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Investigating the possibility of using a supervised neural network to predict the amount of electricity generated by wind farms

***Abstract**. The article presents the state-of-the-art and the results of the authors' own research obtained with the use of an artificial neural network to predict the amount of energy generated by wind turbines. A supervised neural network was used to convert algorithmically inputted meteorological data into output forecast data representing the amount of energy that could be generated by the offshore wind turbines. The amount of energy produced by renewable energy sources is directly linked to unpredictable weather conditions. The stochastic nature of meteorological conditions makes it difficult to extrapolate generation curves, which are necessary for the balancing energy market. Implementing neural networks in national energy systems can make them more resilient and sustainable, by enabling the efficient synergy of RES and conventional energy sources.*

Streszczenie.** W artykule przedstawiono przegląd literatury oraz wyniki badań autorów związane z wykorzystaniem sieci neuronowych do predykcji generowanej energii elektrycznej przez farmy wiatrowe. W pracy wykorzystano nadzorowaną sieć neuronową do konwersji wartości wejściowych, w postaci meteorologicznych danych pogodowych, na dane wyjściowe, w postaci prognozowanej dostępnej generacji energii elektrycznej przez morską farmę wiatrową. Ilość wytwarzanej energii poprzez odnawialne źródła energii jest skorelowana z nieprzewidywalnymi warunkami środowiskowymi. Stochastyczna natura warunków atmosferycznych utrudnia wyprowadzenie ekstrapolowanych krzywych generacji, niezbędnych do zarządzania rynkiem bilansującym energii elektrycznej. Zastosowanie sieci neuronowych w krajowych systemach energetycznych może zagwarantować bezpieczną zrównoważoną synergię OZE z konwencjonalnymi źródłami wytwórczymi.* ***(Zbadanie możliwości wykorzystania nadzorowanej sieci neuronowej do prognozowania ilości generowanej energii elektrycznej przez elektrownie wiatrowe)

Keywords: Supervised neural networks, WECS, wind turbines, generation forecasting, smart grid
Słowa kluczowe: Nadzorowane sieci neuronowe, WECS, turbiny wiatrowe, prognozowanie generacji, inteligentne sieci

Introduction

The rapid development of computing power by computers in the last few decades, combined with access to extensive data resources through Big Data, thanks to the implementation of the Smart Grid and the numerous measurement and control points included in it, enables a new perspective for the control and management of energy flows in the national power grids. The effective use of data collected from the power grid and automation of many management, measurement, and control points in it will be a key task for power distribution operators in the ongoing fourth industrial revolution. The following work presents the possibilities of using artificial neural networks for the above purpose, focusing on the extrapolation and conversion of weather data into generation data for renewable energy sources on the example of offshore wind farm. Numerous publications on this topic, for both solar and wind renewable energy sources, emphasized the significance of this field of study [1, 2, 3, 4, 5].

The production capacity of renewable sources depends on its technical and geographical characteristics, nevertheless, mainly on the stochastic atmospheric conditions, which neither humans nor any machines can fully control. Humans, on the other hand, can effectively predict future data and the mathematical correlations that result from it, including those previously unknown to science, through the development of computerized artificial neural network counterparts based on their own neural networks found in living organisms. In the following work, the neural networks designed to convert the quantities characterizing the moving air masses into wind farm potential generation data by WECS (Wind Energy Conversion Systems) has been analysed. The impact of the neural network parameterization on the effectiveness of mathematical calculations made by them has also been verified. The tested algorithm can also be used to predict future solar plant generation, by the change of input key weather data conditions for this type of energy source in investigated neural network. The change of data sets would be as follows: from those analysed below for wind farms to those most important for solar plants. For the solar plant, the most important weather conditions affecting power generation are humidity, pressure, wind speed, temperature, and time of the day with respect to its geographical location. For wind farms, as has been proved in the presented research, practically only the speed of moving air masses is enough to create efficient WECS.

