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Application of Intelligent and Digital Technologies to the Tasks of Wind Energy

Vladislav N. Kovalnogov , Ruslan V. Fedorov *, Andrei V. Chukalin , Mariya I. Kornilova , Tamara V. Karpukhina and Anton V. Petrov

Laboratory of Interdisciplinary Problems in Energy Production, Ulyanovsk State Technical University, 32 Severny Venetz Street, 432027 Ulyanovsk, Russia
* Correspondence: r.fedorov@ulstu.ru

Abstract: The article considers the relevance and issues of wind turbine modeling, the principles of wind energy conversion (WEC) system operation, working areas and regulation. The influence of soft computing technologies on the different aspects of wind power systems, particularly in the fields of operation and maintenance, is considered. This article discusses the recent research, development and trends in soft computing techniques for wind-energy-conversion systems. For reliable analysis, the interaction of the wind-generator operation with the atmospheric boundary layer is considered. The authors give a detailed description of the approaches for the study and numerical modeling of the atmospheric boundary layer (ABL) in the vicinity of a wind farm. The study of the atmospheric boundary layer in the vicinity of the Ulyanovsk wind farm on the basis of cluster analysis of meteorological data is performed. Ten localizations of ABL homogeneous properties are identified. The subject of the study is the application of the results of cluster analysis to set linguistic variables in fuzzy inference algorithms as well as to adjust the initial conditions in the digital model of a wind generator. The results of cluster analysis made it possible to reasonably construct membership functions for the wind speed value in the fuzzy control algorithm to limit the output power of wind turbines. A simulation of the operation of a three-bladed horizontal type wind turbine for the conditions of one of the resulting clusters is performed, and the main regularities of the flow around the wind turbine are revealed. The results obtained are a valuable source for assessing the mutual influence of wind farms and the environment as well as wind farm site development.

Keywords: wind farm; mathematical modeling; computational fluid dynamics; atmospheric boundary layer; intelligent system

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1. Introduction

1.1. Wind Energy Conversion Systems and Their Control

In the context of digitalization and intellectualization, the wind energy industry is undergoing significant changes. New technologies are emerging, including those with intelligent add-ons, such as digital twins and soft computing. The methods of computational fluid dynamics (CFD) are being developed to simulate and study effective modes of wind turbine operation.

A digital twin is software that allows one to simulate the internal processes and behavior of a real wind power object under controlled environmental conditions. Soft computing technologies, such as fuzzy logic apparatus, neural networks, genetic algorithms and evolutionary calculations, are used to achieve flexibility and reliability of wind energy issue solutions under conditions of inaccuracy, uncertainty, approximation and partial truth [1], which characterize the wind variability. Over the past decade, numerical simulations of the wind turbine aerodynamics and wind farms have become increasingly popular due to the increase in computer processing power, including the development of application software, such as ANSYS, Fluent, SFX, STAR-CCM+ and OpenFOAM.

Wind can be considered as a relatively free, clean and inexhaustible form of solar energy. The nature of wind flow depends on the terrain, environmental conditions and buildings. These factors must be considered in wind power object placement. The development of the Russian wind industry is hindered by difficult meteorological conditions—frequent temperature regime transitions through zero and precipitation. This causes inefficient aerodynamic modes of wind turbine operation and their downtime due to cleaning ice from the working surfaces. As a result, there is a need for redundant and expensive reserves of installed capacity and energy storage [2].

Wind turbines generate power by converting the kinetic energy of the air into the rotating mechanical power of the turbine rotor, which is connected to an electricity generator. Currently, the most common wind turbine is a horizontal axis propeller with three blades mounted on top of a tower. The frequency and voltage are two important system variables; they must be constant for the power consumer. The wind turbine control system includes a turbine speed controller as well as voltage and frequency controllers [3].

The development of wind turbines and their control methods is complicated and reflects various aspects of technological and scientific achievements. The control principles defining the wind generator behavior depend on the wind action. At low wind speeds—up to 5 m/s—the wind generator is mostly inactive, waiting for launching. At nominal wind speeds from 5 to 15 m/s, the wind generator runs in operating mode and generates useful power. To collect the maximum amount of wind energy, two control principles are used: turning the nacelle and changing the rotor speed (for turbines operating with a variable speed of rotation).

At wind speeds exceeds 15 m/s, the work of a wind generator can be dangerous, as the generator may exceed the limits of the calculated electrical and mechanical loads. Therefore, the control system must cut down the collection of wind energy in order to prevent an accident. To dump excess energy, the following methods are used: adjusting the pitch angle of the blades, turning the nacelle and changing the torque of the generator (for turbines operating with a variable speed of rotation).

The mechanical power of a wind turbine is mainly determined by the wind speed. Wind speed is variable, and it is difficult to keep it constant by adjusting the pitch of the blades. The main problems in the electrical circuit, including wind power systems, are due to constant fluctuations in the wind action [4]. These fluctuations can cause unwanted fluctuations in the network. However, the generated voltage and its frequency on the load bus at the consumer must have a constant value. It is necessary to develop intelligent control systems capable of adapting to changes in the object's state and input disturbances.

Methods of soft computing are of great practical interest in solving the problems of controlling wind turbines. The aim of soft computing is to exploit the tolerance for imprecision, uncertainty, approximation and partial truth to achieve tractability, robustness and low cost [4].

The authors of [5] considered the problems of monitoring wind energy systems to ensure security and stability. This article proposed a method for securely managing access to a wind farm monitoring system based on a flexible wind turbine condition sensor authentication model. The authors developed a lightweight key generation algorithm for fixed length compression and encryption of measurement data of any length. The authors used a wind turbine detection dataset provided by the US National New Energy Laboratory for experimental analysis. The results show that the proposed method effectively reduced the computational and communication costs for authentication.

The paper [6] summarizes studies of offshore wind farms in terms of their monitoring, operation and maintenance. The issues of research tasks in the field of intelligent offshore wind farms, as well as weather and climate forecasting and monitoring of the marine environment, were touched upon. Some advanced approaches for the operation and maintenance of smart wind systems were considered: big data, cloud computing and several digital technologies.

The works [7,8] in the field of intelligent energy management are very interesting. The Smart Grid system remains relevant because of wind variability. The main idea is autonomous energy management on the demand side for a wide variety of customers. Energy can be transmitted bidirectionally in a smart grid. The purpose is to use optimal energy consumption planning and advanced management techniques for power grid energy efficiency solutions, including fuzzy models.

