/s and for FFNN was 0.0509 m/s. For the relative percent error (MAPE), the id-FFN model reached 0.0398%, CFNN was 0.0487%, and FFNN was 1.6732%. The RMSE was 0.0127 m/s for id-FFN, 0.0122 m/s for CFNN, and 0.0598 m/s for FFNN, respectively. The use of the MHPSO-BAAC-x algorithm to optimize network weights and parameters proved to be crucial for stable and accurate convergence. Integrating swarm intelligence mechanisms with adaptive acceleration factors based on the bat algorithm enabled effective bypassing of local minima and improved model generalization, which is often a challenge for forecasts of nonlinear atmospheric phenomena. From a practical point of view, the quality of the forecasts obtained – especially for the id-FFN model – makes the system useful in the context of supporting energy planning. The projected wind power was strongly correlated with the actual values, and the average forecasted power generated by the id-FFN model in the year's second half was 300.7795 MW with an actual average of 299.5897 MW. This fit confirms the model's ability to capture temporal variability and regional characteristics of wind conditions.

The proposed solution has practical applications in the processes of planning the operation of renewable sources, and its scalability allows for easy adaptation to other geographical areas and meteorological conditions. The developed model can support activities aimed at increasing the share of wind energy in the national energy mix and contribute to achieving goals related to energy transformation, grid efficiency, and decarbonization of the power sector.

References

2050 long-term strategy - European Commission [WWW Document], n.d. URL https://climate.ec.europa.eu/eu-action/climate-strategies-targets/2050-long-term-strategy_en (accessed 6.28.24).

Aasen, M., Vatn, A., 2018. Public Attitudes Toward Climate Policies: The Effect of Institutional Contexts and Political Values. Ecological Economics 146, 106–114. https://doi.org/10.1016/j.ecolecon.2017.10.008

Ammar, E., and Xydis, G., 2024. Wind speed forecasting using deep learning and pre-processing techniques. International Journal of Green Energy 21, 988–1016. https://doi.org/10.1080/15435075.2023.2228878

Anwar, M.N., Iftikhar, M., Khush Bakhat, B., Sohail, N.F., Baqar, M., Yasir, A., Nizami, A.S., 2019. Sources of Carbon Dioxide and Environmental Issues, in: Inamuddin, Asiri, A.M., Lichtfouse, E. (Eds.), Sustainable Agriculture Reviews 37: Carbon Sequestration Vol. 1 Introduction and Biochemical Methods. Springer International Publishing, Cham, pp. 13–36. https://doi.org/10.1007/978-3-030-29298-0_2

Augutis, J., Martišauskas, L., Krikštolaitis, R., 2015. Energy mix optimization from an energy security perspective. Energy Conversion and Management 90, 300–314. https://doi.org/10.1016/j.enconman.2014.11.033

Bañuelos-Ruedas, F., Angeles-Camacho, C., Rios-Marcuello, S., 2011. Methodologies Used in the Extrapolation of Wind Speed Data at Different Heights and Its Impact in the Wind Energy Resource Assessment in a Region. Wind Farm - Technical Regulations, Potential Estimation and Siting Assessment. https://doi.org/10.5772/20669

Bebis, G., Georgiopoulos, M., 1994. Feed-forward neural networks. IEEE Potentials 13, 27–31. https://doi.org/10.1109/45.329294

Brożyna, J., Mentel, G., Ivanová, E., Sorokin, G., 2019. Classification of Renewable Sources of Electricity in the Context of Sustainable Development of the New EU Member States. Energies 12, 2271. https://doi.org/10.3390/en12122271

Casalicchio, V., Manzolini, G., Prina, M.G., Moser, D., 2022. From investment optimization to fair benefit distribution in renewable energy community modelling. Applied Energy 310, 118447. https://doi.org/10.1016/j.apenergy.2021.118447

Catalao, J.P.S., Pousinho, H.M.I., Mendes, V.M.F., 2009. An Artificial Neural Network Approach for Short-Term Wind Power Forecasting in Portugal, in: 2009 15th International Conference on Intelligent System Applications to Power Systems. pp. 1–5. https://doi.org/10.1109/ISAP.2009.5352853

Clean energy for all Europeans package [WWW Document], n.d. URL https://energy.ec.europa.eu/topics/energy-strategy/clean-energy-all-europeans-package_en (accessed 6.28.24).

