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# Prediction of Electricity Generation by Wind Farms Based on Intelligent Methods: State of the Art and Examples

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**Abstract**

With the rapid growth of wind energy production worldwide, the Wind Power Forecast (WPF) will play an increasingly important role in the operation of electricity systems and electricity markets. The article presents an overview of modern methods and tools for forecasting the generation of electricity by wind farms. Particular attention is paid to the intelligent approaches. The article considers the issues of preparation and use of data for such forecasts. It presents the example of a forecasting system based on neural networks, proposed by the authors of the paper. Wind energy has a great future all over the world and in Ukraine as well. Therefore, the study conducted by the authors is relevant.

**Keywords:** wind power forecasting; intelligent methods; neural networks; statistical approach.

## 1. Wind power forecasting: state of the art

By the end of 2018, the existing wind farms in Ukraine had a total capacity of approximately 700 MW. In 2019, it was planned to build new wind farms with a total capacity of about 1 GW. Unfortunately, the pandemic and military events did it impossible to implement these plans in Ukraine. However, despite all today's problems, there is a great future for wind energy all over the world and in Ukraine. Therefore, forecasting the generation of electricity by wind farms will be relevant in Ukraine in the near future. Let us consider the main approaches to solving this problem.

Over the past two decades, many models, systems and projects dedicated to solving the problem of predicting the generation of energy by wind farms have appeared. The total number of publications focusing on WPF issues is very large. Let us consider the materials of one of the latest reviews of 2020 [1] and the report of 2009 [2].

In paper [1], a systematic review of modern approaches to wind power forecasting (WPF) was carried out, taking into account physical, statistical (time series and artificial neural networks) and hybrid methods, including factors that affect the accuracy and time of calculations in predictive modelling efforts. In addition, this study provided guidance for screening the wind power forecasting process, allowing wind turbine/farm operators to determine the most appropriate forecasting methods based on time horizons, input characteristics, computation time, measurement errors, etc.

Modern forecasting methods can be divided into two main groups. The first group is called a physical approach and focuses on describing the wind flow around and inside the wind farm. The second group is a statistical approach, which consists in modelling the relationship between meteorological forecasts, historical measurements and generation output using statistical models with parameters estimated from data without taking into account any

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physical phenomena. There are some WPF systems that combine the two approaches in order to combine the benefits of both approaches and thus improve predictions.

### 1.1. Physical approach

Numerical Weather Prediction (NWP) forecasts are provided by the global model to several grid nodes covering an area. For a more detailed characterization of the weather variables at the wind farm, an extrapolation of forecasts is necessary. The physical approach uses several submodels, which together provide a transformation of the wind forecast at a certain grid point and a model level into the power forecast at the site under consideration and at the height of a turbine hub. Each submodel contains a mathematical description of the physical processes associated with this transformation. The two main steps are downscaling and conversion to power, as shown in Fig.1.

