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# Adaptive Neuro-Fuzzy System for Detection of Wind Turbine Blade Defects

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**Abstract:** Wind turbines are the most frequently used objects of renewable energy today. However, issues that arise during their operation can greatly affect their effectiveness. Blade erosion, cracks, and other defects can slash turbine performance while also forcing maintenance costs to soar. Modern defect detection applications have significant computing resources needed for training and insufficient accuracy. The goal of this study is to develop the improved adaptive neuro-fuzzy inference system (ANFIS) for wind turbine defect detection, which will reduce computing resources and increase its accuracy. Unmanned aerial vehicles are deployed to photograph the turbines, and these images are beamed back and processed for early defect detection. The proposed adaptive neuro-fuzzy inference system processes the data vectors with lower complexity and higher accuracy. For this purpose, the authors explored grid partitioning and subtractive clustering methods and selected the last one because it uses three rules only for fault detection, ensuring low computational costs and enabling the discovery of wind turbine defects quickly and efficiently. Moreover, the proposed ANFIS is implemented in a controller, which has an accuracy of 91%, that is 1.4 higher than the accuracy of the existing similar controller.

**Keywords:** wind turbine; adaptive neuro-fuzzy inference system; defect detection; subtractive clustering; grid partitioning



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## 1. Introduction and Related Work

Today, the world is deploying renewable energy sources in order to reduce dependence on coal and natural gas imports and to cut back greenhouse gas emissions. The governments will further support solar, wind, hydropower, and biofuels through the variety of programs and strategies they employ. A 50% growth rate in the fastest pace of global annual renewable capacity additions over two decades is believed to increase to nearly 510 GW per year. A total of 66% more wind power plants were added than in the previous year. By the end of 2024, the world promises to install more renewable energy than was commissioned in over a century, from which was no plant built for the first time commercial electricity generator power. This policy support will see close to 3700 GW of new renewable capacity added in more than 130 countries between 2023 and 2028, under the main forecast. By 2020, 95% of the global increase in renewable energy came from solar PV and wind power because of their generation cost that is cheaper than both fossil and non-fossil fuels [1].

Wind turbines are highly efficient from the environmental point of view due to all the below features they come with, making them an excellent choice for energy production over other energy systems. First, wind energy is pollution free and emits no greenhouse gases—the same cannot be said for sources of traditional power like coal, oil, or gas. However, this also leads to a reduction in the contributions towards climate change and thereby contributes to the conservation of nature [2]. Moreover, wind is a renewable resource, so it is virtually unlimited in supply. Modern wind turbines also can perform with high efficiencies in low wind speed environments, giving them an advantage for placement in many areas across the globe. They can be land- and sea-faring weaponry, making them more versatile for firepower options. The economic component is one more aspect that is important. Advancement in technology with a falling price of wind energy production has made it a major competitor to other forms of producing energy. In addition, after being built, wind turbines also have little operating costs, further decreasing the full cost of energy over their life cycle. Lastly, wind turbines can help countries to reduce their energy dependence and protect their security of supply. Further, they directly employ thousands of workers and help drive economic development in the regions where wind turbines are installed. All of these benefits combine to make wind turbines a vital part of contemporary energy infrastructure and an essential weapon in the fight against climate change [2].

It needs to be noted that, wind power has one significant disadvantage. It is fluctuating energy, depending on the wind force. The generator, which transforms mechanical rotational motion into electrical energy, may have issues that cause the output of power to be reduced or maybe stop entirely. Turbine efficiency can be decreased by malfunctions in the control system that keeps the turbine operating at its best in response to variations in wind speed. Damage to the gearbox, which raises the generator's rotational speed, may result in decreased energy transfer efficiency or even the turbine stopping entirely [3].

Wind turbine malfunctions have a big impact on how well they work. For instance, erosion or cracks in a turbine's blades might make it less effective in capturing wind energy, which reduces the amount of power that can be produced. Increased friction and vibration from bearing issues can decrease efficiency and perhaps result in more catastrophic breakdowns [4,5]. These flaws have the potential to drastically reduce the wind turbine's efficiency, raise maintenance expenses, and decrease its lifespan. As a result, routine maintenance and prompt problem diagnosis are critical to the turbine's stable operation [6,7].

The following methods are most often used to detect damage to wind turbine blades [4].

Detection methods based on acoustic emission. The goal of this technique is to identify electrical signals that arise from material deterioration, plastic deformation, or the spread of fissures. By detecting even little flaws in their early stages through acoustic emission, it can stop them from developing further.

Ultrasonic detection method. Using this method, waves reflected from damage in the material are detected. These waves help to determine accurately the location and size of the defect, which allows monitoring of its development and intervening in time to prevent further problems.

Vibration detection methods. These methods are used to keep an eye out for vibrations that might be caused by damage or deformation to turbine parts. The ability to detect anomalous vibrations enables the early detection of issues and the implementation of corrective action before serious failures arise.

Thermographic detection method. This method allows measuring the temperature difference on the surface of the turbine. The detection of abnormal temperature zones can indicate the presence of damage, such as overheating or internal defects in the material, which are not visible.

Detection methods based on machine vision. These methods use images to analyze the condition of the turbine. Machine vision systems can automatically detect defects such as cracks, corrosion, or other damage by analyzing photos or videos from different angles and in high resolution.

Detection methods based on strain measurement. These techniques use strain sensors to detect small changes in length or deformation of turbine components. Measuring such changes helps to identify cumulative defects that can lead to serious breakdowns if not removed in time.

Methods of machine learning, feature engineering, deep learning, and transfer learning. A robotic RV reducer can be used, for example, to investigate mechanical damage to a wind turbine engine [8,9]. Detection of malfunctions in bearings of servomotors can be carried out on the basis of deep learning, which makes it possible to increase the accuracy of their detection [10]. The application of such modern approaches demonstrates a high probability of the detection results of various mechanical damages in wind turbines.

Wind turbines are complex systems with non-linear relationships between parameters. An adaptive neuro-fuzzy inference system (ANFIS) successfully models these relationships, providing a better understanding of turbine processes and more accurate identification of defects. Compared to traditional neural networks, ANFIS adapts to new data faster, making it more convenient for real-time monitoring. Wind turbine research methods based on adaptive neuro-fuzzy inference systems combine elements of fuzzy logic and neural networks for modeling and optimization of turbine performance [11–16]. Key wind turbine properties, including power factor, rotor speed, and power output, are frequently modeled using ANFIS. The model uses input variables to predict the output performance of the turbine, trains on historical data, and is used to accurately predict turbine behavior under various conditions [17]. ANFIS is used to develop adaptive controllers that can effectively control turbine operation under variable wind speed conditions. Such a controller provides optimal control of the turbine, adapting to different operating conditions. This makes it possible to increase the efficiency of the turbine and stabilize its operation during disturbances. Using information from the blade parameters and other turbine attributes, ANFIS is used too to forecast the power factor of wind turbines. By optimizing the turbine's functioning, this method allows for the accurate prediction of its performance and the reduction in energy losses.