COP28 UAE - United Nations Climate Change Conference [WWW Document], n.d. URL https://www.cop28.com/en/ (accessed 6.28.24).

Data collection survey on renewable energy development in Pakistan : final report. - [WWW Document], n.d. URL https://openjicareport.jica.go.jp/643/643/643_117_12086740.html (accessed 6.24.21).

Dawid, L., 2018. Perspectives on offshore wind farms development in chosen countries of European Union. Journal of Water and Land Development no. 38. https://doi.org/10.2478/jwld-2018-0039

Dorrell, J., Lee, K., 2021. The Price of Wind: An Empirical Analysis of the Relationship between Wind Energy and Electricity Price across the Residential, Commercial, and Industrial Sectors. Energies 14, 3363. https://doi.org/10.3390/en14123363

Du, P., Wang, J., Yang, W., Niu, T., 2019. A novel hybrid model for short-term wind power forecasting. Applied Soft Computing 80, 93–106. https://doi.org/10.1016/j.asoc.2019.03.035

El-Hendawi, M., Wang, Z., 2020. An ensemble method of full wavelet packet transform and neural network for short term electrical load forecasting. Electric Power Systems Research 182, 106265. https://doi.org/10.1016/j.epsr.2020.106265

Ellahi, M., Abbas, G., 2020. A Hybrid Metaheuristic Approach for the Solution of Renewables-Incorporated Economic Dispatch Problems. IEEE Access 8, 127608–127621. https://doi.org/10.1109/ACCESS.2020.3008570

Ellahi, M., Abbas, G., Satrya, G.B., Usman, M.R., Gu, J., 2021. A Modified Hybrid Particle Swarm Optimization With Bat Algorithm Parameter Inspired Acceleration Coefficients for Solving Eco-Friendly and Economic Dispatch Problems. IEEE Access 9, 82169–82187. https://doi.org/10.1109/ACCESS.2021.3085819

Energetyki, U.R., n.d. Moc zainstalowana (MW) [WWW Document]. Urząd Regulacji Energetyki. URL https://www.ure.gov.pl/pl/oze/potencjal-krajowy-oze/5753,Moc-zainstalowana-MW.html (accessed 6.28.24).

Energy Policy of Poland until 2040 (EPP2040) - Ministry of Climate and Environment - Gov.pl website [WWW Document], n.d. . Ministry of Climate and Environment. URL https://www.gov.pl/web/climate/energy-policy-of-poland-until-2040-epp2040 (accessed 6.28.24).

Feedforward Neural Networks - an overview | ScienceDirect Topics [WWW Document], n.d. URL https://www.sciencedirect.com/topics/chemical-engineering/feedforward-neural-networks (accessed 6.15.21).

"Fit for 55": delivering the EU's 2030 Climate Target on the way to climate neutrality [WWW Document], n.d. URL https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52021DC0550&from=EN (accessed 6.28.24).

Graczyk, D., Pińskwar, I., Choryński, A., Stasik, R., 2024. Less power when more is needed. Climate-related current and possible future problems of the wind energy sector in Poland. Renewable Energy 232, 121093. https://doi.org/10.1016/j.renene.2024.121093

Hassan, M.W., Manowska, A., Kienberger, T., 2025. A breakthrough in achieving carbon neutrality in Poland: Integration of renewable energy sources and Poland's 2040 energy policy. Energy Reports 13, 653–669. https://doi.org/10.1016/j.egyr.2024.12.033