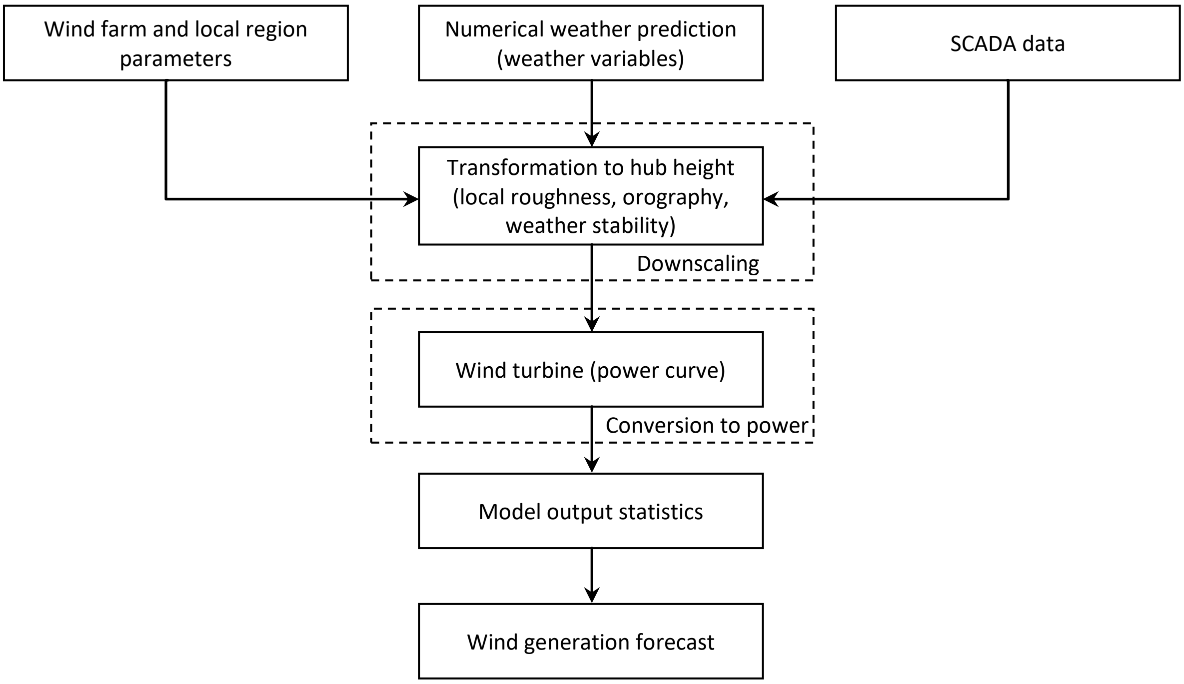



Fig.1. Main steps of the physical approach.

### 1.2. Statistical approach

An alternative approach is the statistical one (Fig.2). The statistical approach is easier to model and inexpensive. It is intended for short-term periods, and as the estimation time increases, the accuracy of its prediction decreases. Major developments in statistical approaches to wind power forecasting focus on the use of multiple weather forecasts (ensembles) as a combination of input parameters and forecast. This approach can combine input data such as NWP speed, direction, temperature, etc. together with operational measurements such as wind strength, speed, direction and others. With these models, it is possible to directly estimate regional wind energy from input parameters.

A Statistical Model block (Fig.2) may include one or more statistical linear and non-linear models of different types. Some of them are so-called "black box" models. These types of models include the artificial intelligence based models such as neural networks (NNs) and support vector machines (SVMs). As it was shown in paper [3], ensemble, hybrid and single methods are used very often for predictions, including machine learning (ML) solutions like Gradient-Boosted Trees (GBT), Random Forest (RF), Multi-Layer Perceptron (MLP), Long Short-Term Memory (LSTM), K-Nearest Neighbours Regression (KNNR) and Support Vector Regression (SVR).

As authors emphasize in [4], accurate prediction of wind speed and wind power is recognized as an essential part in implementing energy balance and scheduling power generation. In recent years, various wind energy forecasting models have been successfully proposed. Among them, intelligent models have an irreplaceable dominance and have tremendous potential due to their accuracy and robustness. This paper gives a broad literature survey of the intelligent predictors in the field of wind energy forecasting, including four types of shallow predictors (artificial neural network, extreme learning machine, support vector machine and fuzzy logic model) and four types of deep learning-based predictors (autoencoder, restricted Boltzmann machine, convolutional neural network, and recurrent neural network). Their theoretical backgrounds, applications, merits and limitations are thoroughly discussed. Then, two commonly used auxiliary methods for hybrid intelligent models are reviewed, i.e., ensemble learning and metaheuristic optimization. The ensemble learning models are categorized by the sources of diversity and ensemble strategies. According to the specific optimized objects, the metaheuristic optimization algorithms are classified into two groups. Moreover, the general process of metaheuristic optimization and differences between single-objective and multi-objective algorithms are also clarified. A group of representative models is summarized to show the frameworks of mainstream predictive models in artificial intelligence. Finally, this paper gives three possible development directions of wind energy forecasting for subsequent research.

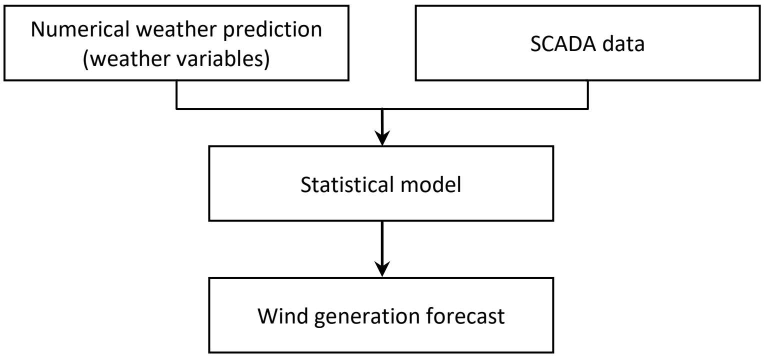



Fig.2. Main steps of the statistical approach.

As the authors of the paper [5] note, wind energy always faces uncertainty because of fluctuations in wind speed. Accurate forecasts of wind power generation are important for large power grid operation. This paper presents a hybrid neural network with high learning capacity for predicting wind power generation 24 hours ahead. This new method is based on Convolutional Neural Network (CNN). The simulation has used the actual wind power generation measured at a wind farm. The proposed method is implemented using the TensorFlow and Keras libraries.