The main methods, which are used in wind turbine research based on ANFIS, are next [18–21]. Research techniques based on ANFIS generally enable efficient modeling and optimization of wind turbine operation, boosting the machines' stability and efficiency in the face of fluctuating external influences. The study [22] discusses the creation of a novel ANFIS-based controller for managing a power system that includes a wind turbine. Improving the power system's dynamic responsiveness when faults occur is the primary objective of the research. System modeling has shown that using ANFIS can greatly reduce fluctuations and guarantee system stability in the face of a variety of shocks. Paper [23] investigates the combination of ANFIS and a proportional–integral (PI) controller for voltage regulation in a power system with a wind turbine and a static reactive power compensator. The PI controller is optimized using a genetic algorithm. The results of the study show that such a combination of controllers provides better voltage regulation and improves the transient stability of the system. Paper [24] deals with ANFIS-based real-time power estimation for power systems. The use of ANFIS for power prediction and control allows power estimation with high accuracy, making it suitable for use in real-world environments. The application of ANFIS to increase stability and control efficiency in power systems outfitted with wind turbines and other renewable energy sources is the main theme of all noted publications. To make power systems more stable in the face of diverse disruptions and adjustments to operating parameters, the integration of adaptive intelligent control systems is prioritized. For example, the ANFIS-based controller for regulating the operation of a power system containing a wind turbine is suggested in [25]. Improving the system's dynamic response following malfunctions receives the majority of emphasis. Thanks to the use of ANFIS, the system demonstrates high performance and the ability to quickly damp oscillations. The advantage of the approach lies in the ability of the controller to adapt to different conditions and ensure stable operation of the system during disturbances. The disadvantage is the complexity of the controller implementation and the need for significant computing resources.

In Ref. [26], a new scheme for controlling the angle of inclination of wind turbine blades is considered. A hybrid strategy combining a self-similar PI controller with ANFIS-based compensation is used to improve system performance under variable wind speeds. Studies show that this approach increases system response speed and improves turbine stabilization. The main benefit is reduced system setup time and increased accuracy, but setup complexity remains a significant challenge. Article [27] is devoted to the use of ANFIS for forecasting the power factor of wind turbines. The ANFIS model is based on blade profile type parameters and other variables such as the Schmitz coefficient. Research results show that the ANFIS model outperforms neural networks in power factor prediction. The advantage of this approach is high prediction accuracy, but training the model requires a large amount of data, which can be a challenging task. The articles [28–33] demonstrate the successful application of neuro-fuzzy systems to optimize the operation of wind turbines, especially in the context of increasing the efficiency and stability of the system.

The work of [34] is the closest related work for the proposed system for the detection of wind turbine defects. This paper is devoted to the development of intelligent systems for fault detection and isolation in wind turbine drive systems. The authors are focusing on the drive part of the horizontal-axis wind turbine using ANFIS. As a result, the described intelligent system can effectively detect the faults in the drive part of wind turbines. The adaptive neuro-fuzzy method [34] has the number of rules, which vary from 16 to 32, depending on the number of prerequisite parameters. The simulated faults of this ANFIS are from 0.97 to 0.3 due to the modification of the proposed method.

The work of [35] is the closest related work describing the controller for wind turbine blade defect detection based on virtual reality technology and deep learning. The controller employs the U-Net architecture to segment blade images for detecting four main types of defects: cracks, edge erosion, delamination, and lightning damage. This U-Net architecture is used for the segmentation of images with the size of $512 \times 512$ pixels, similar to the ANFIS structure proposed in this article. After training of 100 epochs, the controller obtains the Dice coefficient of 0.658. Moreover, this type of controller needs big computing resources and couldn't work in real time.

The system, proposed by the authors, uses an unmanned aerial vehicle (UAV) that automatically takes pictures of wind turbines. The UAV takes a series of pictures of the turbines from different angles and transmits them in real time to the administrator's computer. These images are processed in a computer frame-by-frame using a neural network, such as YOLO [36], for automatic detection of possible defects on the blades or other parts of the turbine. YOLO and the other traditional CNNs specialize in object recognition, determine the existence of defects such as cracks or damage, and create a data vector containing information about these probabilities [37–40].

Besides this, the two-stage object detection models, which are used by UAVs, have shown significant progress in detecting wind turbine blade defects. However, they still face several challenges. Specifically, these models often have a large number of parameters, resulting in significant computational demands, particularly for real-time applications. Additionally, their detection speed remains insufficient, limiting the practical use of these models for online identification of wind turbine blade defects. Therefore, despite the relatively high detection accuracy, these two-stage defect detection models need further improvements to increase their real-time performance and simplify their integration into engineering applications [41]. For example, the CNNs, which are used in modern two-stage object detection models on UAV images, give the result of the presence of damage on the wind turbine as a sequence of probabilities on how to assign damages to a certain class on the analyzed image [36,41]. This can lead to some uncertainty in damage recognition. Fuzzy logic and neural networks can model and manage these uncertainties more reliably than traditional methods [42]. This is achieved by the fact that ANFIS systems process fuzzy input values based on known formulas and rules, and they make a proper inference regarding the class of wind turbine defect afterwards [8].

The main problems of noted applications remain the complexity of setting up models and the need for significant computing resources for training and insufficient accuracy. Therefore, the goal of this study is to develop the improved adaptive neuro-fuzzy system for wind turbine defect detection, which will reduce computing resources and increase its accuracy. To achieve the goal, the following objectives were formulated:

- Development of a neuro-fuzzy system model for wind turbine blade defect detection;
- enhancing the system learning process to increase the accuracy of defect detection while minimizing computing costs;
- improving the accuracy of the ANFIS.

The rest of the paper is structured as follows: in Section 2, the existing methods for the control and detection of wind turbine blade defects are considered. In Section 3, the architecture of the ANFIS for detecting wind turbine defects is described, as well as neuro-fuzzy system models. In Section 4, the results of testing models are presented, and the proposed neuro-fuzzy controller is described. Section 5 summarizes the results and includes future research directions.

## 2. Methods and Materials

### 2.1. ANFIS Architecture

As was noted in the Section 1, the data about the probability of the defect's existence can be fuzzy, so fuzzy logic is used for further analysis. This allows for more accurate processing of these probabilistic data, taking into account the possible uncertainty. For this, the ANFIS system is used, which combines the capabilities of neural networks and fuzzy logic. Moreover, ANFIS works without packet processing, so it is optimal in speed compared to image processing by a convolutional neural network, which is most often used by UAVs. ANFIS analyzes the data vectors obtained from YOLO and determines the probability of the defects existence on the turbines, providing additional accuracy and reliability in the operation of the system.