Hirth, L., Mühlenpfordt, J., Bulkeley, M., 2018. The ENTSO-E Transparency Platform – A review of Europe's most ambitious electricity data platform. Applied Energy 225, 1054–1067. https://doi.org/10.1016/j.apenergy.2018.04.048

Houssein, E.H., 2017. Particle Swarm Optimization-Enhanced Twin Support Vector Regression for Wind Speed Forecasting. Journal of Intelligent Systems 28, 905–914. https://doi.org/10.1515/jisys-2017-0378

Jiang, Y., Song, Z., Kusiak, A., 2013. Very short-term wind speed forecasting with Bayesian structural break model. Renewable Energy 50, 637–647. https://doi.org/10.1016/j.renene.2012.07.041

Jonkers, J., Avendano, D.N., Van Wallendael, G., Van Hoecke, S., 2024. A novel day-ahead regional and probabilistic wind power forecasting framework using deep CNNs and conformalized regression forests. Applied Energy 361, 122900. https://doi.org/10.1016/j.apenergy.2024.122900

Kardaś, S., n.d. From coal to consensus: Poland's energy transition and its European future | ECFR | Policy Commons.

Kisvari, A., Lin, Z., Liu, X., 2021. Wind power forecasting – A data-driven method along with gated recurrent neural network. Renewable Energy 163, 1895–1909. https://doi.org/10.1016/j.renene.2020.10.119

Koć, J., 2022. WindEurope: Morskie plany zagospodarowania przestrzennego państw UE pozwolą na 220 GW morskiej energetyki wiatrowej. Baltic Wind. URL https://balticwind.eu/pl/windeurope-morskie-plany-zagospodarowania-przestrzennego-panstw-ue-pozwola-na-220-gw-morskiej-energetyki-wiatrowej/ (accessed 6.28.24).

Krajowe zapotrzebowanie na energię elektryczną w 2020 r. - RYNEK ENERGI ELEKTRYCZNEJ I GAZU [WWW Document], n.d. URL https://www.cire.pl/artykuly/rynek-energii-elektrycznej-i-gazu/180463-krajowe-zapotrzebowanie-na-energie-elektryczna-w-2020-r (accessed 6.28.24).

Kumar, N., Tripathi, M.M., Gupta, S., Alotaibi, M.A., Malik, H., Afthanorhan, A., 2023. Study of Potential Impact of Wind Energy on Electricity Price Using Regression Techniques. Sustainability 15, 14448. https://doi.org/10.3390/su151914448

Lannoye, E., 2015. Renewable energy integration: practical management of variability, uncertainty, and flexibility in power grids [book reviews]. IEEE Power and Energy Magazine 13, 106–107. https://doi.org/10.1109/MPE.2015.2458758

Lashof, D.A., Ahuja, D.R., 1990. Relative contributions of greenhouse gas emissions to global warming. Nature 344, 529–531. https://doi.org/10.1038/344529a0

Liebe, U., Bartczak, A., Meyerhoff, J., 2017. A turbine is not only a turbine: The role of social context and fairness characteristics for the local acceptance of wind power. Energy Policy 107, 300–308. https://doi.org/10.1016/j.enpol.2017.04.043

Liu, Z., Gao, W., Wan, Y.-H., Muljadi, E., 2012. Wind power plant prediction by using neural networks, in: 2012 IEEE Energy Conversion Congress and Exposition (ECCE). Presented at the 2012 IEEE Energy Conversion Congress and Exposition (ECCE), pp. 3154–3160. https://doi.org/10.1109/ECCE.2012.6342351

Main page - PSE Raport [WWW Document], n.d. URL https://raport.pse.pl/en (accessed 6.28.24).

