Identification of Probable Precipitation Formation Zones using Data Mining and Control Actions by Local Injections of Moisture Concentrators

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Abstract

The study of the atmosphere and the determination of probable precipitation formation zones is of practical interest for researchers in the fields of climatology, dynamic meteorology, in the tasks of aviation meteorology and wind power. This paper proposes a new approach to determining the areas with the highest probability of precipitation based on the use of neural network modeling. In addition, the scientific problem of knowing the influence of wind farms on the state of the atmospheric polydisperse boundary layer and their potential impact on the local meteorological situation is touched upon. This is due to the significant role of wind turbines in slowing down geostrophic wind, creating additional turbulence and increasing vertical mixing of momentum, heat and moisture. In order to effectively use local territories, the authors carried out a study a study of the possibility of controlling the meteorological situation. The paper presents the results of forecasting precipitation formation in a given area – the Ulyanovsk Wind Farm area. The results of a numerical study of the state of the atmospheric boundary layer are presented, and the impact of the wind farm on the local meteorological situation is assessed. An approach to controlled precipitation by influencing the atmospheric boundary layer with injections of moisture concentrators is proposed.

Keywords: Atmospheric boundary layer, precipitation, wind farm, neural network, modeling

1. Introduction

The short- and long-term forecasts of meteorological phenomena makes it possible to design and create optimal configurations of large wind farms, since they occupy large areas and are significantly influenced by the atmospheric boundary layer state. Correct consideration of the features (climatic, territorial) of Russia makes it possible to study the mutual influence of wind farms with the local meteorological situation.

To perform predictive studies, it is necessary to process a huge amount of data, traditionally statistical approaches have been used for these purposes to identify regular variability against the background of random factors and causes, however, this approach is based on available statistical data from previous periods and requires the completeness of these data to ensure the accuracy of the calculation [1].

In order to maintain the energy efficient operation of wind farms, weather forecasting should include a lot of meteorological studies. The existing methods of precipitation identification are mostly based on visual analysis of cloud cover images, and the success of their application significantly depends on the qualification of the meteorologist. The precipitation data obtained in this case does not meet the requirements of operational models of numerical weather forecast [2]. Artificial intelligence methods serve as a promising direction for determining the probable precipitation formation zones, since neural networks, genetic algorithms and evolutionary calculations allow performing very accurate forecasts in meteorology in conditions of inaccuracy, uncertainty, and the need for approximation. To solve the problems of weather forecasting, the most effective and widespread method is the analysis of weather time series, the use of regression analysis [3-5].

The conditions of the region under consideration are characterized by frequent temperature transitions through zero degrees, which can lead to icing of the wind turbines blades and, as a result, to failures of wind farm power. Thanks to the ability of machine learning systems, it becomes possible to predict control effects and precipitation management on the atmospheric boundary layer.

To study the effect of wind packs on the state of the atmospheric boundary layer and the prediction of wind generation, a number of researchers use hybrid modeling systems, for example, WindSim, as well as hybrid modeling systems combining Numerical Weather Prediction, Artificial Neural Network, Computational Fluid Dynamics [6-9].

To solve the problem of precipitation management, the method of seeding clouds with moisture concentrators is used [10]. Currently, such effects are mainly based on a change in the phase state of the cloud when it is "seeded" with some reagents, in particular solid carbon dioxide and silver iodide smoke. The physic-chemical properties of carbon dioxide and silver iodide allow the crystallization of supercooled cloud droplets. Clouds turn into mixed ones, acquire colloidal instability as a result and give precipitation, as it happens naturally in mixed clouds.

Modeling of the atmospheric boundary layer using CFD packages allows you to accurately predict the structure of the atmospheric boundary layer in the area of the wind farm location. A prerequisite for setting up a digital model is the correct setting of boundary weather conditions: velocity profiles, temperatures, turbulent characteristics, etc. To solve the problem of assessing the influence of wind farms on the evolution of the atmospheric boundary layer and local weather conditions, Frandsen's theory of effective roughness length is acceptable [11], according to which wind turbines can be considered as an element of increased roughness of the bottom surface. In this case, wind turbines are presented in the form of permeable actuator discs with or without rotation, as for example in the works [12-14].