As a result, the system provides an estimate of the probability of the defect's existence for each turbine image. These data can be transmitted to the operator or used to generate reports for maintenance. This approach helps to detect problems in time, reduce the risk of missing defects, and optimize the process of diagnosing turbines.

An adaptive neuro-fuzzy inference system is a combination of two approaches: neural networks and fuzzy logic. Such a system uses the strengths of both methods to create models and controllers that can work with uncertain and fuzzy data while having the ability to learn and adapt [43].

The ANFIS architecture consists of five layers (Figure 1):

Fuzzification layer: In this step, the inputs transform into fuzzy variables using membership functions. Each variable is described by fuzzy rules such as "low", "medium", or "high" defined by membership functions (e.g., Gaussian or triangular).

Rule layer: At this level, vague rules of the type "If . . ., then . . ." are formed. These rules define the relationship between input variables and desired outputs.

Normalization layer: At this stage, all the output signals are normalized so that the sum of the weights of all the rules is equal to one. This helps to standardize the results of each rule.

Defuzzification layer: The results of fuzzy rules are transformed into crisp values that correspond to the input data. This is done by applying linear functions to each fuzzy rule. Output layer: At this level, all the results of the previous layers are summed up, and the final output of the system is obtained.

The typical structure of the ANFIS consists of a multilayer feedforward network where each node performs a specific function, known as a nodal function, on the signals it receives. Each node is associated with a set of parameters that define its behavior. The formulas for these nodal functions can differ between nodes, and their selection depends on the input–output relationship of the network.

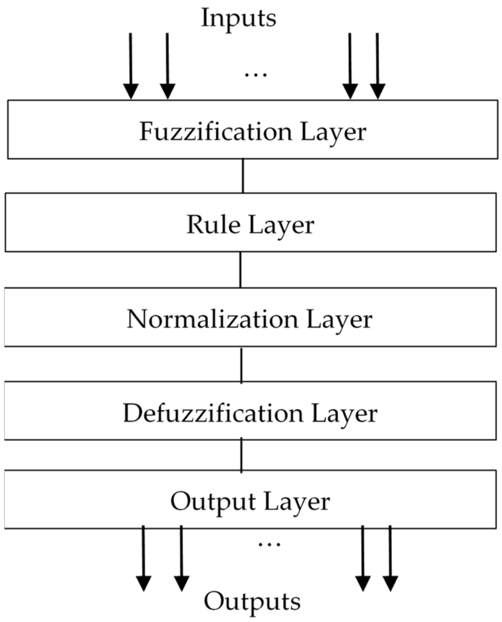


**Figure 1.** Typical components of the adaptive neuro-fuzzy system.

In the ANFIS network, the connections between nodes merely represent the flow of signals and do not have weights. To distinguish node types, the adaptive (square) nodes represent those with associated parameters, while fixed (circular) nodes lack parameters. The complete set of parameters for the adaptive network is the combined set of parameters from all its adaptive nodes.

To achieve the desired mapping between inputs and outputs, the network parameters are adjusted during the training process using the provided training data and a defined learning algorithm. The typical architecture of ANFIS with two inputs and two outputs is presented in Figure 2 [44].

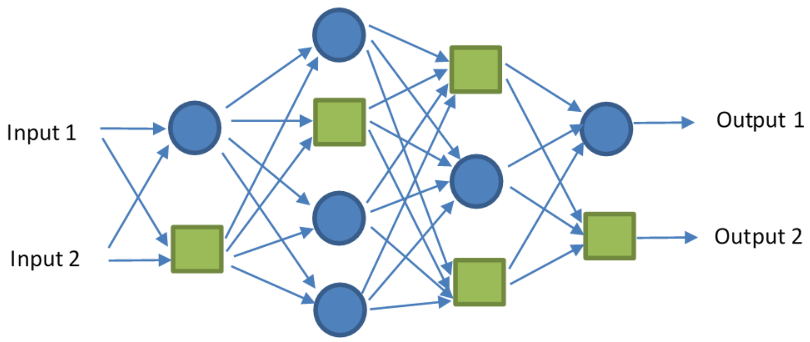


**Figure 2.** Architecture of the adaptive neuro-fuzzy system ([44], reworked by authors).

Advantages of neuro-fuzzy systems:

1. A combination of the strengths of neural networks and fuzzy logic: Neuro-fuzzy systems combine the ability of neural networks to learn from data and adapt with the ability of fuzzy logic to work with uncertain or fuzzy data.
2. Adaptability: The system can learn and adjust its parameters on the fly, making it very flexible and suitable for tasks where data or conditions may change.
3. Ability to process vague information: Fuzzy logic allows the system to work with vague, uncertain, or incomplete data, which is a big plus in situations where precise information may not be available.

ANFIS is widely used in systems that require adaptability, accuracy, and processing of fuzzy data. Considering these advantages, the authors use the neuro-fuzzy system to detect wind turbine defects.

### *2.2. Neuro-Fuzzy System Models*

According to objective 1 above, the authors developed neuro-fuzzy system models for wind turbine defect detection, which are described below.

For building a neuro-fuzzy model, it is necessary to change the input data, the methods of generating the initial fuzzy models, as well as conduct its training.

#### 2.2.1. Input Set for Proposed Neuro-Fuzzy System Model

To build a model of a neuro-fuzzy system for analyzing the existence of wind turbine defects, the MATLAB R2023a environment neuro-fuzzy designer has been used.

The input to ANFIS is a vector of features that contains the observation level corresponding to each of the defect classes. It is important that the dataset contains enough examples of each type of defect and the normal state of the wind turbine. This ensures that the model is trained to recognize all the right classes and it is not biased. If the task of detecting wind turbine blade defects is reduced to recognizing simple regularities or typical patterns in the data, the ANFIS is able to train even on a small sample. Moreover, thanks to the fuzzy logic, the ANFIS can generalize from limited data, which reduces the need for a large number of examples.

The input data for the simulation are vectors of features that correspond to the presence of wind turbine blade defects in the image. For example, the vector of features 0.8492, 0.0185, 0.1318, and 0.0004 indicates, accordingly, the probability of corrosion in the image is 0.85, erosion—0.02, cracks—0.12, and almost no defect (0.00). That corresponds to the real image that is given in Figure 3.

**Figure 3.** An example of an image for a wind turbine with corrosion [45].

To train the ANFIS, the authors used a training sample of 400 images (100 vectors of features per each damage class) as the results of image classification by the SqueezeNet neural network [46].