Control systems based on fuzzy logic and fuzzy controllers have been compared with traditional control methods based on PI controllers using the analysis of systems of differential equations and have shown their advantage. The PI controller depends on an accurate mathematical model. The control efficiency decreases as the system parameters are violated or as the wind speed changes abruptly.

According to the results of a literature review, a fuzzy approach to wind turbine control is more appropriate under these conditions. The fuzzy logic apparatus is aimed at working under conditions of uncertainty, parameter scatter and the need to consider the influence of various factors on the control process [4]. The use of fuzzy logic in wind turbine control solutions currently consists of the following issues:

1. Tracking the maximum power generation point according to the WEC system schedule.
2. Controlling a wind turbine blade angle.
3. Predicting the generated power by wind farms and wind speed on the territory of a wind farm.

Many works [9–12] on fuzzy control use the MPPT (Maximum Power Point Tracking) strategy, because wind turbine variable speed is the dominant type. The use of a fuzzy approach was found to be sufficient. It was shown that a wind turbine controlled by a fuzzy controller has less voltage fluctuations and ripples than does a PI controller. Sufficient results for the total harmonic distortions (THD) (in terms of power quality). To increase the accuracy of the MMPT approach, an improved MPPT strategy for wind turbines based on a permanent magnet synchronous generator PMSG was proposed in [13] using an extended Kalman filter and a fuzzy control system. The authors calculated an increase in accuracy of 1.341 units when estimating the optimum speed and tracking the maximum power output at various wind speeds.

The work [14] considered a wind turbine with a variable rotation speed based on an asynchronous generator. To obtain the optimal power and extract the maximum wind energy, the authors proposed a fuzzy logic method for controlling active and reactive power. In [15], fuzzy control of an existing grid inverter was applied to improve the quality of electricity in three-phase distributed generating systems. There is a well-known fuzzy-logic-based control algorithm for changing the length of a wind turbine blade [16]. In all cases, fuzzy control provided better performance than did the classic PI controller.

The works [17–19] consider wind turbines within the hybrid power system. When the wind speed was sufficient, the entire system was powered by the wind turbine and, otherwise, by the fuel cell (batteries and supercapacitor). When using fuzzy logic, the performance of the entire system increased. When replacing the PI controller with a fuzzy controller, the authors managed to significantly reduce the voltage distortion.

There is a known algorithm based on fuzzy logic for limiting the output power of a turbine [20–22] by changing the pitch angle at wind speeds above the nominal value. If the wind is below the nominal value, the angle maintains a constant optimal value.

Fuzzy inference algorithms require the assignment of linguistic variables, and this operation is typically performed on the expert or retrospective data. In wind turbine control tasks, one of the input linguistic variables is wind speed. Considering the operation of wind turbines in the conditions of the Ulyanovsk wind farm, it is necessary to consider the continental climate of the region with pronounced seasonal differences in weather conditions.

For a more reliable simulation of a wind generator, the assignment of membership functions should be performed carefully. Therefore, in order to construct the membership function "wind speed", the authors propose to study in detail the atmospheric boundary layer in the vicinity of a wind farm. Given the large amount of meteorological data and significant seasonal differences, it is proposed to use cluster analysis. The authors consider the approaches of fuzzy pitch angle control and implement this algorithm in MATLAB.

Digitalization and intelligent technologies in wind energy make it possible to optimize wind farm maintenance strategies, increase the reliability and availability of wind turbines and increase the annual energy production.

1.2. Atmospheric Boundary Layer in the Vicinity of a Wind Farm

When considering a series of wind turbines as a part of a wind farm, it is more complicated to maintain an overall effective aerodynamic regime since it is necessary to consider the mutual influence of wind turbines and the atmospheric boundary layer (ABL) in the vicinity of the wind farm. The study of the movement of air flows in the vicinity of wind farms and their interaction with the ABL is performed by researchers in the fields of atmosphere and wind energy as well as meteorologists.

The ABL is the lower layer of the atmosphere. The ABL properties are determined by the interaction with the surface and its properties. The thickness of the ABL depends on the roughness of the underlying surface, turbulence, temperature stratification and wind impacts. The state and structure of ABL are subject to diurnal variations [23].

To study the processes in a turbulent ABL in the vicinity of an operating wind farm, it is necessary to consider vertical turbulent flows of heat, moisture and momentum according to the thickness of the ABL as well as to consider the location of wind turbines, their operating mode and the surface topography.

Currently, three approaches are used to simulate the atmospheric boundary layer of a wind farm: Solution of Navier–Stokes equations systems, averaged by Reynolds (Reynolds-Averaged Numerical Simulation, RANS models), Large Eddy Simulation (LES models) and Direct Numerical Simulation (DNS).

High-precision prediction of the mutual influence of ABL and a wind farm is particularly important for optimizing the turbine placement in order to maximize the generation of useful power and reduce mechanical loads on wind turbine elements. Numerical modeling can provide valuable quantitative information about the potential impact of wind farms on local meteorology. This is due to the significant role of wind turbines in slowing down the wind, creating turbulence and enhancing the vertical mixing of momentum, heat, moisture and other scalars.

ABL modeling in the vicinity of a wind farm with the LES model was performed in [24–26] to study the characteristics of wind turbine wakes and their cumulative effect on wind farm performance. Using the LES model, a study of the interaction of wind turbines with the ABL was made. The dependence of energy generation on the aerodynamics of a wind farm is considered. It is revealed that different types of ABL create completely different turbulent structures. Large-eddy simulation (LES) was developed as an intermediate approach between DNS and RANS, the general idea being that the large, non-universal scales of the flow are computed explicitly while the small subgrid-scales are modeled. In [24], subgrid-scale turbulent eddies were described using Lagrangian models.

During the ABL study for choosing a modeling tool for LES approaches, the implementation of this method requires large computing power but less than for the DNS. The researchers of atmospheric boundary layer flow in a wind farm area usually use the Reynolds-Averaged Navier–Stokes (RANS) approach to model turbulence.