Precise weather forecasting is a difficult and expensive task. Access to those data is necessary for many industries, such as aviation, sailing, agriculture, and many others, including the power grid, especially when using renewable energy sources [6]. Multiple governments have noticed that weather forecasting is necessary for the security of their countries. Great Britain, for example, through cooperation with Microsoft, invested a whopping £1.2 billion for the supercomputer, dedicated solely to making predictions of weather conditions [7]. Data obtained from those types of computing machines, which also use artificial intelligence, can greatly accelerate the achievement of decarbonization and other key goals set by the IEA's plan for NET-ZERO by 2050 [8]. Implementation of those systems in pair with the smart grid, V2G electric vehicles, growing popularization of RES, energy storages and other innovative technologies, also supported by smart buildings, will accelerate the decarbonization of the economies in the UE [9].

The structure of this article is presented as follows, in the next section, authors present state-of-the art studies addressing the presented research problem. Next, logic and mathematics behaviour of neural networks are briefly explained. Afterwards, authors present and discuss their own research and its methodology. Finally, selected experimental results are summarized, conclusions are drawn and ideas for the development and potential usage of created ANNs is presented. The results, presented in this work, have been detailed in one of the authors master's thesis's [10], in which different architectures of supervised neural networks were used for the presented purpose.

State-of-the art study

Mathematical correlations between atmospheric conditions and the power output of renewable sources are nonlinear. For example, for wind turbines, there must be enough kinetic energy from moving air masses to set the turbine blades into motion. The generator does not produce the energy below the specified cut-in speed. The same applies for high values of the wind speed, for which, when the cut-off speed is exceeded, damage risk for the rotor arises. When above cut-off speed occurs, a wind turbine turns off and does not produce any energy at all, meaning that although the wind speed increases and the power output decreases [11]. Conventional derivation of equations, describing the above variables correlations, must consider not only technical and geographical conditions, but also phenomena like the Wake Effect [12] to create precise, manually obtained algorithms. Those algorithms should be derived individually for each wind farm [13]. The use of a supervised neural network for this purpose reduces the complexity of the task that must be solved. With the use of NN one must collect the right training sets, find the optimal neural network model and its calibration for a given mathematical problem. The authors of numerous works have analysed this problem with the use of artificial intelligence [1,2,4,5]. Extrapolated wind turbine power data is required not only for power grid balancing, but also for the forecasting possible risks and dangers in distribution networks [2]. It also allows for advanced planning of a wind farm’s operational and service brakes.

In the energy networks of some countries, like Poland, where generation sources are based on conventional energy sources, mostly coal, medium and long-term prediction systems are a necessity. In Poland, based on data from 2021, more than 75% of energy demand was covered by coal-based power stations [14]. This type of power plant is characterized by very slow dynamics, and that’s why medium- and long-term predictions, exceeding 24 hours of prediction for renewable sources, are a necessity. The seemingly low share of wind farms and other renewable sources, amounting to only 10.75% of the total generation coverage in 2020 for the Polish National Power System [14], may mistakenly underestimate their importance. This value may be significantly higher, depending on the day and its time. Installed power of renewable sources alone in 2018 was equal to 8593 GW [15], this value has increased rapidly from 2556 GW in 2010 to 8593 GW in 2018. The vast majority of this power was and is provided by the wind farms, in 2018 of the 8593 GW installed RES power, 5864 GW were provided by wind farms alone. The potential usage of this power on individual days may vary significantly and can exceed the value of 10.75%. Knowing the weather conditions in advance is essential for proper economic and prudent power grid management with RES.

ANNs are able to predict data generation based on measured weather conditions around the given renewable source, for this purpose, recurrent neural networks can be used [16], such as IIR-MLN, RNN, or LAF-MLN. Those systems can predict, based on measured data, the future wind speed and, resulting from it, the wind power. The effectiveness of such systems based on artificial intelligence increases significantly if many wind farm prediction systems are tested at the same time, and then their performances are averaged. Extrapolated wind power curves, calculated by the usage of ANN for an hourly wind power prediction of a single farm, typically have an error of around 6%. For 24 hours this value is about 11%, and for 48 hours it is almost 14%. When analysing the prediction of 120 wind farms at once and then averaging their performance, the MSE error reduces for an hourly prediction to only 1.3%, for 24 hours to about 5%, and for 48 hours to about 7.5% [3]. Other studies confirm similar effectiveness of systems predicting wind power by the usage of ANNs [1, 2]. The performance results of the prediction systems were obtained based on the measured past atmospheric quantities, based on which predictions of wind power were made. The authors of this article did not specify how precise was the part of their networks responsible for converting the already extrapolated meteorological data into generation data. The networks created by them usually directly process historical weather data into future generation potential. In this article, authors assumed that the predicted weather data may come from an external source of prediction, responsible solely for forecasting weather data. The authors of this article evaluated the effectiveness of the ANNs in the task of converting the obtained atmospheric data forecast into the generation potential of the analyzed wind farm.