Manowska, A., 2021. Forecasting of the Share of Renewable Sources in the Total Final Energy Consumption for Selected European Union Countries. IOP Conf. Ser.: Earth Environ. Sci. 906, 012134. https://doi.org/10.1088/1755-1315/906/1/012134

Manowska, A., 2020a. Using the LSTM Network to Forecast the Demand for Electricity in Poland. Applied Sciences 10, 8455. https://doi.org/10.3390/app10238455

Manowska, A., 2020b. Analysis and Forecasting of the Primary Energy Consumption in Poland Using Deep Learning. Inżynieria Mineralna 1, 217–222. https://doi.org/10.29227/IM-2020-01-77

Manowska, A., Bluszcz, A., Chomiak-Orsa, I., Wowra, R., 2024. Towards Energy Transformation: A Case Study of EU Countries. Energies 17, 1778. https://doi.org/10.3390/en17071778

Menegaki, A.N., Tiwari, A.K., 2017. The index of sustainable economic welfare in the energy-growth nexus for American countries. Ecological Indicators 72, 494–509. https://doi.org/10.1016/j.ecolind.2016.08.036

Monfared, M., Rastegar, H., Kojabadi, H.M., 2009. A new strategy for wind speed forecasting using artificial intelligent methods. Renewable Energy 34, 845–848. https://doi.org/10.1016/j.renene.2008.04.017

Multilayer feedforward neural network mapping function for nonlinear ARX models (requires Deep Learning Toolbox) - MATLAB [WWW Document], n.d. URL https://www.mathworks.com/help/ident/ref/idfeedforwardnetwork.html?s_tid=srchtitle_site_search_1_id%20FeedforwardNetwork (accessed 6.28.24).

Ochoa, G.V., Alvarez, J.N., Acevedo, C., 2019. RESEARCH EVOLUTION ON RENEWABLE ENERGIES RESOURCES FROM 2007 TO 2017: A COMPARATIVE STUDY ON SOLAR, GEOTHERMAL, WIND AND BIOMASS ENERGY. IJEEP 9, 242–253. https://doi.org/10.32479/ijeep.8051

Office, E.R., n.d. Energy Regulatory Office [WWW Document]. Energy Regulatory Office. URL https://www.ure.gov.pl/en (accessed 6.28.24).

Offshore wind in Europe - key trends and statistics 2020 | WindEurope [WWW Document], n.d. URL https://windeurope.org/intelligence-platform/product/offshore-wind-in-europe-key-trends-and-statistics-2020/# (accessed 6.28.24).

Piotrowski, P., Kopyt, M., Baczyński, D., Robak, S., Gulczyński, T., 2021. Hybrid and Ensemble Methods of Two Days Ahead Forecasts of Electric Energy Production in a Small Wind Turbine. Energies 14, 1225. https://doi.org/10.3390/en14051225

Polskie Sieci Elektroenergetyczne – Integrated Impact Report – Homepage [WWW Document], n.d. URL https://raport2020.pse.pl/en (accessed 6.28.24).

PSE Capital Group - Suntech S.A. [WWW Document], n.d. URL https://www.suntech.pl/en/customers/telecom/36-pse-capital-group-2 (accessed 6.28.24).

Ren, C., An, N., Wang, J., Li, L., Hu, B., Shang, D., 2014. Optimal parameters selection for BP neural network based on particle swarm optimization: A case study of wind speed forecasting. Knowledge-Based Systems 56, 226–239. https://doi.org/10.1016/j.knosys.2013.11.015

Renewable Power Generation Costs in 2019 [WWW Document], 2020. URL https://www.irena.org/publications/2020/Jun/Renewable-Power-Costs-in-2019 (accessed 6.28.24).

Renewables will be world's top electricity source within three years, IEA data reveals - Carbon Brief [WWW Document], n.d. URL https://www.carbonbrief.org/renewables-will-be-worlds-top-electricity-source-within-three-years-iea-data-reveals/ (accessed 6.28.24).

Report on the review of the report upon expiration of the additional period for fulfilling commitments for the second commitment period of the Kyoto Protocol of Finland submitted in 2023. Note by the expert review team | UNFCCC [WWW Document], n.d. URL https://unfccc.int/documents/638632 (accessed 6.28.24).