Thus, ref. [27] considered the simulation of wind turbines immersed in a stable, neutral or unstable boundary layer of the atmosphere was performed. The influence of the ABL temperature gradient on the performance of wind turbines. The RANS model was used to describe the aerodynamics of a wind turbine. The turbulence model k-ε was used to close the system of equations. With stable stratification, the output power of the wind turbine was 4% lower than in the neutral state ABL, while, in an unstable situation, the power became 3% higher. Note, however, that the RANS approach is too stream-specific to be used as a generally applied method.

The DNS method was not detected in works on modeling wind farms due to its applicability for a limited group of problems characterized by small Reynolds numbers and the use for analyzing flows in simple geometric configurations. A great contribution to the development of modeling the aerodynamics of wind farms was made by [25]. There, an extensive review of the energy extraction process physics by wind turbines was conducted, and the near and far wakes of wind turbines were analyzed in detail. Furthermore, high-precision prediction of the mutual influence of ABL and a wind farm becomes important in the tasks of assessing the impact of wind farms on the climate due to the vertical mixing of heat, moisture, torque and other scalar quantities.

A well-known work [28] studied the possible impact of a large wind farm on flat terrain on local meteorology under synoptic time scales and typical summer conditions. The results showed that the wind farm significantly slows down the wind at the height of the turbine hub. The turbulence generated by the rotors creates eddies. The eddies can enhance the vertical mixing of momentum, heat and scalars, which usually leads to the warming and drying of ground air and a decrease in surface heat flux. This effect is the most intense in the early morning when the boundary layer is stably stratified and the wind speed at hub height is the strongest due to the nighttime low-level jet.

To analyze the ABL, as well as to study its impact on the wind farm, a cluster analysis of meteorological data for 2020 in the vicinity of the Ulyanovsk wind farm was performed. A fuzzy control algorithm was implemented to limit the output power of the wind turbine for the conditions of one clusters, and the study movement of air masses in the zone of wind turbines modeling was performed using CFD methods.

The study of the aerodynamics of wind turbines and their influence on ABL is the fundamental basis for the efficient use of wind energy. Such modeling helps us to better understand the complex physical interactions between ABL, wakes and wind turbines. Thus, less expensive engineering tools can be improved. In the long term, this will contribute to the sustainable development of wind energy.

2. Materials and Methods

2.1. Modeling of the Atmospheric Boundary Layer in the Vicinity of a Wind Farm

Reliable and accurate prediction of the ABL interacting with a wind farm over a wide range of spatial and temporal scales provides valuable quantitative information about the potential impact on the local meteorological situation. Furthermore, these data are of great importance for design optimization (turbine placement) and operation of wind farms. Therefore, it is necessary to provide high-precision modeling of heat and mass transfer and phase transformations during the interaction of a polydisperse air flow with a network of wind turbines and the relief surface of a local territory, considering the pressure gradient of the flow.

Traditionally, for the numerical study of ABL, a system of differential equations is solved to obtain the distribution of the desired parameters in time and spatial coordinates. However, considering the ABL in the area of the wind farm, the task becomes significantly more complicated, since it is necessary to consider a number of complicating factors: the relief of the wind farm and the location of wind turbines as well as their aerodynamic effect on the ABL. Therefore, in order to model the ABL-wind turbine system of the Ulyanovsk wind farm, it was necessary to solve a conjugate problem—namely, to perform a numerical analysis of the state of the ABL based on one of the known RANS or LES models [29,30] and then use the results of this solution as input information for setting boundary and initial conditions when modeling wind turbines.

Given the mesoscale conditions of the problem, this approach required significant computational and time costs. The authors investigated the ABL by one of the methods of data mining—by clustering meteorological observation data on the territory of the Ulyanovsk wind farm. The method made it possible to identify similar modes of ABL by seasons of the year. For one of the identified modes, it was possible to reasonably configure the solver for reliable modeling of the operation of the wind turbine in the current mode.

The proposed approach allows saving computational resources for solving an applied three-dimensional non-stationary problem.

2.2. Cluster Analysis of the ABL in the Vicinity of a Wind Farm

To study the processes occurring in the boundary layer of the atmosphere in the wind turbine zone, a cluster analysis of meteorological observations of the Ulyanovsk wind farm was performed. Cluster analysis is a process of dividing a set of objects into homogeneous groups—clusters. The purpose of the ABL cluster analysis is to identify ABL areas with similar aerodynamic conditions and to obtain average values for each cluster. This information allows revealing the hidden regularities of the wind farm influence on the state of the atmospheric polydisperse boundary layer.

The analysis is based on meteorological observation data on the territory of the Ulyanovsk wind farm in 2020. The results of the cluster analysis of the ABL states made it possible to construct membership functions in the fuzzy inference algorithm as well as to adjust the initial conditions in the digital model of the wind generator.

There are several clustering algorithms. One of the most common is the k-means algorithm. The k-means++ algorithm is a refinement of the standard k-means algorithm in terms of finding better initial values of cluster centers [31]. It is the algorithm that was implemented in this work in the C# programming language.

2.3. Intelligent Systems in the Tasks of Wind Energy

The possibility of using fuzzy control applications for wind power engineering is considered by the example of regulating the output power of a turbine by changing the pitch angle. An algorithm for changing the pitch angle was proposed in [20].

The following objectives can be distinguished for controlling the pitch angle:

- Optimization of the output power of the wind turbine. At wind speed from cut-in speed to cut-out speed, the pitch angle must maintain a constant optimal value so that the turbine produces the maximum possible power.
- Limitation of the turbine output power. With winds speed above cut-out speed, the angle changes according to a certain law, thereby, regulating the aerodynamic power and rotor load.

Usually, standard PI controllers are used to change the pitch angle; however, they require knowledge of the system dynamics. A controller with an algorithm based on fuzzy logic embedded in it does not require knowledge about the system and can be applied under non-linearity of parameters. The process of implementing fuzzy control is shown in Figure 1.

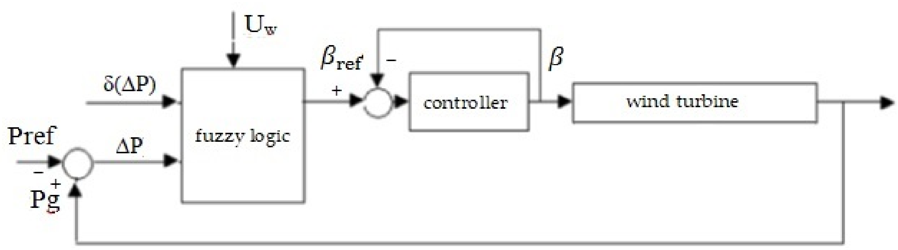


Figure 1. A block diagram of a controller with an algorithm based on fuzzy logic for changing the pitch angle blade of the wind turbine.