Supervised Neural Network

A supervised neural network is a type of artificial intelligence capable of finding mathematical correlations between sets of data. The input signals are provided to the neurons through connections with established weights. During the training, supervised neural network, using the backpropagation algorithm, modifies the weights of neurons connections to make them properly respond to the presented learning patterns. The basic exemplary structure of a neuron is presented in Figure 1. The matrix of an input data looks as follow: each row consists of a certain number of components of the input vector (for example, variables *x1*, *x2*, *x3*) multiplied by the number of training patterns. Such a matrix is loaded into ANNs. During training, the supervised neural network has also access to the output matrix, which contains required answers, related to input data, with the same number of samples as the input matrix. Those sets combined create a training data set, based on which supervised neural network, during training, can find optimal weights from its input to hidden and output layers. During the neural network training process, the output values are compared with the correct answers to calculate the error of the network. Next, the error is fed back to the network, so that the weights of each individual neuron can be adjusted to diminish the error value of the established system.

Based on this rule, after repeating this process for an appropriate number of learning cycles (epochs), a neural network of this type will usually find the global minimum of an error function. Trained network, after a successful process of learning, is able to properly generate the output data for the input signals that it has never seen before. The relationships, determined during the learning process, allow for the precise determination of output data, even for non-linear problems.

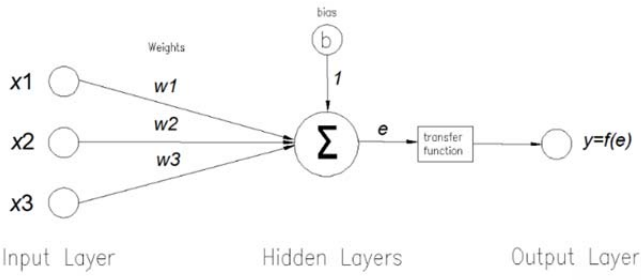

Fig. 1 Basic structure of a neuron [10]

Supervised and other types of neural networks find applications in countless areas of engineering and medicine

[17, 18, 19, 20]. The ANN's mystery stems from the fact that the mathematical correlations established in them, between input and output data, are frequently unknown. The logic behind the dependencies created in NNs may be unknown, both to the creator of a given network and even to the current state of science. Networks are also incomparably faster than humans at making decisions and deriving complicated mathematical correlations. In addition to the obvious relationships between data, ANNs can find correlations that are not so obvious. In the presented article, the authors verified the problem where NNs had to find correlations between weather variables and wind farm power generation. When analysing a given problem, one can consider such variables as turbulence of flowing air masses behind turbines, adjacent topography, and much more related to examined wind farm. ANNs can do it all based on simple data sets containing only basic measurement data, which will be explained in the next section. ANN uses a backpropagation algorithm to detect prediction errors during the learning process. The authors used a stochastic gradient descent to find optimal weights for each synapse in a network and each neuron's bias. Both weights and biases are learnable parameters. Often in ANNs, including those researched in this paper, Levenberg-Marquardt training functions (1) are used [21], which is a modification of Gauss–Newton algorithm. This method is used to solve non-linear least squares problems. The goal of the problem is to find a model with the lowest possible error (*d*) expressed in relation to the reference output of ANNs described by *V*(*d*) function. The error (*d*) is expressed as a difference between an ANNs output (*y*) and a reference data (*z*).

(1) $$\Delta\underline{d} = -[\nabla^2 V(\underline{d})]^{-1}\nabla V(\underline{d})$$

In the equation (1), $\nabla^2 V(\underline{d})$ is a hessian matrix, while $\nabla V(\underline{d})$ is an error gradient. The error function is expressed by the vector field, i.e., the differential operator denoted by the nabla ∇. By applying the Levenberg-Marquardt modification to (1) one obtains equation (2) where $\underline{J}(d)$ (3) is the Jacobian matrix.