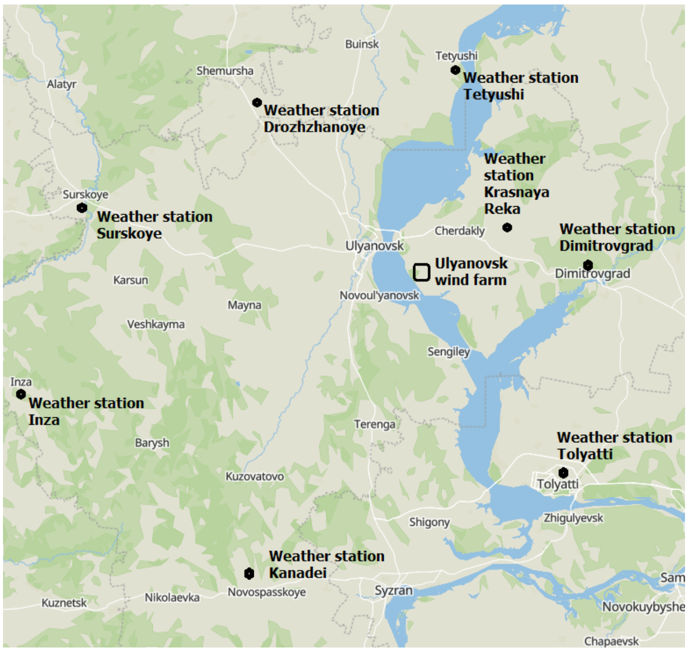
Wind turbines lead to significant turbulence of the flow, redistribution of vertical air layers. This is most clearly seen in the vertical distribution of wind velocity fields and turbulence intensity. The turbulent flow regime leads to an increase in the intensity of exchange between the boundary layer, the free atmosphere and the upper layers of the soil. Turbulence modeling is a complex and very non-trivial process, currently several approaches are used: RANS, LES, DNS. Taking into account the specifics of the task and its multiscale, it was decided to use the LES approach.

2. Forecasting precipitation in a designated area.

To predict precipitation, one of the machine learning methods is used – neural network modeling. One of the main advantages of using machine learning methods in precipitation forecasting is their ability to take into account nonlinear dependencies and complex interactions between various factors affecting the weather. Another important feature of these methods is their adaptability and the ability to improve the accuracy of forecasts as new data is accumulated and models are updated. A program complex has been developed that includes a neural network for classifying precipitation and an analytical module for making decisions on the application of control actions [15].

Archived data from Ulyanovsk weather stations for 2020-2022 were used to train the neural network [16]. The preprocessing of the data consisted in their systematization with a time interval of one hour. To take into account the influence of the wind farm, the weather stations closest to it were selected. During the analysis of the region and consideration of the area around the wind farm eight weather stations were identified (see Figure 1).

Figure 1: Area with Weather Stations to Study the Weather Conditions (the area of the Wind Farm is Marked in White)



The best accuracy of calculations was achieved with the following neural network architecture: the number of input layers is 10, the number of internal layers is 6, each layer contains 60 neurons. Each layer uses the «relu» activation function [17].

The following weather characteristics were used as input and output data: relative direction of the weather station; wind speed, m/s; wind direction, degrees; distance, m; air temperature, °C; dew point temperature, °C; relative humidity, %; atmospheric pressure, hPa; precipitation, mm; weather phenomena (weather characteristics): rain, snow, hail, blizzard, fog, etc.

Encoding of each parameter was performed based on the conditions of estimated significance for the input data and the probabilistic phenomenon for the output data. The encoded values ranged from 0.01 to 0.99 from the minimum to the maximum value.

Based on the presented data, two classes were obtained: 0 - no precipitation during the day, 1 - their presence. The level of accuracy in training was 82.44%, completeness 73.61 and accuracy 80.18%. Visualization of the calculation results is shown in Figure 2. Here, by color indication, it is possible to identify areas with different precipitation probabilities. As can be seen from Figure 2, the cloud front is moving from the southeast to the northwest. The area of the wind farm is marked in white, precipitation was not observed in the area of the wind farm at the current network settings.