Consider an algorithm for changing the blade pitch angle. This algorithm is based on the power deviation from the nominal value ΔP and the power gradient $\delta(\Delta P)$. The rules for fuzzy inference are given in the following form:

(1) If $\delta(\Delta P)$ and $\delta(\Delta P)$ negative are very large, then the output power is greater than the nominal value, and the amplitude of the power change increases; therefore, it is necessary to reduce the pitch angle.

(2) If $\delta(\Delta P)$ negative is very large and $\delta(\Delta P)$ positive is very large, then the output power is higher than the nominal; however, the amplitude of its change is reduced, and thus the change in the pitch angle will be minor [20].

Table 1 shows the rules for the input and output variables. The proposed fuzzy system uses nine fuzzy sets: NL—negative very large; NML—negative large; NM—negative average; NS—negative small; ZE—zero; PS—positive small; PM—positive average; PML—positive large; PL—positive very large.

Table 1. rules for input and output variables.

			PS					**PM**					**PL**		
	NL	NS	ZE	PS	PL	NL	NS	ZE	PS	PL	NL	NS	ZE	PS	PL
NL	NL	NML	NM	NM	PS	NL	NM	NM	NS	PS	NML	NM	NS	NS	PS
NS	NL	NM	NS	PS	PM	NML	NM	NS	PS	PM	NML	NM	NS	ZE	PS
ZE	NML	NS	ZE	PS	PML	NM	NS	ZE	PS	PM	NM	NS	ZE	PS	PM
PS	NM	NS	PS	PM	PL	NM	NS	PS	PM	PML	NS	ZE	PS	PM	PML
PL	NS	PM	PM	PML	PL	NS	PS	PM	PM	PL	NS	PS	PS	PM	PML

2.4. CFD Methods for the Wind Turbine Modeling

To actively control the behavior of a wind turbine, it is necessary to consider the interaction of the blade surface with the air flow. The pitch angle of the blade largely determines the aerodynamic effect of the wind wheel with the wind flow. Having determined the necessary aerodynamic values (the main rotational force of the wind, air resistance, the resulting rotational force and the power of the wind generator), according to the methodology proposed in [32], we found that the maximum output power was achieved at an angle of 0.7 rad.

To create a digital model of a wind generator, we propose the use of the commercial package STAR CCM+ [33]. The simulation was conducted for the conditions of the regime of one of the ABL clusters. The analyzed wind generator is of horizontal type and has three blades. The dimensions of the wind generator: the height of the tower was 100 m, and the diameter of the rotor was 120 m. The geometry of the model was made on a scale of 1:1. The wind speed was set to 12.26 m/s, and the number of rotations was 4 rpm. The rotor was attached to a small wind generator motor with a hub.

The rotation of the moving mesh starts the rotation of the wind turbine blades. For numerical calculations, a mesh with cells in the form of polyhedrons was used. The grid in the rotation zone was refined to 0.01 m, to 0.8 m in the near wake zone, and to 5 m in the wind tunnel zone. A series of computational experiments was performed in STAR CCM+ to validate the choice of mesh and turbulence model (Figure 2). The wind generator was investigated using the following models: k-Epsilon, k-omega, Reynolds Stress and Spalart Allmaras. Three calculations with different grids were performed for each model (Table 2). The closest results to the experimental ones [34] are shown by the k-ε model with a grid with the number of cells as 20,988,172.

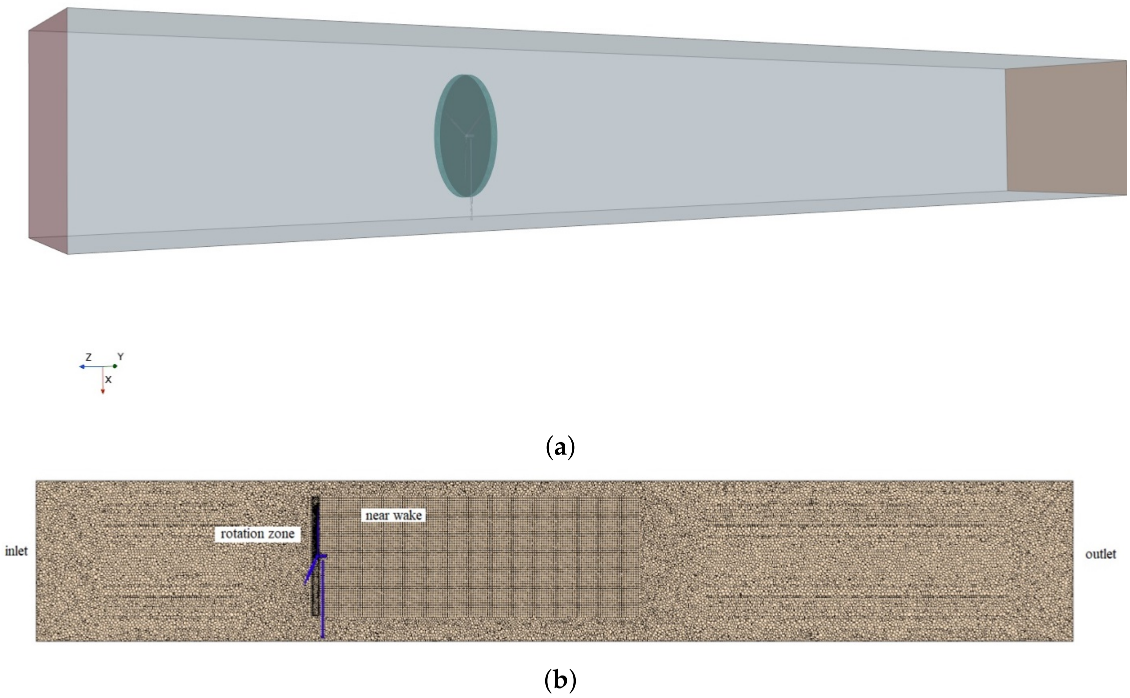


Figure 2. (**a**) Calculation area of the wind generator and (**b**) mesh for modeling a wind turbine.