#### 2.2.2. Comparing Methods of Improved ANFIS

In MATLAB, the different methods of generating initial fuzzy models are used for designing neuro-fuzzy system models in the neuro-fuzzy designer environment [47]. The two main methods are grid partitioning and subtractive clustering. They have different approaches to building fuzzy systems.

Both of these methods are implemented based on Sugeno–Takagi fuzzy inference. A typical rule of the proposed ANFIS is the following:

$$if\ corrosion \in mf_i \text{ and } erosion \in mf_j \text{ and } crack \in mf_k \text{ and } normal \in mf_l \text{ then } output \in f(u),$$

where *mf* is a membership function of correspondence input value and $f(u)$ is a linear function of the input variables. This linear function is $f(u) = p_1x_1 + p_2x_2 + \ldots + p_nx_n + r$, where $x_1, x_2, \ldots, x_n$—inputs of the system, $p_1, p_2, \ldots, p_n$—linear parameters that are adjusted during training ANFIS, and $r$—a free member, which is also set during training [44].

Grid partitioning creates a fuzzy system by uniformly partitioning the input space into segments or grids. Each variable of the input space is partitioned into several levels (usually uniformly), and then all possible values of these levels are combined to form fuzzy logic rules. This leads to the creation of a large number of rules for each combination of the input variable values. The advantage of this approach is the simplicity of implementation and clear interpretation of the fuzzy system. However, this method can become inefficient for large data sets or when the number of input variables increases, since the number of rules grows exponentially with the number of levels and variables.

The fuzzy system generated by grid partitioning has four variables at the input: corrosion, erosion, crack, and normal, which are given by data in the range [0;1]. That demonstrates the probability of the presence of each of the defects in the image. The general scheme of the generated fuzzy system is presented in Figure 4.

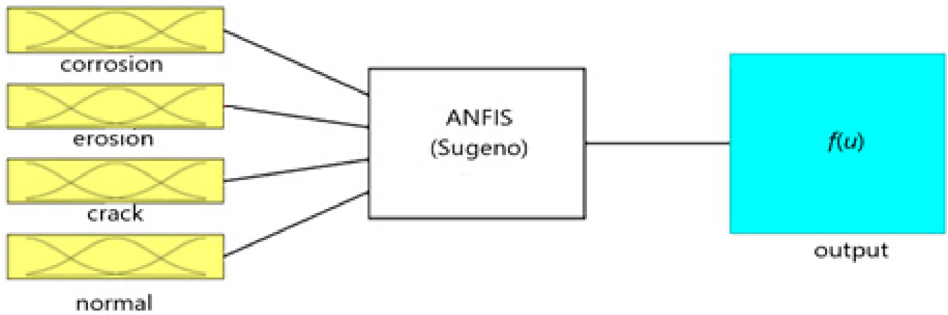


**Figure 4.** General scheme of a fuzzy system generated by grid partitioning.

Implementation of the Sugeno–Takagi inference mechanism of the fuzzy system generated by the grid partitioning method is carried out in the block ANFIS (Sugeno).

This fuzzy system defines the corrosion variable by four membership functions of the Gaussian form; the other input variables are defined by only three similar membership functions, which are described by the formula:

$$f(x, c, \delta) = e^{\frac{-(x-c)^2}{2\delta^2}} \quad (1)$$

where $f$ is a function, $x$ is a variable, $c$ is the coordinate of the maximum, and $\delta$ is concentration coefficient [48].

The MATLAB environment automatically selected the membership functions. This is the most optimal choice for further processing by a neural network. The number of membership functions is selected experimentally for the best ANFIS training result.

Accordingly, the rule base of such a fuzzy system contains 108 rules. It is worth noticing that ANFIS works based on the Sugeno fuzzy inference mechanism (Figure 5).

Subtractive clustering uses clustering to identify groups of data points that have similar characteristics and creates fuzzy logic rules based on these clusters. After that, the centers of the clusters are used as the centers of the fuzzy sets, and the number of rules depends on the number of clusters found. This approach does not partition the input space uniformly but adapts to the distribution of the data. This approach is effective for large data sets, especially when the data distribution is uneven. Subtractive clustering creates fewer rules compared to grid partitioning, which makes the system more compact and faster. However, such a fuzzy system can be difficult to adjust the clustering parameters to obtain an optimal fuzzy system. The method may also take more time to set up compared to grid partitioning.

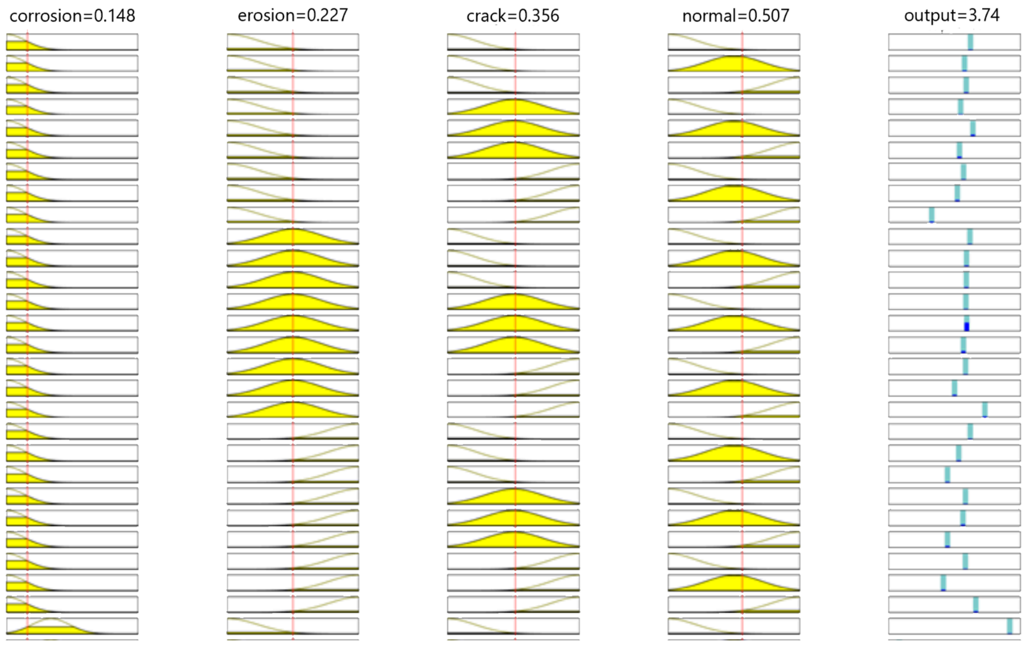


**Figure 5.** Fragment of the rule base for the fuzzy wind turbine blade defect detection system (generated by the grid partitioning).