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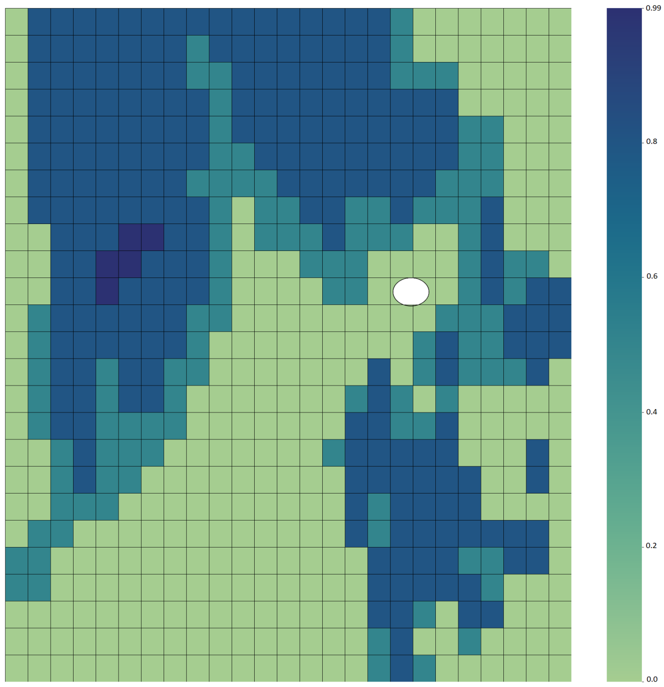
Figure 2. Visualization of Predicted Scenes of the Probable Precipitation Formation Zones



3. Controlled Precipitation

It is known that the main contribution to precipitation in the middle latitudes of Russia in the cold season is provided by supercooled clouds, and in summer precipitation falls from warm, primarily convective clouds. Therefore, in order to organize controlled precipitation, it is necessary to influence those clouds that are involved in precipitation formation in a given season. With the right choice of objects for exposure and with the correct sowing, it is possible to obtain an additional 10-30% of precipitation, and under favorable conditions – up to 50-70% [10], as well as to achieve their redistribution.

As a control effect, the authors consider an approach based on the injection of moisture concentrators in the form of silver iodite by spraying. The purpose of the management is to prevent precipitation on the territory of the wind farm, to prevent icy rains and hail. The determining criteria for the suitability of clouds to achieve the management goal are the temperature and humidity of the environment, wind speed and direction, and the water content of clouds. Based on these parameters, it is possible to predict the time course of atmospheric moisture storage and cloud water storage.

Thus, according to the forecast values of the meteorological parameters of the atmosphere, it is possible to purposefully perform local injections of moisture concentrators into clouds to redistribute precipitation in a designated area.

4. Numerical study of the state of the atmospheric boundary layer in the vicinity of the wind farm

The Simcenter STAR-CCM+ commercial CFD package was used to calculate the atmospheric boundary layer state in the area of the wind farm [18]. Numerical simulation is based on the finite volume method (FVM) built into the program. The turbulence model was chosen as a large-eddy simulation (LES) turbulence model with closure of subgrid stresses according to Smagorinsky theory [12]. To simulate the effects of wind turbines, a model of a rotating actuator disc - 1B Momentum Method was used. The calculated area is shown in Figure 3. The ccomputation domain was 10x10x1 km. The total number of mesh cells in this area was 146268 742.