(2) $$\Delta\underline{d} = [J^T(\underline{d})J(\underline{d}) + \mu I]^{-1}J^T(\underline{d})\underline{e}(\underline{d})$$

The Jacobian matrix is used in vector calculus, it contains first order partial derivatives of multivariate vector functions. Using the Euclidean is necessary since it contains not only information about magnitude but also its direction, which enables monitoring both the speed and its direction of change in researched data sets. To summarize, it represents partial derivatives of the new coordinates with respect to the previous coordinates in the matrices under consideration.

(3) $$J(\underline{d}) = \begin{bmatrix} \frac{\partial e_1(\underline{d})}{\partial d_1} & \cdots & \frac{\partial e_1(\underline{d})}{\partial d_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial e_n(\underline{d})}{\partial d_1} & \cdots & \frac{\partial e_n(\underline{d})}{\partial d_n} \end{bmatrix}$$

Methodology

The effectiveness of a learning process, performed by researched supervised neural networks, was measured by the mean squared error (MSE) defined by equation (4). Where *y* is the response of the network, z is an expected answer, and *N* represents number of learning patterns.

(4) $$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - z_i)^2$$

In each experiment, the efficiency of the data obtained from ANNs was also measured by comparing the output ANNs' data with reference data never seen before in tested ANN, using formulas written in Excel script. The relative (5) and the absolute (6) errors were then calculated and presented in the next section, for the best analyzed models.

(5) $$\delta = \frac{\sum_{i=1}^{n}(\frac{|y_i - z_i|}{y} \cdot 100\%)}{n}$$

(6) $$\Delta y = \frac{\sum_{i=1}^{n}(|y_i - z_i|)}{n}$$

The block diagram illustrating the research methodology is presented in Figure 2. For each chosen architecture of ANN, 10 tests were performed with different initial weights values. The initial values of the weights and biases, related to the each individual neuron, were selected randomly and were close to zero. The number of neurons in the hidden layer, the number of hidden layers, the size of a training set, the type of a transfer function as well as the training vector size were the subject of an optimization. Such investigations are very important because for example the effective training process strongly depends on the number of neurons in the hidden layer and many other parameters. Neural networks, after their parametrization and successful training, made predictions based on uploaded test sets. Those obtained predictions were then compared with the reference data, after that the absolute and the relative errors were calculated. The MSE of a given training session was calculated each time and its value was presented automatically as a function of each training epoch by used MATLAB software like in Figure 5.

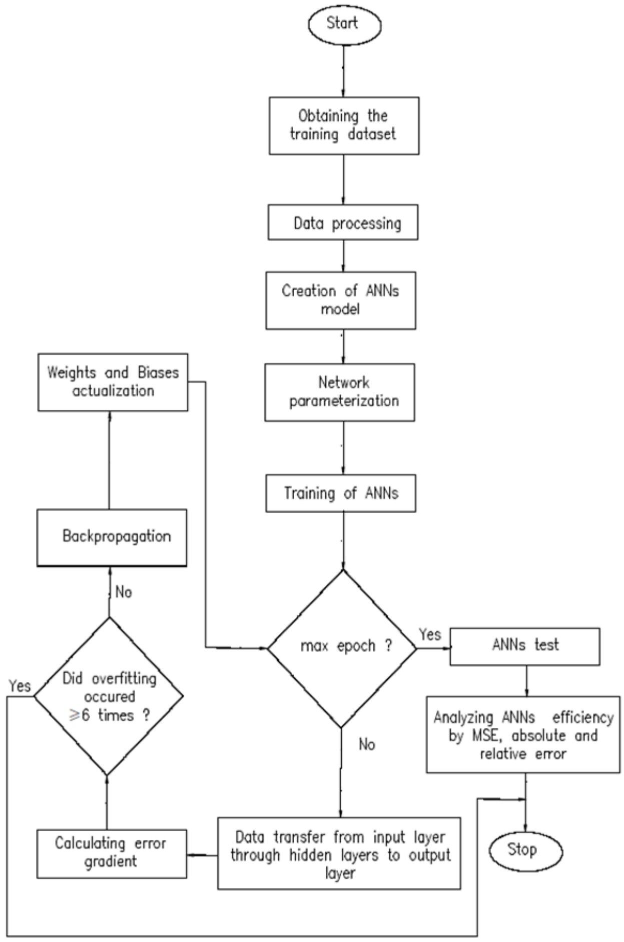

Fig. 2 The block diagram showing the research methodology [10]