There are a number of works that use combinations of different types of models in one forecasting system. For example, in [6] a wind power forecasting system for several hours ahead was proposed, which includes a physical model, a multi-criteria decision scheme and two artificial intelligence models. Namely, two Adaptive Neuro-Fuzzy Inference System (ANFIS) models were used to adjust the wind speed forecasts and define a power curve model that converts the improved wind speed forecasts into wind strength forecasts. Using a set of historical wind data from a wind farm in China, it was demonstrated that the WRF-TOPSIS-ANFIS model provides good wind speed and power predictions for time horizons from 30 minutes to 24 hours.

It should be noted that the quality of a forecast in any area always depends on the quality of the available data used for this forecast. The wind energy forecast is usually carried out on the basis of SCADA systems data. The aim of [7] is to develop a forecasting method by interpreting SCADA data collected from wind turbines, which have already been collected, but have been ignored for a long time due to the lack of appropriate data interpretation tools. The main contributions of this work are: firstly, to develop an efficient method for processing raw SCADA data; secondly, to propose an alternative method of condition monitoring based on the study of the relationships between the relevant SCADA data; and thirdly, to quantify the state of the turbine under various operating conditions.

## 2. Solving the problem of predicting energy generation by a wind farm

The authors propose for consideration the solution of the problem of forecasting the generation of electricity by means of the artificial neural network (ANN) based on a specific example [8].

### 2.1. Data preparation for forecasting

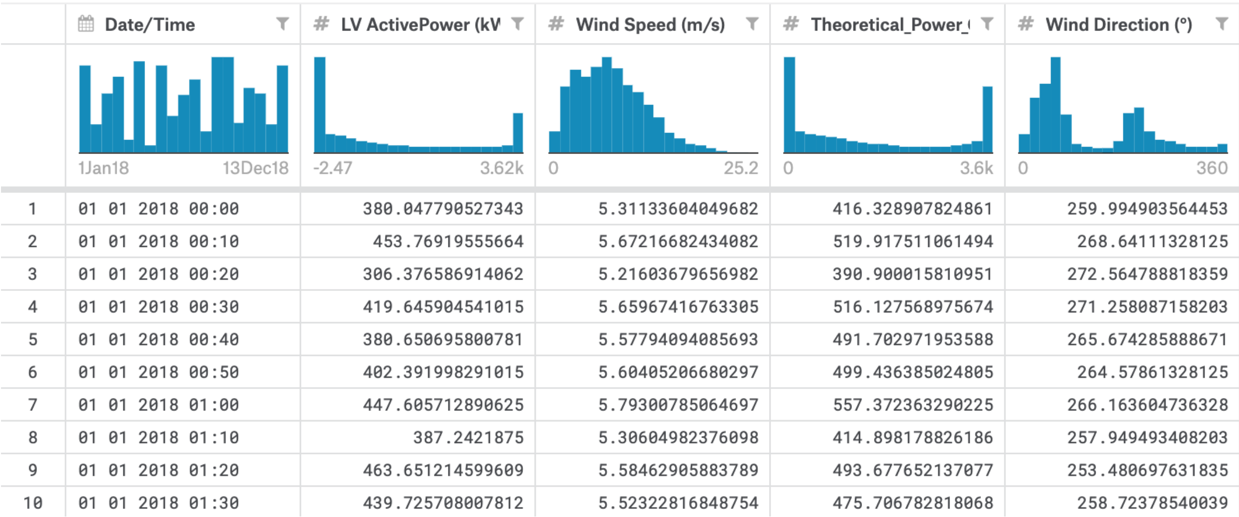
First of all, it was necessary to find and analyse the historical data of the operation of a real wind station over a long period of time (from one year), as well as to collect historical data from the nearest weather station. Since it was difficult to find data on wind energy in Ukraine, data from one of the Turkish wind farms was used to train the ANN, which were in an accessible SCADA system and contained information for 2018 with a fixation interval of

10 minutes. The nearest weather station to the wind power station was determined to obtain historical weather forecast data in the region for 2018.

One of the main problems in the field of Machine Learning is to process and interpret a data set for training. This process includes:

- Data analysis, cleaning and filtering, as well as determining influencing factors;
- Reduction of "raw" data to a format suitable for learning by ANN.