Figure 3. Computation Domain for modeling the Atmospheric Boundary Layer State in the Wind Farm Area

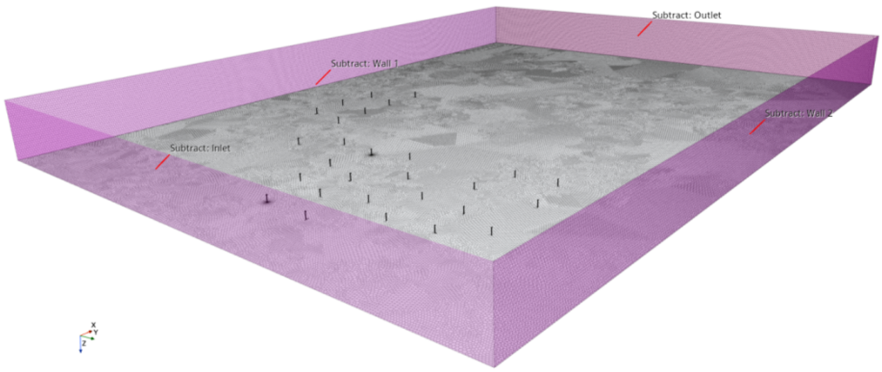
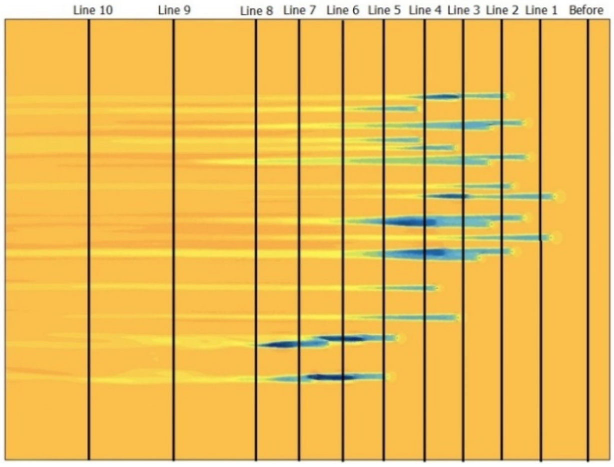
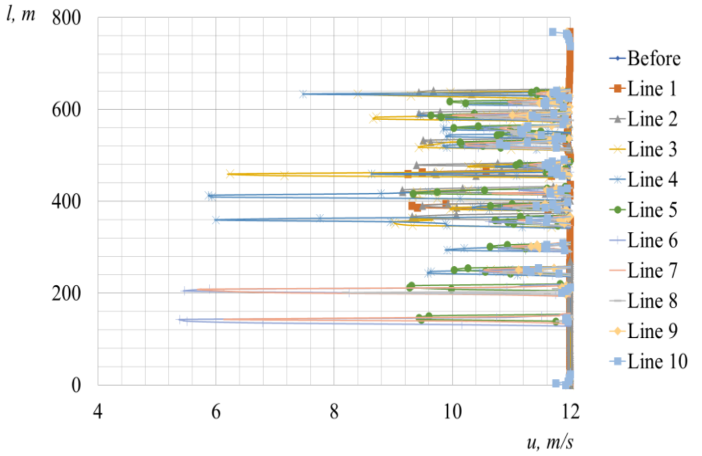


Figure 4 shows the results of modeling: studying velocity profiles in the computational domain in various sections along the flow with a westerly wind direction. The calculation error lies within the confidence probability and is less than 5%. Figures 4 show a scalar scene in one of the calculated sections with a color indication of velocity and digitized data on velocities.

Figure 4: Calculated Velocity Fields in the Westerly Wind Direction



(a)



(b)

The figure clearly shows areas with reduced velocity values, the so-called areas with a velocity deficit. At the same time, the greatest turbulence is observed in these areas. The calculation results were verified using telemetry data, as well as data from other researchers [11-13].

5. Conclusions

Identification of probable precipitation formation zones based on one of the methods of machine learning – neural network modeling is performed in the work. Archived data from Ulyanovsk weather stations for 2020-2022 were used to train the neural network. The level of accuracy in training was 82.44%. An approach is proposed to control precipitation through the use of moisture concentrators. Modeling and numerical study of atmospheric boundary layer in the area of the Ulyanovsk wind farm has been performed. The paper used the LES approach for the calculation. The LES approach made it possible to simulate aerodynamic processes in the wind farm area very accurately. The obtained experimental data on the development of aerodynamic wakes allowed us to establish the influence of wind turbines on the state of the atmospheric boundary layer. The calculation error did not exceed 5%.

Acknowledgment

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