Multiple ANN models were created and calibrated using MATLAB software. Networks have been created, calibrated, and tested by the use of “nntool” command before further tests were made on them. This command opens graphical user interference which allows creation and parametrization of ANNs. Matrices that formed training and test data sets have been selected using “xlsread” code before they were uploaded into created NN models. Further work consisting of network creation, parametrization and test was made by the GUI provided by the “nntool” command. Before created ANN models could substitute data into (2) formula through used software, most important variables had to be declared. These variables were, among others, number of epochs, goal, min_grad, max_fail, mu, mu_dec, mu_inc and mu_max [22]. Parameter mu is the initial value of μ in equation (2). This variable each time the MSE (4) improves, meaning its value decreases, is multiplied by mu_dec equal to 0.1. Contrary when the MSE value increases μ is multiplied by mu_inc equal to 10. Value of μ can be set to a maximum value for which when $\geq \mu$ process of supervised ANN learning is stopped. In the ANNs researched in this article, this value was set high, allowing a study of learning processes including also those unfavorable. Value of mu_max was set to 10^{10}. In equation (2) parameter I represents identity matrix while μ dumping factor. When parameter μ is a low value, equation (2) is close to Gauss-Newton method (1), when μ is high equation (2) it is close to a gradient descent. Number of epochs to perform was set to 1000, only training sessions that successfully exceeded 300 epochs were registered, and further tests performed on them. The learning process was programmed to stop immediately, when the measured MSE for the validation test increased six times (in the following six epochs). This number was set by the variable max_fail.

The consecutive rise of the MSE value for validation test can indicate that the analyzed ANN cannot find sufficiently general connection parameters. Generalized connections are a necessity for the ANN if we want them to predict not only the already seen test data but also these sets that ANN has never seen before. This phenomenon is called overfitting, it makes it impossible for ANN to predict new data from test sets precisely and that’s why it is undesirable. This explains why a learning process where there is overfitting must be stopped immediately.The maximum time of learning, expressed in seconds, was taken as infinity and a target was set to zero because the lowest error *d* is desired. The algorithm was also set to stop the training process when gradient descent was below calibrated min_grad, reflecting scalar magnitude of gradient descent vector, it would indicate correct ANN calibration.

Selected experimental results

After the NN parametrization, including the most important variables described in the previous section, various ANN models were created. These models are shown in Figure 3.

In order to carry out the training and testing of NNs synthetic data sets were used: input data, including the speed of moving air masses expressed in m/s and their direction expressed in degrees, output data represented wind farm generation in megawatts [23]. Data used did not take into account changing power demand of the connected power grid or any potential service or operational breakdowns in the investigated wind farm. Those assumptions were beneficial since main goal of WECS system is to show how much power will be available to consume from a wind farm, not how much it will really produce. This ensured that the examined data sets did not include underestimated generation data for good weather conditions, which are common in real data sets. The investigated offshore wind farm was a Dogger Bank phase A, B located in North Sea, west to Great Britain. The analysed farm consists of 190 Haliade-X turbines, each characterized by a 13 MW rated maximum power output, giving a total of 2470 MW of installed power. Researched wind farm is still under construction, planned to finish in 2026 [24]. In the conducted research, the authors analyzed the influence of the following conditions on the effectiveness of the learning process:

- The size of the input vector: containing variables like wind direction and speed data or only speed data,
- Different number of neurons in the hidden layer: 5,10 or 15,
- Different number of samples in the training set: representing monthly, quarterly or yearly data matrixes with hourly intervals,
- Different transfer functions in the hidden layer: hyperbolic tangent sigmoid transfer function (TANSIG), Log-sigmoid transfer function (LOGSIG) or Linear transfer function (PURELIN),
- Wind speed and correlated range of power generation (from 0 to 2470 MW) were divided into 10 equal ranges, in which the effectiveness of the NN was independently tested.