Risks Related to Energy Policy of Poland Until 2040 (EPP 2040), 2023. . Archives of Mining Sciences. https://doi.org/10.24425/ams.2020.135183

Robak, S., Raczkowski, R., Piekarz, M., 2023. Development of the Wind Generation Sector and Its Effect on the Grid Operation—The Case of Poland. Energies 16, 6805. https://doi.org/10.3390/en16196805

Shahid, F., Zameer, A., Muneeb, M., 2021. A novel genetic LSTM model for wind power forecast. Energy 223, 120069. https://doi.org/10.1016/j.energy.2021.120069

Sun, X., Liu, H., 2024. Multivariate short-term wind speed prediction based on PSO-VMD-SE-ICEEMDAN two-stage decomposition and Att-S2S. Energy 305, 132228. https://doi.org/10.1016/j.energy.2024.132228

Valodka, I., Valodkienė, G., 2015. The Impact of Renewable Energy on the Economy of Lithuania. Procedia - Social and Behavioral Sciences, 20th International Scientific Conference "Economics and Management 2015 (ICEM-2015)" 213, 123–128. https://doi.org/10.1016/j.sbspro.2015.11.414

Wang, J., Zhou, Q., Jiang, H., Hou, R., 2015. Short-Term Wind Speed Forecasting Using Support Vector Regression Optimized by Cuckoo Optimization Algorithm [WWW Document]. Mathematical Problems in Engineering. https://doi.org/10.1155/2015/619178

Warsito, B., Santoso, R., Suparti, Yasin, H., 2018. Cascade Forward Neural Network for Time Series Prediction. J. Phys.: Conf. Ser. 1025, 012097. https://doi.org/10.1088/1742-6596/1025/1/012097

West, T.O., Marland, G., 2002. A synthesis of carbon sequestration, carbon emissions, and net carbon flux in agriculture: comparing tillage practices in the United States. Agriculture, Ecosystems & Environment 91, 217–232. https://doi.org/10.1016/S0167-8809(01)00233-X

Wind energy in Europe: 2022 Statistics and the outlook for 2023-2027 | WindEurope [WWW Document], n.d. URL https://windeurope.org/intelligence-platform/product/wind-energy-in-europe-2022-statistics-and-the-outlook-for-2023-2027/ (accessed 6.28.24).

Wood, G., Finnegan, J.J., Allen, M.L., Allen, M.M.C., Cumming, D., Johan, S., Nicklich, M., Endo, T., Lim, S., Tanaka, S., 2020. The comparative institutional analysis of energy transitions. Socio-Economic Review 18, 257–294. https://doi.org/10.1093/ser/mwz026

World Energy Outlook 2023 – Analysis [WWW Document], 2023. . IEA. URL https://www.iea.org/reports/world-energy-outlook-2023 (accessed 6.28.24).

Wrigley, E.A., 2013. Energy and the English Industrial Revolution. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 371, 20110568. https://doi.org/10.1098/rsta.2011.0568

Xu, Q., He, D., Zhang, N., Kang, C., Xia, Q., Bai, J., Huang, J., 2015. A Short-Term Wind Power Forecasting Approach With Adjustment of Numerical Weather Prediction Input by Data Mining. IEEE Transactions on Sustainable Energy 6, 1283–1291. https://doi.org/10.1109/TSTE.2015.2429586

Zhang, Z., Yin, J., 2024. Spatial-temporal offshore wind speed characteristics prediction based on an improved purely 2D CNN approach in a large-scale perspective using reanalysis dataset. Energy Conversion and Management 299, 117880. https://doi.org/10.1016/j.enconman.2023.117880

Zou, C., Xiong, B., Xue, H., Zheng, D., Ge, Z., Wang, Y., Jiang, L., Pan, S., Wu, S., 2021. The role of new energy in carbon neutral. Petroleum Exploration and Development 48, 480–491. https://doi.org/10.1016/S1876-3804(21)60039-3