Table 2. Comparison of various meshes and models (wind speed 12.26 m/s).

Type	**k-Epsilon**			**k-Omega**		
Mesh	№1	№2	№3	№1	№2	№3
Number of cells	3,436,784	5,479,298	20,988,172	3,436,784	5,479,298	20,988,172
Velocity deficit normalized with the free stream velocity (4D)	0.35	0.39	0.42	0.36	0.39	0.41
Experimental value	0.43	0.43	0.43	0.43	0.43	0.43
Difference in values (%)	18.6	8.256	1.163	16.28	8.6	4.23
Type	**Reynolds Stress**			**Spalart Allmaras**		
Mesh	№1	№2	№3	№1	№2	№3
Number of cells	3,436,784	5,479,298	20,988,172	3,436,784	5,479,298	20,988,172
Velocity deficit normalized with the free stream velocity (4D)	0.33	0.38	0.41	0.31	0.37	0.40
Experimental value	0.43	0.43	0.43	0.43	0.43	0.43
Difference in values (%)	23.25	12.65	5.58	27.91	14.36	7.31

3. Results

3.1. Results of the Cluster Analysis of the Atmospheric Boundary Layer in the Vicinity of a Wind Farm

Each clustering object, ABL coordinate, is represented by two characteristics: wind speed and temperature. Figures 3–6 show the results of cluster analysis of ABL data in the winter, spring, summer and autumn periods of 2020; the abscissa shows the air flow temperature values; and the ordinate shows the wind speed. In each case, the data is grouped into 10 clusters.

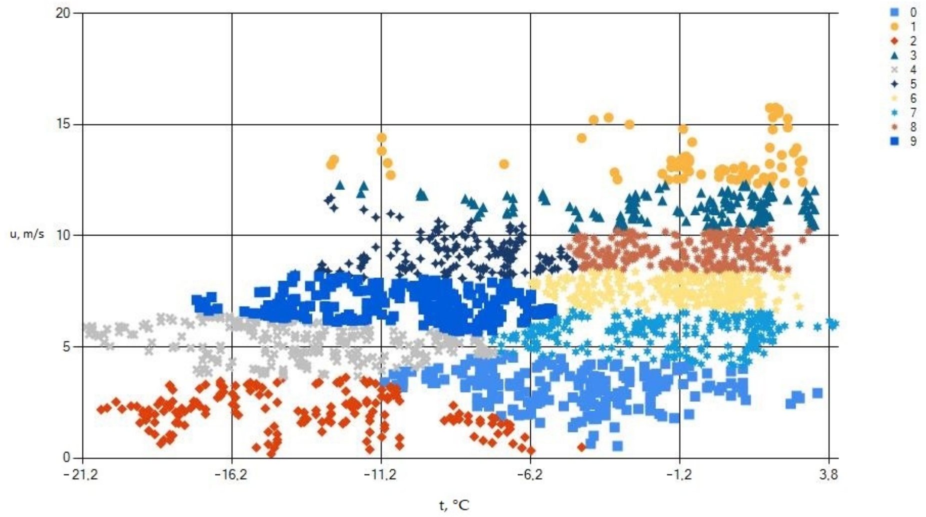


Figure 3. The results of ABL cluster analysis in winter.

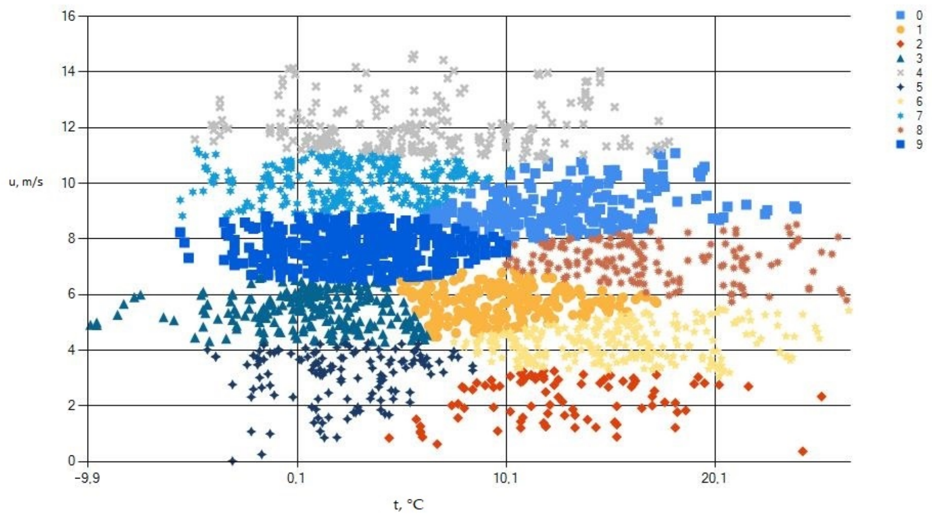


Figure 4. The results of APS cluster analysis in spring.

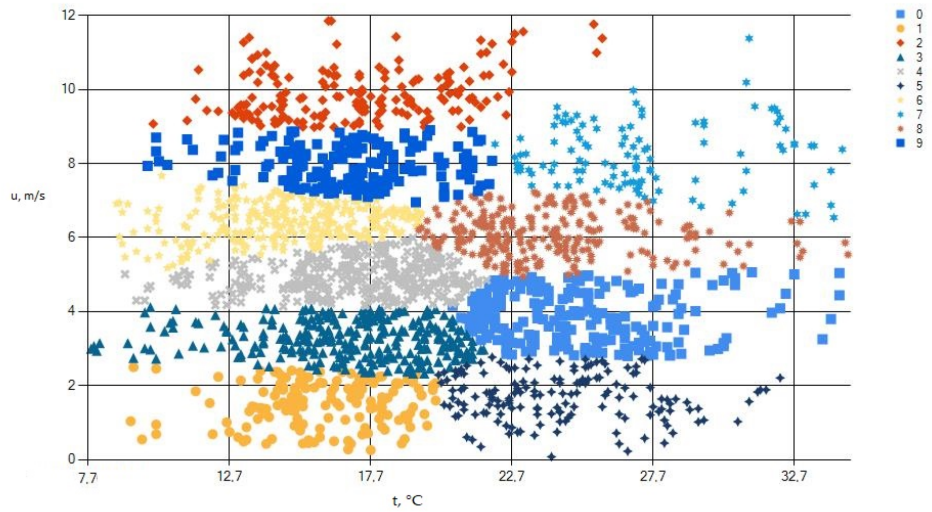


Figure 5. The results of ABL cluster analysis in summer.