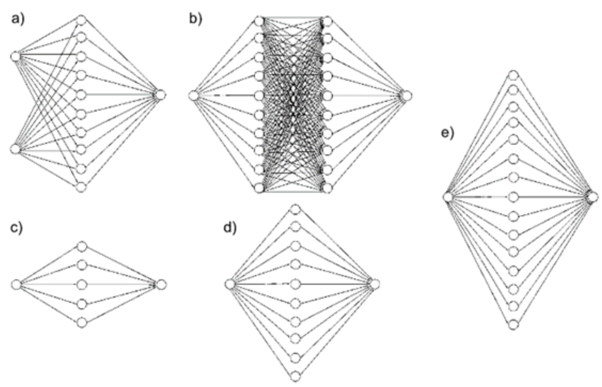

Fig. 3 Verified structures of supervised neural networks [10]

The goal was as follows: for each experiment (for the different conditions listed above), 10 ANNs were taught successfully, with more than 300 epochs without any interruptions. In total, more than 80 different neural networks have been learned to make predictions. Each time, after ANN has made a prediction, the MSE was designated, then the absolute and the relative error was calculated and registered. Initially, by trial-and-error method, a model with one hidden layer and 10 neurons in it was chosen as the best. In subsequent experiments, the authors attempted to improve the obtained results by making numerous changes in the tested NN. The results of those tests are described below and the most important are also presented in Table 1 and Table 2.

At the beginning, the experiments were carried out for structures of NN presented in Figure 3a and d. Training matrices consisted of yearly weather and generation data for the whole year of 2018 with hourly intervals, which gave the total number of training patterns equal to 8760 samples. The input vector consisted of wind direction and speed data (for structure presented in Fig. 3a or only speed data (for structure presented in Fig. 3d. During training, the supervised neural network had also access to the generation power output values correlated with the weather data entered into the input layer. After the learning process, only weather conditions were uploaded into the network and ANN had to predict generation for the whole 2019 year, also with hourly intervals. As explained, the authors assumed that the weather data came from the external forecasting software. Each analyzed NN had to predict generation for the entire year 2019 in each test performed.

The best obtained results, in 10 conducted tests, for the model presented in Fig. 3a, were as follows: the MSE error equal to 1,304, the absolute error equal to 0,818 and the relative error equal to 0,033%. For the model presented in Fig. 3d, the best registered results of taught network were characterized by the MSE error equal to 0,233, the absolute error equal to 0,319 and the relative error equal to 0,013%. The relative error was calculated in reference to the installed power equal to 2470 MW. In those tests TANSIG transfer function was used. Overfitting occurred much more often in the model shown in Fig. 3a, resulting in interruption of the learning process. Complicating the structure from (d) into (a), by adding additional neuron in its input layer, did not bring tangible results. Currently most turbines are equipped in Yaw systems thanks to which upwind turbine position is provided. Wind direction changes are slow, so values representing them are of marginal importance. Including them in the input data may even unnecessarily complicate the system and reduce its effectiveness, as one can see in the above studies. The same conclusions were made in research [1].

In the next step, for the model (d), the influence of different number of samples in the training set (representing monthly, quarterly or yearly data matrixes with hourly intervals) for the quality of the learning process were investigated. The obtained results are presented in Table 1. As can be seen, the differences in the obtained results, depending on the size of the training set, are significant for all analyzed cases. Naturally, the results improved as the training set expanded.

Table 1. Results obtained by ANN with different sizes of training data

Samples in learning data set	Best taught network for a given data set		
	Learning	Simulation	
	MSE	Δy	Δy [%]
745	0,329	1,267	0,051
2737	0,850	0,866	0,035
8760	**0,233**	**0,319**	**0,013**

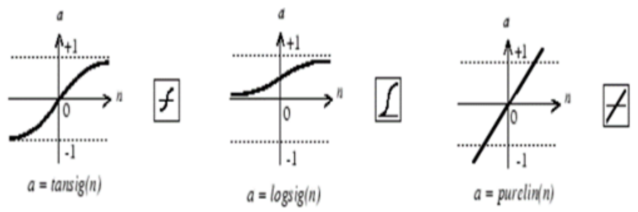

Fig. 4 Researched transfer functions [26]