The fuzzy system of detection for wind turbine blade defects, created by subtractive clustering, is presented in Figure 6. Implementation of the Sugeno–Takagi inference mechanism of the fuzzy system generated by the subtractive clustering method is carried out in the block ANFIS_clust (Sugeno).

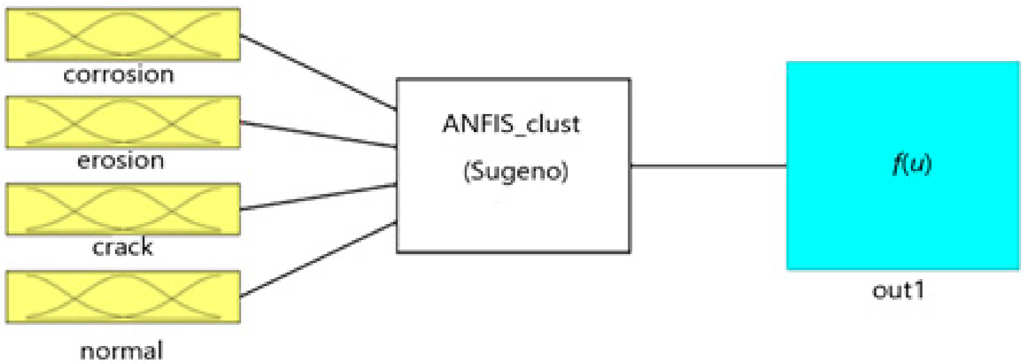


**Figure 6.** General scheme of the fuzzy system generated by subtractive clustering.

Each of the input variables is defined by three Gaussian membership functions as well as the grid partitioning model. This fuzzy system contains the three fuzzy rules only, which significantly increases the speed of the overall system compared to the previous one. The operation of the rule base is shown in Figure 7.

The main difference between these two methods is how they create rules for the fuzzy system. Grid partitioning evenly partitions the input space into grids, which is suitable for small systems but becomes unwieldy for large datasets. Subtractive clustering finds clusters in the data, creating a more adaptive and compact system. However, this method can require more careful setup.

The difference between these two generated fuzzy systems is clearly visible from their structure (Figures 8 and 9).

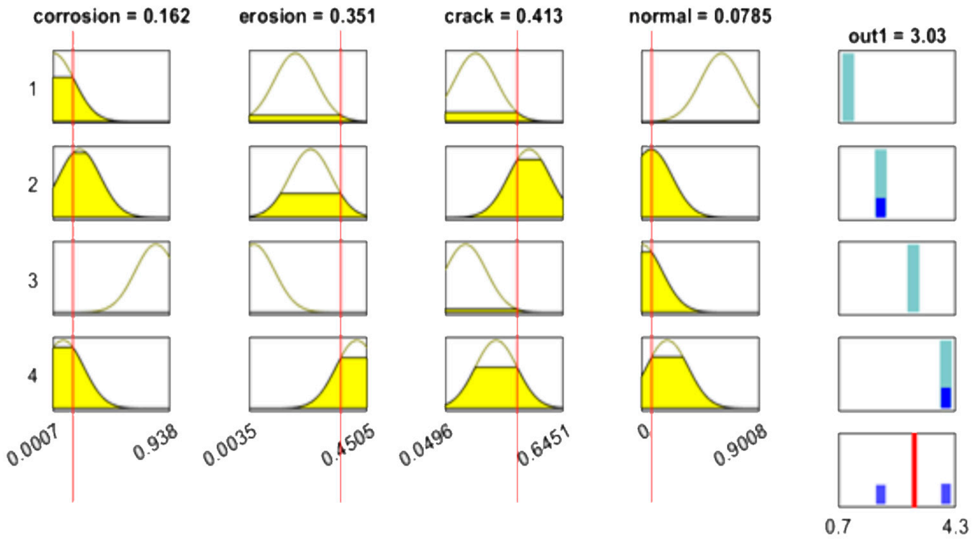


**Figure 7.** Demonstration of the fuzzy system generated by subtractive clustering.

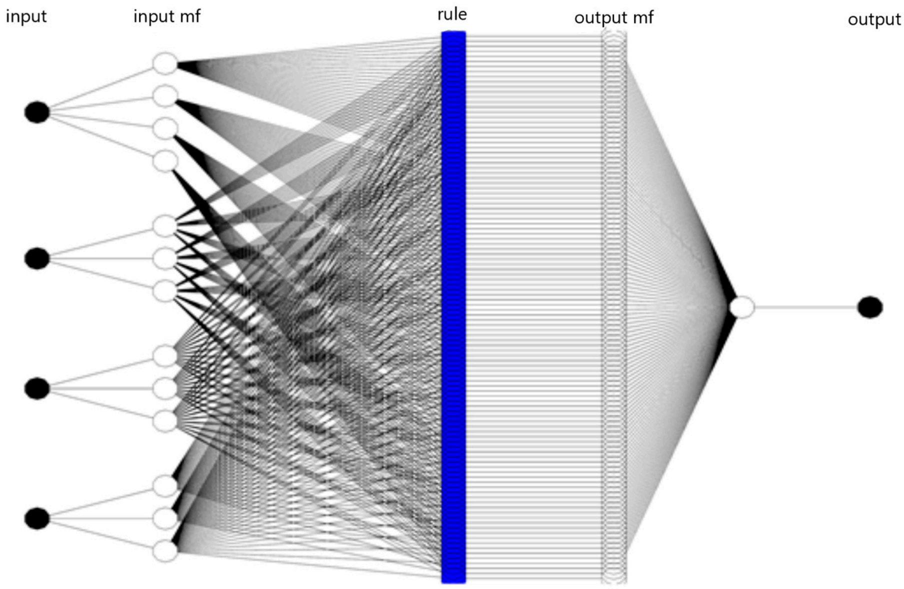


**Figure 8.** The structure of the ANFIS for wind turbine blade defects detection generated by the grid partitioning.

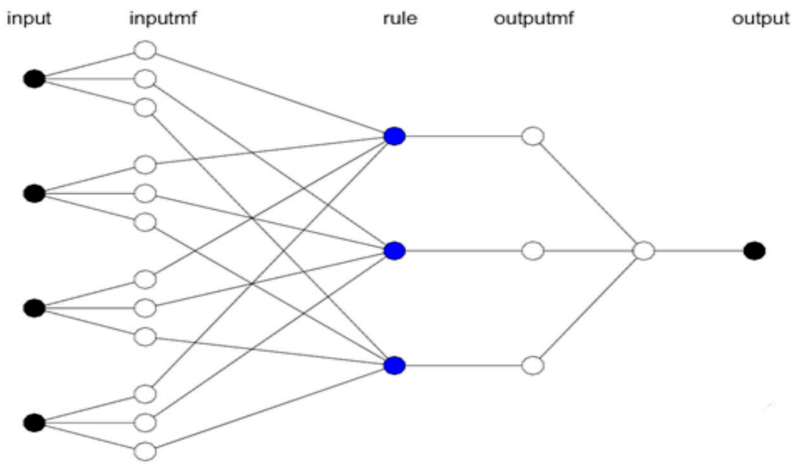


**Figure 9.** Structure of ANFIS for blade defects detection generated by the subtractive clustering.

2.2.3. Training of the Improved ANFIS

To reach objective 2 regarding the increasing accuracy, the authors propose employing grid partitioning and subtractive clustering methods, which are described below.