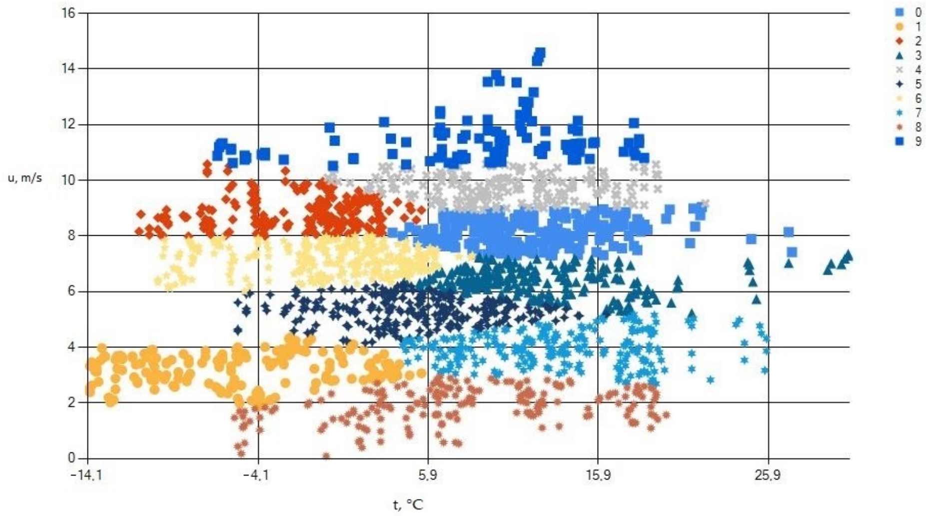


Figure 6. The results of ABL cluster analysis in autumn.

Figures 3–6 show that the state of ABL has a strong seasonal pattern. Most clustering objects in winter are concentrated in the seventh cluster (15.3%) and are characterized by an average speed of 7.6 m/s and an average temperature of 1.3 °C below zero.

Most clustering objects in spring are concentrated in the tenth cluster (18.3%). They are characterized by an average speed of 7.66 m/s and an average temperature of 3 °C. Most clustering objects in the summer season are concentrated in the fifth cluster (15.9%). They are characterized by an average speed of 4.96 m/s and an average temperature of 17.2 °C.

Most clustering objects in autumn are concentrated in the seventh cluster (13.5%) and are characterized by an average speed of 7.17 m/s and an average temperature of 0 °C. In the sixth cluster (13.3%), they are characterized by an average speed at 5.33 m/s with an average temperature of 5.2 °C.

ABL cluster analysis can be a valuable source of information in many applications, including the assessment of the mutual influence of wind farms and the environment, as it gives better results for short-term forecasts compared with traditional physical models based on weather modeling. The authors intend to use the results of cluster analysis of weather data in a wind farm in their further research to predict the generation of wind farms as well as to manage local precipitation in the area of existing wind farms.

3.2. Results of Wind Turbine Fuzzy Modeling

The block for changing the pitch angle using a controller based on fuzzy logic is shown in Figure 7. The values of the power deviation from the nominal value, wind speed and the last power increment are used as input variables. For its fuzzy inference, the Larsen algorithm is used.

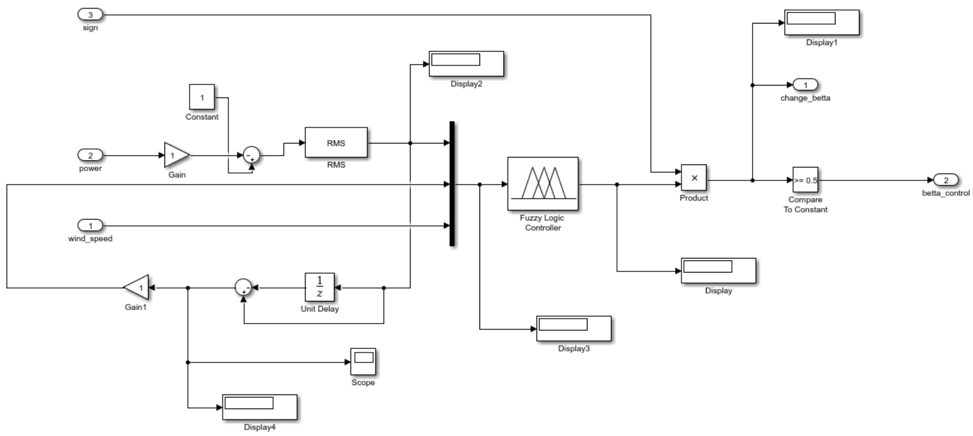


Figure 7. Pitch angle change block in MATLAB.

The membership functions for input and output values, the rule base, the result of defuzzification and the dependence surface of the output value on the input values are shown in Figures 8–12.

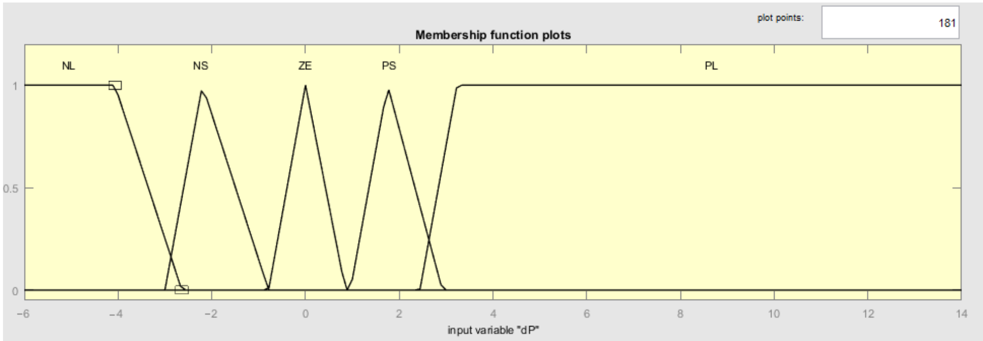


Figure 8. Membership function of the input value "power deviation".