Changing the number of neurons in the hidden layer and adding an additional hidden layer did not improve the obtained results (according to the models presented in Fig. 3b, 3c and 3e). Only changes in transfer function (for model presented in Fig. 3d) has improved the obtained results. Inside the neurons of hidden layer, there are summation blocks in which values can range, depending on ANNs weights, from minus infinity to plus infinity. Thanks to use of a transfer function those values are limited to for example range from -1 to 1 for TANSGIG function. Because the weather-to-power curve has a non-linear correlation, the use of the linear transfer function (7) has no effective application in the researched topic. However, the PURELINE function can be used as an approximator or linear regression function in the output layer [25]. Nonetheless, in conducted experiments, the LOGSIG transfer function (8) outperformed the TANSGIG transfer function (9).

$$y(e) = e \tag{7}$$

$$y(e) = \frac{1}{(1 + exp^{-e})} \tag{8}$$

$$y(e) = \frac{2}{(1 + exp^{-2e})} - 1 \tag{9}$$

Analyzed transfer functions, explained and represented by the formulas above, have been graphically presented in Figure 4.

After replacing TANSIG with the LOGSIG transfer function in the model shown in Fig. 3d results improved.The best recorded score of taught ANN from Fig. 3d with LOGSIG transfer function had an absolute error equal to 0,241, the MSE equal to 0,155, and the relative error equal to 0,010%. Each registered score, for all ten performed tests, for described calibration of ANN is presented in Table 2. As one can observe the relative error δ range from 0,010% to a maximum recorded error equal to 0,706%. No recorded error exceeded 1%, but a total of 13 learning processes were required to obtain the 10 results shown in Table 1. Out of 13 learning processes, three had to be terminated before reaching 300 epochs due to overfitting. Only those 10 other networks, that were successfully trained, were tested and the results are shown in Table 2.

Table 2. Results obtained by ANN with LOGISG transfer function

Test	Learning	Simulation	
	MSE	Δy	Δy [%]
1	0,229	0,730	0,030
2	**0,155**	**0,241**	**0,010**
3	0,206	0,300	0,012
4	0,882	1,461	0,059
5	0,227	1,242	0,050
6	0,218	0,320	0,013
7	1,839	0,902	0,037
8	0,217	1,225	0,050
9	237,621	17,428	0,706
10	1,745	9,372	0,379

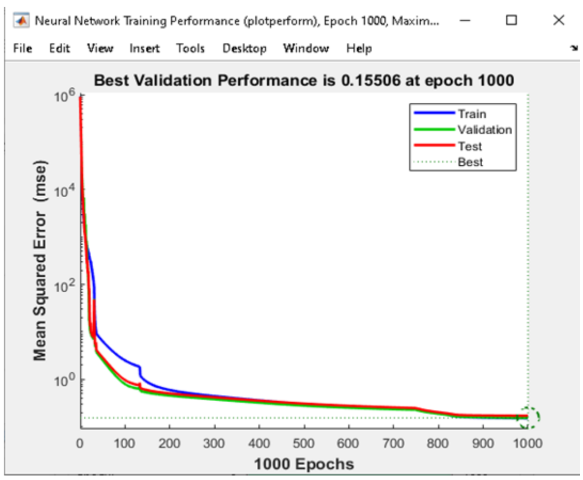

Fig. 5 Training performance for the best analyzed ANN [10]

The relative error of 0,010% was calculated for the installed power of 2470 MW, the error calculated for the average generation of wind farm power in 2019 equal to 1485 MW would be 0,016%. This score was the best obtained in all tested and all analyzed structures from Figure 3. The course of the learning process as a function of the number of epochs, for which the best result was obtained, is shown in Figure 5. As can be seen, the effectiveness of the learning process initially increased rapidly, then with the increase in the number of epochs, the learning process stabilized. The efficiency of the NN learning process means a decrease in the value of the MSE error. As shown below, the number of epochs, when one must stop the learning process, is a key factor for the final ANN effectiveness.