The neuro-fuzzy system is a combination of two methods: neural networks and fuzzy logic. The basic idea is, firstly, to create a fuzzy system that can handle uncertain or fuzzy data and, secondly, to use the learning ability of a neural network to automatically adjust the parameters of that system [49–51].

ANFIS is training and modeling in the MATLAB environment, employing the hybrid training approach. The last one combines the backpropagation with the least squares methods. Backpropagation is used to adjust the parameters of membership functions in a fuzzy system, and the least squares method is employed to learn the parameters of linear regression in the original rules. This hybrid approach provides the efficient and accurate optimization of ANFIS parameters, combining the advantages of both methods: fast correction of inference parameters using least squares and slower, but more detailed, tuning of membership functions through backpropagation.

The learning process usually starts with defining the input data and dividing it into fuzzy sets. This is done using membership functions. Next, a set of "If . . ., then . . ." rules are formed, which connect these fuzzy sets with the expected initial data [52]. Once the system is configured, it goes through a learning process. This means that the system receives inputs along with known outputs and uses them to adjust its parameters. Basically, the neural network learns from this data and gradually improves the accuracy of the system by changing the weights or parameters of the membership functions to reduce the difference between the predicted and actual results.

Learning usually takes place in two stages. First, the system adjusts the linear parameters using the least squares method, which helps to make the output as close as possible to the correct result. Then, in the error backpropagation process, nonlinear parameters such as membership functions are tuned to further improve the accuracy of the system.

The learning process of the neuro-fuzzy system based on the fuzzy system generated by the grid partitioning method is shown in Figure 10. The training result for 100 epochs showed an accuracy of about 82%.

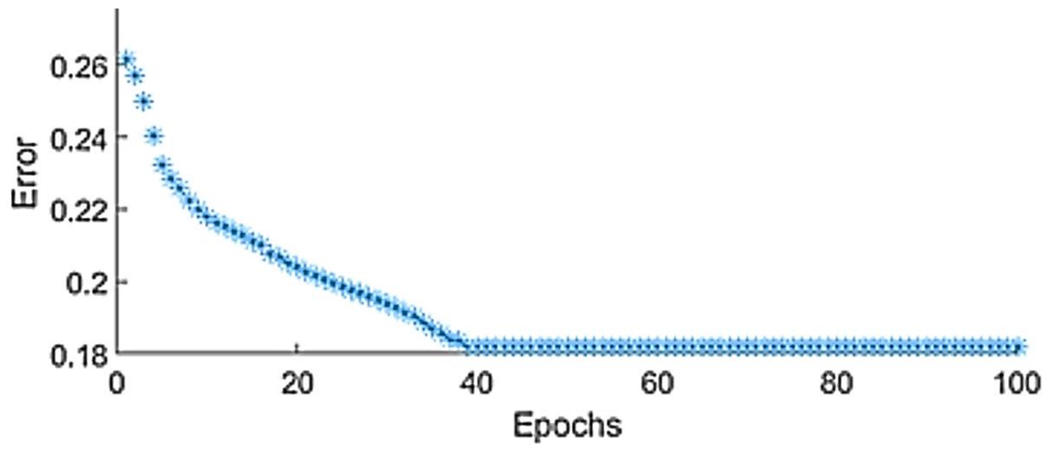


**Figure 10.** The process of training a neuro-fuzzy system based on a fuzzy system generated by the grid partitioning.

The process of learning a neuro-fuzzy system based on a fuzzy system generated by subtractive clustering was carried out for 100 epochs and showed a learning result at an accuracy level of 91% (Figure 11). This significantly improves the performance of the defect detection system based on ANFIS.

Even if additional inputs were not used during training, the system ought to be able to predict results for them with accuracy once it has been trained.

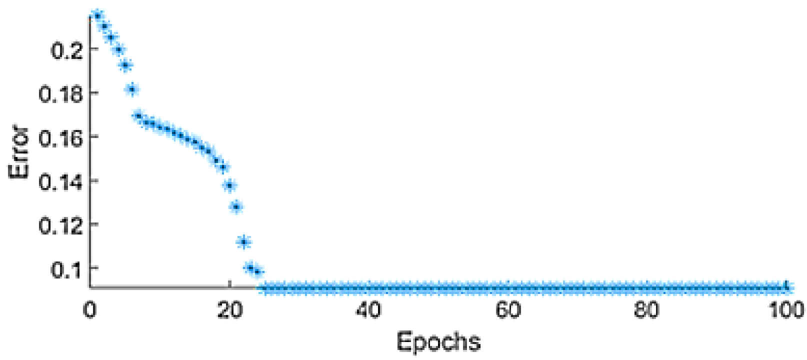


**Figure 11.** The process of training a neuro-fuzzy system based on a fuzzy system generated by subtractive clustering.

## 3. Case Study and Implementation

### *3.1. Results of Testing*

To reach objective 2 regarding reducing computer costs, the authors propose employing the subtractive clustering method because of its small rule base, as is noted below.

Testing of the proposed neuro-fuzzy system was based on a sample of 60 data vectors. The test result of the neuro-fuzzy system based on the fuzzy system generated on the basis of grid partitioning (Figure 12) shows an average test error of 18%.

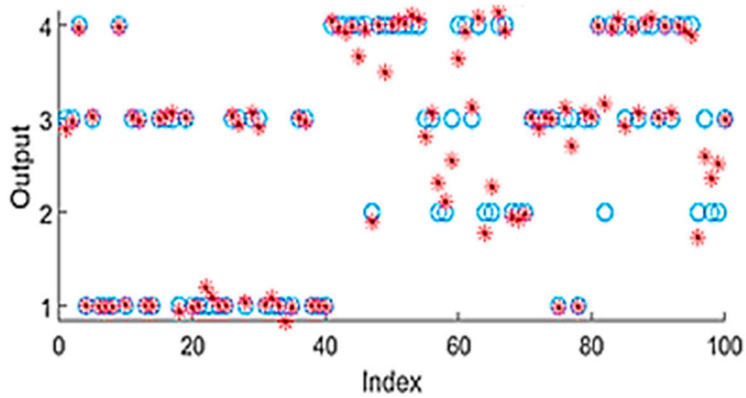


**Figure 12.** The result of testing a neuro-fuzzy system based on grid partitioning (o—training data, *—FIS output).

Testing ANFIS based on subtractive clustering gives the result of an average error of 9% (Figure 13).