At the beginning of the work, the data on the wind power station had the form of a table in Fig.3.



| | Date/Time | LV ActivePower (kV | Wind Speed (m/s) | Theoretical_Power_( | Wind Direction (°) |
|---|---|---|---|---|---|
| | 1Jan18 – 13Dec18 | -2.47 – 3.62k | 0 – 25.2 | 0 – 3.6k | 0 – 360 |
| 1 | 01 01 2018 00:00 | 380.047790527343 | 5.31133604049682 | 416.328907824861 | 259.994903564453 |
| 2 | 01 01 2018 00:10 | 453.76919555664 | 5.67216682434082 | 519.917511061494 | 268.64111328125 |
| 3 | 01 01 2018 00:20 | 306.376586914062 | 5.21603679656982 | 390.900015810951 | 272.564788818359 |
| 4 | 01 01 2018 00:30 | 419.645904541015 | 5.65967416763305 | 516.127568975674 | 271.258087158203 |
| 5 | 01 01 2018 00:40 | 380.650695800781 | 5.57794094085693 | 491.702971953588 | 265.674285888671 |
| 6 | 01 01 2018 00:50 | 402.391998291015 | 5.60405206680297 | 499.436385024805 | 264.57861328125 |
| 7 | 01 01 2018 01:00 | 447.605712890625 | 5.79300785064697 | 557.372363290225 | 266.163604736328 |
| 8 | 01 01 2018 01:10 | 387.2421875 | 5.30604982376098 | 414.898178826186 | 257.949493408203 |
| 9 | 01 01 2018 01:20 | 463.651214599609 | 5.58462905883789 | 493.677652137077 | 253.480697631835 |
| 10 | 01 01 2018 01:30 | 439.725708007812 | 5.52322816848754 | 475.706782818068 | 258.72378540039 |

Fig.3. Raw data received from the SCADA system for the period of 2018.

The data set in our case is in CSV file and contains a table with 5 columns and 50530 records. The time interval between recordings is 10 minutes. The data are “raw” and require processing and exclusion of insignificant factors from consideration. In this case, you should be especially careful. For example, at first glance, the theoretical power is not used for prediction, since the real power of the wind power station at the particular time is already known, calculated for the known wind speed and direction at the current time. However, if further comparative analysis is carried out, new useful factors for prediction can be established based on the value of theoretical power. Pre-processing of raw data was carried out and primary data analysis was performed. To visualize the behaviour of the predicted indicators, comparative diagrams were built (Fig.4 and Fig.5).

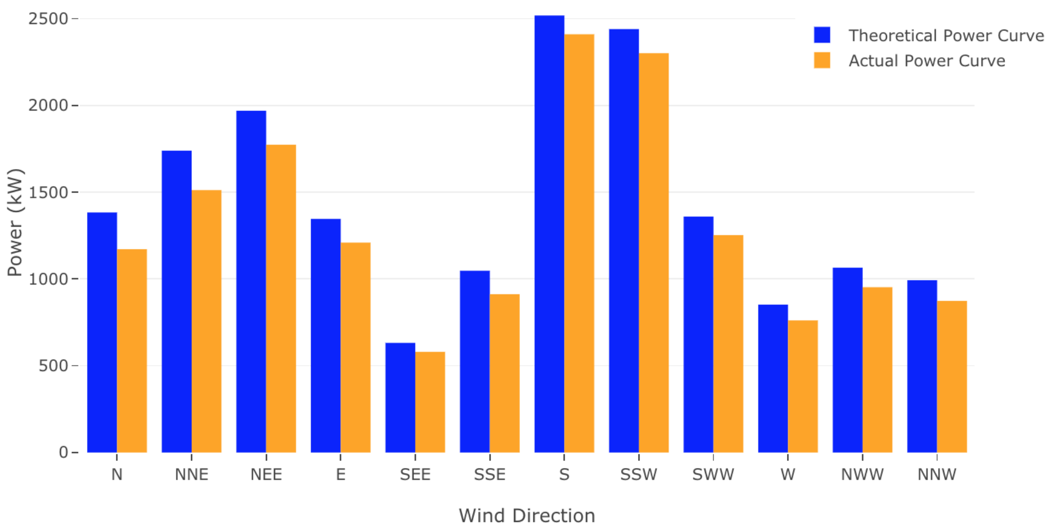



Fig.4. Theoretical and actual average wind station power for different wind directions.