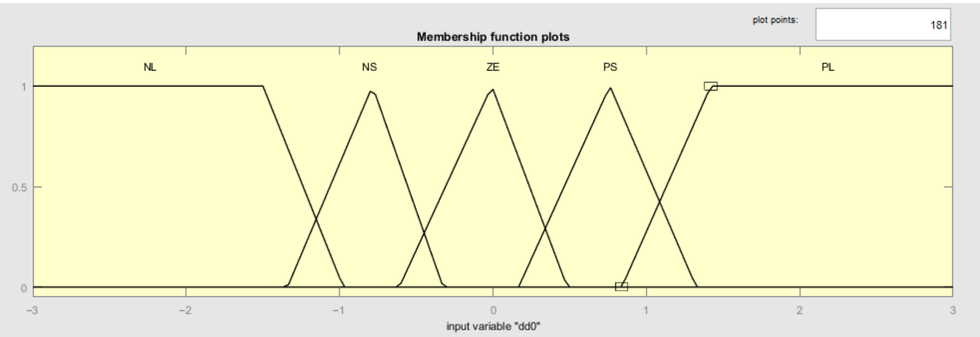


Figure 9. Membership functions of the input variable "power gradient".

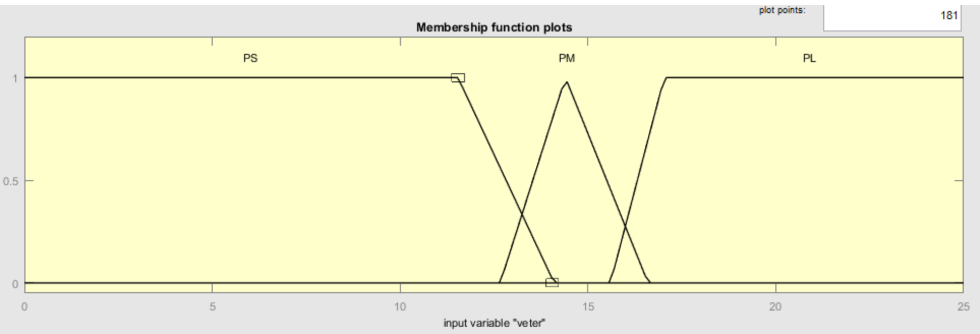


Figure 10. Membership functions of the input variable "wind speed".

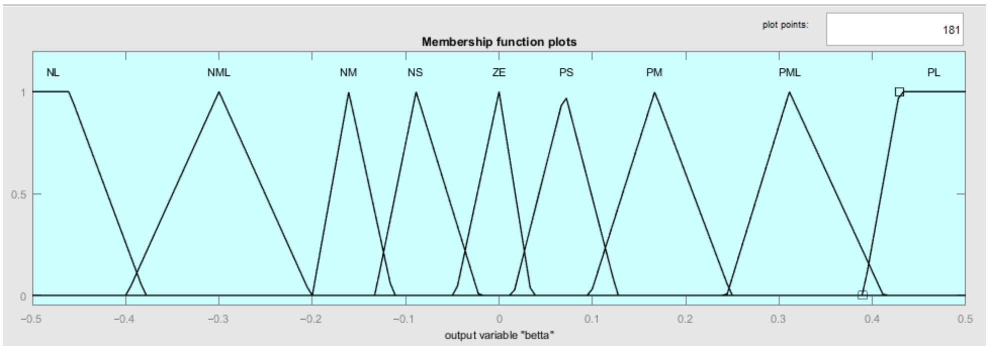
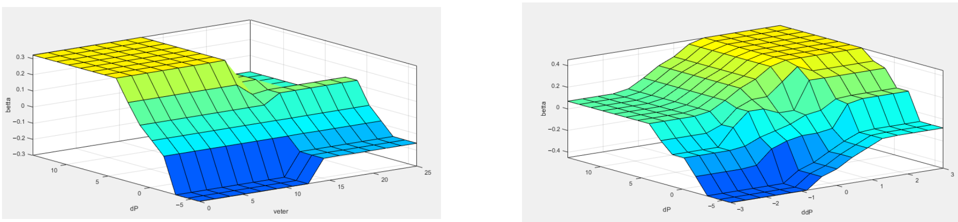


Figure 11. Membership function of the output value "blade pitch angle".



(**a**) (**b**)

Figure 12. The surface of the algorithm defuzzification results depends on: (**a**) power deviation, pitch angle and wind speed; (**b**) pitch angle, power deviation and power deviation error.

In this case, a system of fuzzy pitch angle control of WEC system is modeled without specifying an exact formal mathematical description—instead, expert knowledge is used. Despite its practical success, fuzzy logic has been criticized for its limitations, such as the lack of a formal design methodology and the difficulty of predicting the stability and robustness of FL-controlled systems.

3.3. Results of Wind Turbine CFD-Modeling

To calculate the wind turbine aerodynamics, the RANS approach with the standard k-ε turbulence model was used. The physics of the process in Star-CCM+ was described by the following models: three-dimensional, unsteady implicit, gas, separated flow, ideal gas, turbulent and k-ε turbulence model. The boundary conditions were set by Star-CCM+: Input—Velocity Inlet, constant speed; output—Pressure Outlet, constant pressure; and other walls—No-Slip Wall.

Figures 13 and 14 make it possible to identify the main patterns of the flow around a wind turbine and the characteristic features of the flow. The wind turbine leaves behind significant disturbances in the near wake in the form of sinusoidal vortices. Behind the turbine, the free flow slows down, as the wind turbine extracts part of the energy from it, creating waves with a reduced speed—the so-called speed deficits. Furthermore, in the near wake of the wind turbine, a higher level of turbulence (additional turbulence intensity) is observed rather than in a free flow. Figure 14 shows the streamlines in front of and behind the wind turbine.