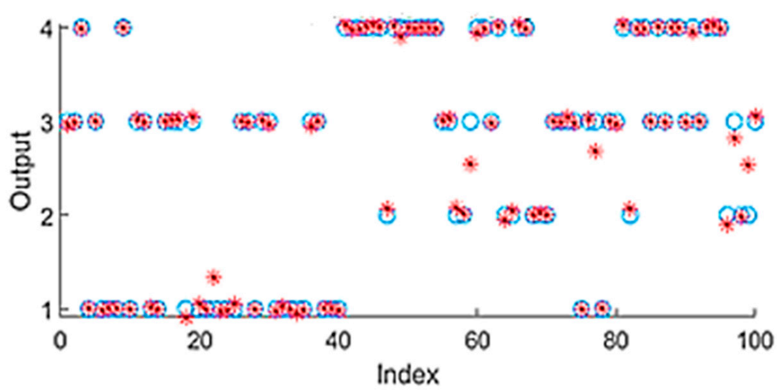


**Figure 13.** The result of testing a neuro-fuzzy system based on subtractive clustering (o—training data, *—FIS output).

The analysis of the proposed models of neuro-fuzzy systems shows that both systems can be used in the wind turbine system for defect detection. However, to increase the effectiveness and speed of such a system on a small sample of input data vectors, it is better to use the ANFIS based on the subtractive clustering.

In the similar ANFIS method [34], the number of rules varies from 16 to 32, depending on the number of prerequisite parameters, which creates an additional load on computing resources. In comparison, the proposed improved ANFIS based on subtractive clustering method, which uses only three rules for fault detection, ensures high accuracy (average error only 9%) and low computational costs.

### *3.2. Implementation of the Improved ANFIS*

To reach objective 3, the authors proposed an improved controller, which is described below.

A neuro-fuzzy controller is a system that combines two approaches: neural networks and fuzzy logic. Its task is to manage various processes automatically, adapting to changes in the environment and working with vague or uncertain data.

For example, fuzzy logic helps the controller to work with vague concepts such as "a little cold" or "very fast" that cannot be precisely determined by conventional methods. A neural network, for its part, allows the controller to learn from experience, improving its actions based on past results.

A neuro-fuzzy controller is used where it is difficult to create accurate mathematical models, but the system must still respond to changes in conditions. It can control various devices, such as wind turbines, cars, or robots, helping them work more efficiently and adaptively.

The Simulink environment was used to model the neuro-fuzzy controller. The 1D lookup table module is used to enter data vectors of input variables, which allows reading all values of input variables from the data file (Figure 14). The controller is programmed by a neuro-fuzzy network generated by the subtractive clustering method.

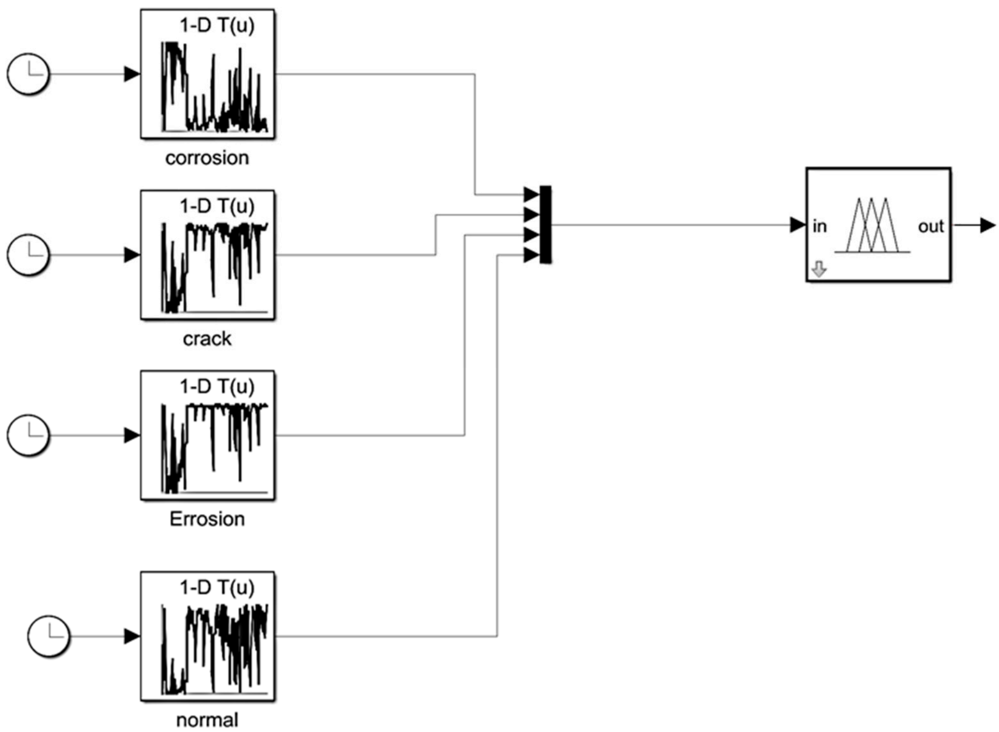


**Figure 14.** General scheme of the neuro-fuzzy controller for blade defect detection of wind turbine.

The ANFIS block in Simulink contains tools for implementing an adaptive neuro-fuzzy controller. It includes input variables, membership functions to translate values into fuzzy sets, a set of "if-then" rules to define relationships between inputs and outputs, a fuzzy inference engine to process the rules, defuzzification to transform fuzzy results into a crisp value, and learning to adapt parameters based on input data. As a result, the block generates output signals that are used to control the system.

Graphic display of input variables and output data is presented in Figures 15 and 16.