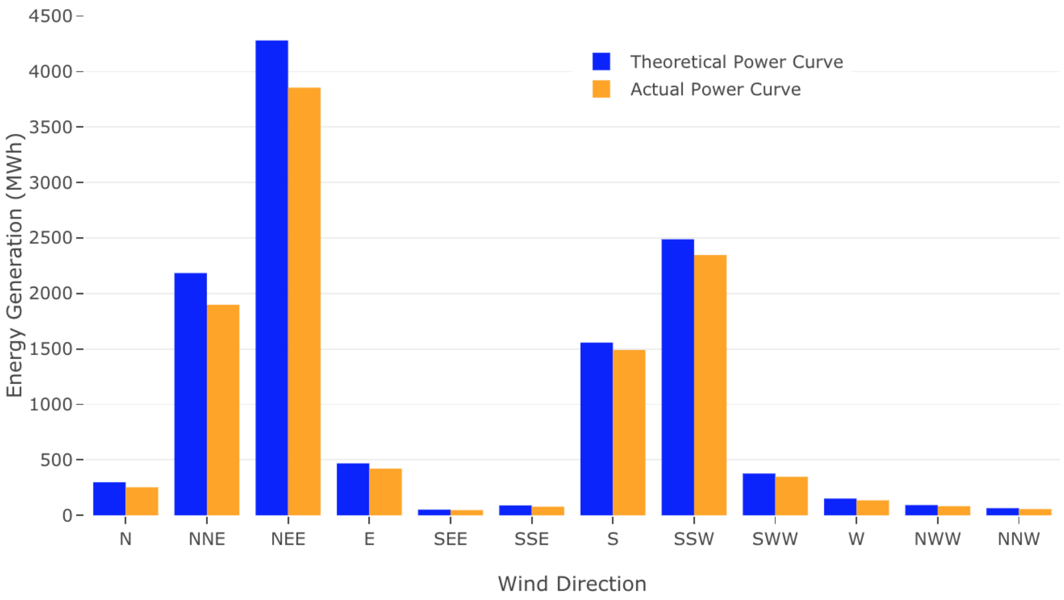



Fig.5. Theoretical and actual amount of the wind station's energy produced for different wind directions.

From the analysis of the diagrams mentioned, it can be concluded that the highest power of the wind station is achieved in the presence of south and southwest winds, however, the wind power station generates the largest amount of electricity in the presence of east-north and north-east winds.

In turn, the historical weather forecast data in the region contains such parameters as forecast time, air temperature, wind speed, wind direction, air humidity, atmospheric pressure, visibility. These data also require pre-processing.

### 2.2. Using a neural network to solve the forecasting problem

After preliminary processing of all data, the resulting dataset was used as a training set for the created feed-forward neural network. The forecast for the every next 8-hour period was based on the data for the previous 8 hours. Upon completion of the ANN training process, sufficiently accurate forecasting results were obtained that provide the target values of the generated electricity. The forecasting accuracy was about 87%. Therefore, there was no need to use more complex models in the form of convolutional or recurrent neural networks, as demonstrated in a number of publications. In addition, based on the obtained graphs illustrating the learning process, the optimal number of neurons in the layers and the number of required epochs were determined. Thus, a quite acceptable ANN model was obtained for a short-term forecast of electricity generation by the particular wind farm.

## 3. Conclusion

The authors of the work reviewed a number of publications and reports on the problem of forecasting the generation of electricity by wind farms. Hundreds of papers are dedicated to the consideration, analysis and comparison of various approaches, mostly intelligent ones, for solving the problem of forecasting. We emphasize the importance of pre-processing of raw data, usually supplied by SCADA systems and weather stations. It is clear that the quality of these data may be low. As shown in the work, good data pre-processing can allow using a relatively simple feed-forward neural network for prediction. When conducting a preliminary data analysis, you should always adhere to the GIGO principle ("garbage at the input – garbage at the output"). That is, the effectiveness of any mining method is always determined by the quality of the data. As shown by the simulation performed by the neural network, pre-processing and data analysis carried out within the study ensured an acceptable accuracy of the results of the subsequent forecasting.

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# Прогнозування генерації електроенергії вітровими станціями на основі інтелектуальних методів: стан справ та приклади

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**Анотація**

У зв'язку зі швидким зростанням виробництва вітрової енергії в усьому світі, прогнозування вітроенергетики відіграватиме важливу роль у роботі електроенергетичних систем та ринків електроенергії. У статті наведено огляд сучасних методів та інструментів прогнозування вироблення електроенергії вітровими електростанціями. Особлива увага приділяється інтелектуальним підходам. Розглянуто питання підготовки та використання даних для таких прогнозів. Подано розробку системи прогнозування на основі нейронних мереж, виконану авторами статті. У вітроенергетики велике майбутнє у всьому світі та в Україні також. Тому дослідження, проведене авторами, є актуальним.

**Ключові слова:** прогнозування вітрогенерації; інтелектуальні методи; нейронні мережі; статистичний підхід.