At the next stage of research, the ANN model presented in Fig. 3d with the LOGSIG transfer function was evaluated from different point of view. The wind speed and correlated range of power generation (from 0 to 2470 MW) were divided into 10 equal ranges, in which the effectiveness of the NN was independently tested. The mean absolute error was calculated for the chosen forecasted power generation ranges. The research has been performed for all 10 tests in this experiment. The ranges and the obtained results have been presented in Figure 6. The reference generation data from 2019 year had 8760 samples. The most numerous ranges of generated power, that is from 0 MW to 247 MW (1271 samples) and from 2223 MW to 2470 MW (3168 samples), were characterized by the biggest prediction error. Only 3 of 10 taught ANNs models found good approximation connections for the whole range of wind farm generation. In the rest of examined models, ANN found it difficult to predict in the lowest and the highest range of possible wind farm power generation range. Observed correlations are tight with nonlinear cut-in speed and cut off speed phenomena. The presented research clearly shows that ANNs often have trouble taking these phenomena into account, so they are more accurate in prediction ranges closer to linear (from 247 MW to 2230 MW). The LOGSIG transfer function is chosen more frequently in various areas where ANNs are used. However, there is no universal rule according to which the use of a given transfer function is the most optimal. However, it has been found in various publications that biological neurons are characterized by variability that closely resembles the sigmoid function, which is probably why it is so effective and widely used [27,28], also in the presented studies.

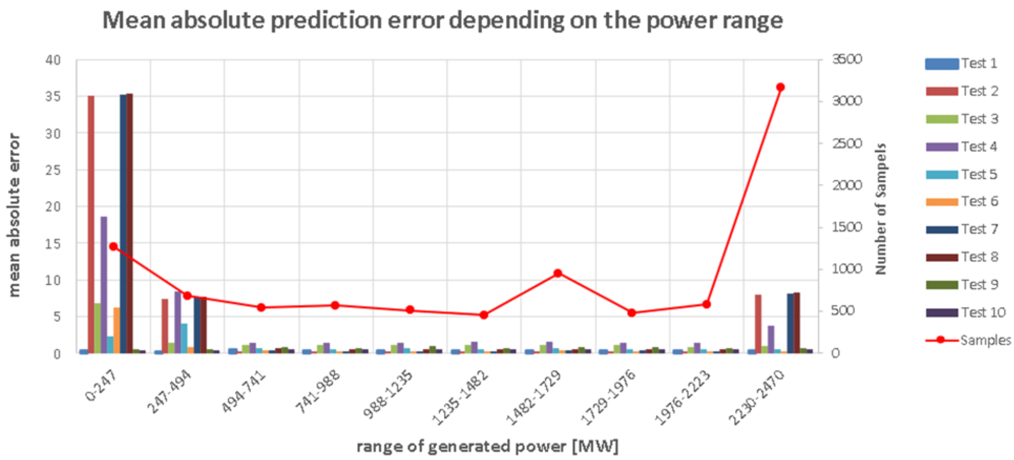

Fig. 6 The mean absolute error of prediction as a function of the predicted power generation ranges [10]

Summary

In this paper, the potential use of artificial neural network for the wind energy conversion system was analyzed. The most effective created network model, taught with a training set containing only the speed and correlated with it generation capacity, for the annual data range achieved a prediction accuracy of 99.84% for the test set that contained 8760 predictions. This score was achieved in reference to the analyzed wind farm Dogger Bank A, B with installed power equal to 2470 MW. The achieved accuracy indicates high precision of investigated ANN in converting the weather data into the available power generation of a wind farm. It has been proved that ANN can be taught to accurately predict the available power across the entire wind power curve spectrum. Based on the carried out research, it can be concluded that in real applications, where forecasted wind speed would have to be uploaded into ANN to predict power

generation potential, practically only wind speed prediction accuracy plays a role in the accuracy of the whole system. The created ANN model, in one of rolled out smart grid project, can be synergized with dedicated weather condition forecasting system, those systems are created for the needs of multiple industries, with great financial costs. Authors assume that it would be more efficient to synergize ANN like researched one, with a central weather forecasting system. Those national weather prediction systems can have access to the great access of variables opposite to independent systems, such as LSTM dedicated solely to a given WECS.

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