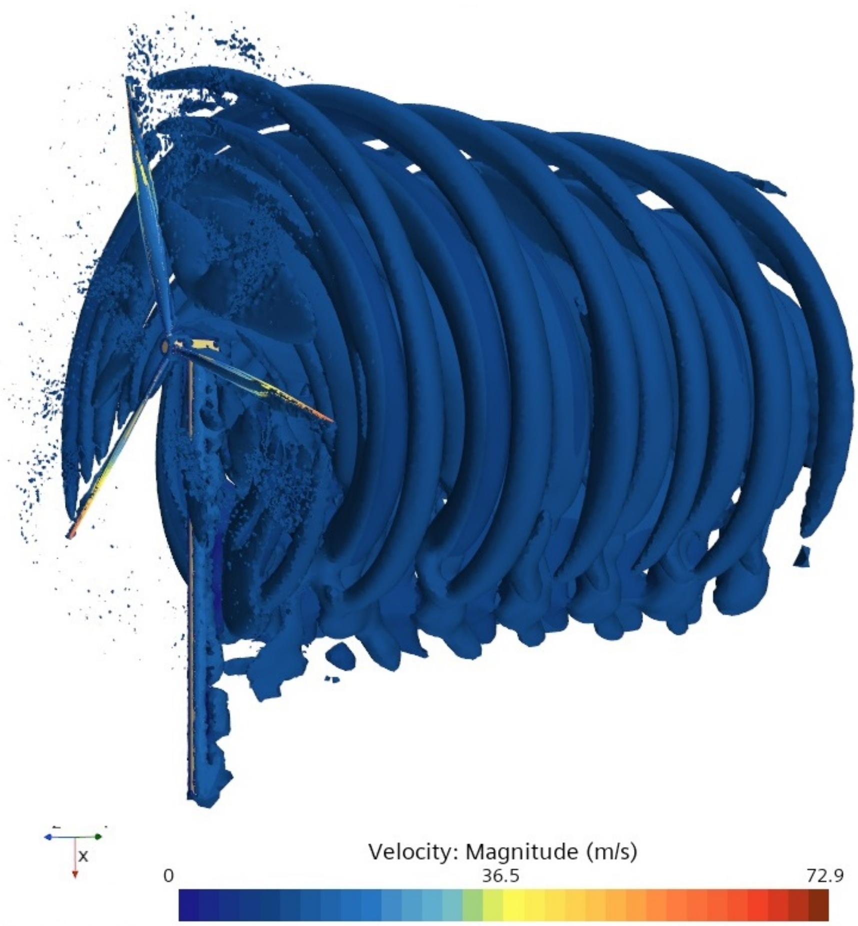


Figure 13. Wind turbine near wake display scene.

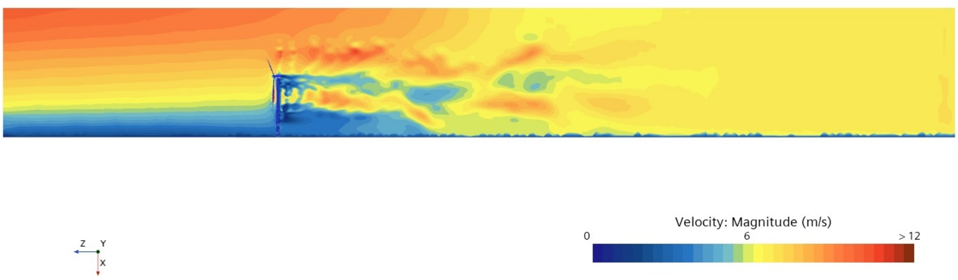


Figure 14. Scalar scene velocity: magnitude.

Figure 15 illustrates the change in the energy of the air flow along the near vortex wake during the rotation of the wind turbine.

Figure 15 shows that turbulence levels are highest at the tip of the blade due to the presence of a strong shear layer. In general, wind turbine aerodynamics are characterized by three main sources of turbulence: atmospheric turbulence, due to surface roughness and temperature difference along the height, turbulence caused by the flow around the rotor and wind turbine tower (the so-called mechanical turbulence) as well as additional turbulence caused by shear phenomena due to the collapse of the vertex vortices. In this work, the last two sources of turbulence are considered.

Figure 15. Scalar scene total energy in the near wake.

The reliability of the obtained results is ensured by comparing the obtained data with the data of other authors. The adequacy of the obtained numerical solution is confirmed through the convergence of calculations and because the residuals of the values are stable, without fluctuations and are limited in magnitude.

Simulation results can be a source of valuable information for maintaining efficient aerodynamic modes of operation of wind turbines, for predicting the generated power under conditions of variability of the wind effect and for a reasonable choice of wind turbine control methods.

In addition, the results obtained can be used in the study of wind farms. The total power generated by the wind farm is less than the total power of the wind turbine. This is explained by the slowdown of the wind flow after the turbine, which was revealed by the authors. Turbines located upstream extract a part of the energy from the wind flow and leave behind regions of lower speeds, which later interact with downstream turbines. Therefore, downstream turbines produce less power. A higher level of turbulence in the wakes of the upstream turbines can increase the dynamic load experienced by the downstream turbines and, as a result, reduce their durability.

The site for a wind farm should be chosen in such a way as not to create obstacles for the free wind movement on the site of wind turbines. The wind turbine layout plan should be designed considering the wind speed rose, the wind energy rose, the topographic features of the site and the shading effect based on an analysis of alternative options.

4. Conclusions

We considered approaches to the study and numerical modeling of the ABL in the vicinity of a wind farm in detail. A cluster analysis of the states of ABL by seasons was performed. As a result, 10 localizations of ABL homogeneous properties were identified. Simulation of a three-bladed horizontal wind turbine was performed. Thus, the main regularities of the flow around wind turbines were revealed.

A fuzzy algorithm for control of the output power of the wind turbine by changing the pitch angle was considered in detail. The considered intellectual and digital technologies proposed by the authors can optimize and improve the efficiency of a wind farm as a whole, and the results of the cluster analysis of weather data in the wind farm can be used to predict the generation of wind farms as well as to manage local precipitation in the area of operating wind farms.

In the future, the authors plan to consider phase transformations during the interaction of a polydisperse flow with a wind turbine and the effect of orography on the operation of a wind farm.

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Abbreviations

The following abbreviations are used in this manuscript:

WEC	wind energy conversion
ABL	atmospheric boundary layer
CFD	computational fluid dynamics
MPPT	maximum power point tracking
THD	total harmonic distortions
PI	proportional–integral
MMPT	maximum power point tracking
THD	total harmonic distorsions
FLC	fuzzy logic conversion
RANS	Reynolds-averaged Navier–Stokes
LES	large eddy simulation
DNS	direct numerical simulation

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