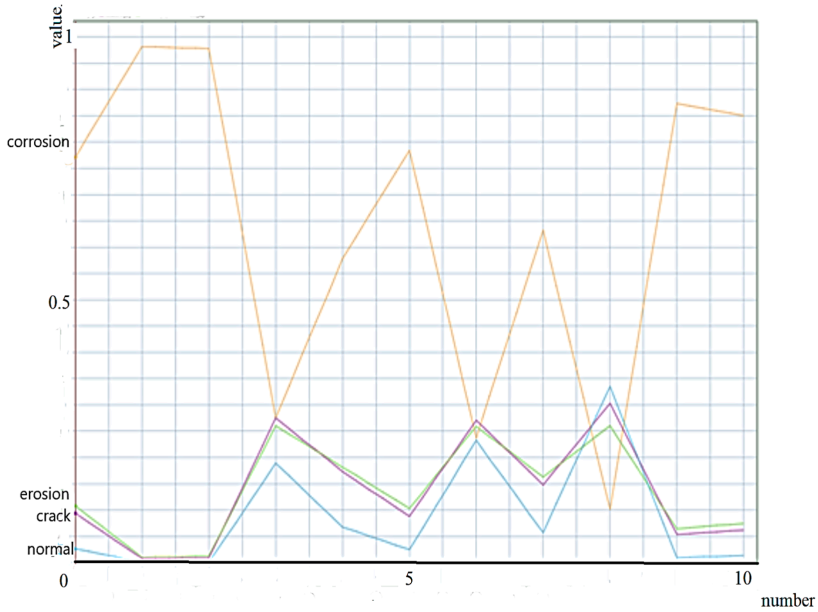


**Figure 15.** Display of the values for the input variables of the neuro-fuzzy controller.

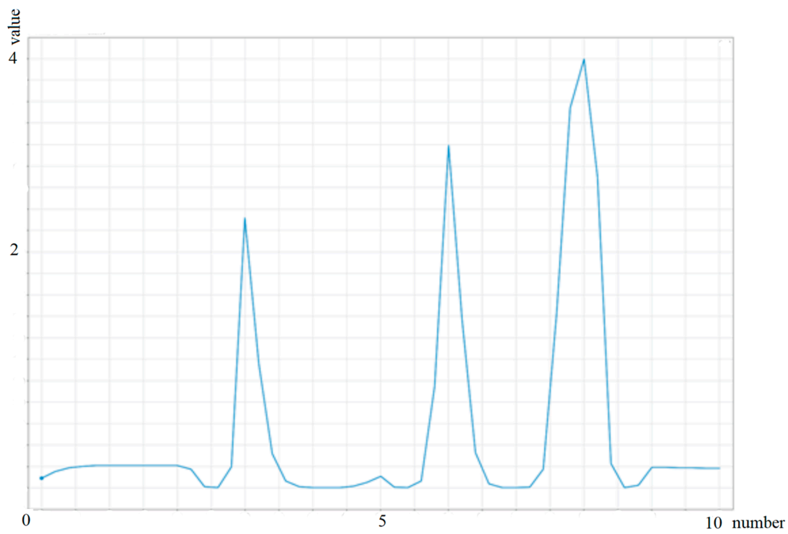


**Figure 16.** The value of the output variable for the neuro-fuzzy controller.

The analysis of modeling and simulation results demonstrates the correct operation and efficiency of the developed neuro-fuzzy controller. For example, with the value of the input variables belonging to the interval [0;1], the output of the system is a value from the interval [0;4]. The output value reflects the type of damage: corrosion, which is situated in the interval [0;1], erosion—(1;2], crack—(2;3], and the value, which displays the image without blade defects and is situated in the interval (3;4].

After processing the data by the neuro-fuzzy controller, the results are transmitted to the system operator. These may include estimates of the probability of a defect, recommendations for action, or automatically generated reports. It is important that the results are presented in an understandable format for quick decision making. Once installed, the system continues to learn and adapt its algorithms based on new incoming data. This allows it to constantly improve and increase the accuracy of defect detection. The proposed controller provides an accuracy 1.4 higher than the existing controller [35], which has an accuracy near 66%. Therefore, the inclusion of a neuro-fuzzy controller into the wind turbine defect detection system allows automating the process of detecting defects and creating the possibility for reducing maintenance costs.

## 4. Discussion

The paper represents a significant improvement of the adaptive neuro-fuzzy inference system [34]. In existing adaptive neuro-fuzzy models, the number of rules varies from 16 to 32, depending on the number of prerequisite parameters, which creates an additional load on computing resources.

In comparison, the authors investigated grid partitioning and subtractive clustering methods and proved that subtractive clustering has advantages, which are presented in Table 1. In particular, the proposed ANFIS model, which is based on the subtractive clustering method, uses the three rules only for fault detection. As a result, that ensures the low computational costs and allows finding wind turbine defects quickly (about an 11% increase in the image processing speed during system testing) and accuracy (about a 9% accuracy of wind turbine defect detection).

**Table 1.** Comparison ANFIS' generated by grid partitioning and subtractive clustering methods.

| Method | Number of Rules | Execution Time, s | Accuracy, % |
|---|---|---|---|
| Grid partitioning | 108 | 9.83 | 82 |
| Subtractive clustering | 3 | 8.75 | 91 |

It is worth noting that, despite the redundancy, the grid partitioning method can also be used in real defect detection systems, especially in the scaling system stage. In such cases, this method can increase the accuracy of ANFIS training, which is important for systems with a large set of input parameters.

As it follows from Section 3.2 above, the existing controller [35] has an accuracy of about 66%, while the proposed ANFIS controller has an accuracy of 91%. Moreover, the developed controller is trained using real images for wind turbine defects, while the existing controller [35] is trained on the basis of synthesized images.

A potential drawback of the proposed ANFIS is the relatively long training time of the neuro-fuzzy model using the subtractive clustering method in comparison with the grid partitioning method. It is caused by the small rule base of the first one. However, due to all the advantages of the subtractive clustering (the low computational costs and the high speed), its disadvantages are not so significant.

Therefore, the use of the proposed adaptive neuro-fuzzy inference system allows for the detection of wind turbine defects with lower complexity and higher accuracy.

## 5. Conclusions

This paper considered the use of an improved adaptive neuro-fuzzy inference system for the detection of wind turbine defects. Simulation results demonstrated the effectiveness of using ANFIS to analyze defect data such as cracks, erosion, and corrosion.

A comparison of two methods for building fuzzy systems—grid partitioning and subtractive clustering—showed that the controller built on subtractive clustering has a high accuracy of 91% after training for 100 epochs. This is significantly better than the grid partitioning result, where the accuracy was only 82% for the same number of epochs. The system built by the subtractive clustering method has only three rules, which makes it more compact and faster compared to the 108 rules in the grid partitioning system. Due to fewer rules and a more compact structure, the system based on subtractive clustering consumes fewer computing resources, making it more efficient for large data sets or complex tasks such as the detection of wind turbine defects.

A comparison of the proposed ANFIS for the detection of wind turbine defects with the noted related system showed that it has significant advantages in the number of rules and a low calculation error (9%).

The improved ANFIS is implemented as a controller, and simulation results confirmed its efficiency. The accuracy of the developed controller is higher by more than 25% compared with the existing one.

The introduction of a neuro-fuzzy system into a real wind turbine monitoring system allows automating the process of detecting defects, reducing the risk of serious breakdowns, and increasing the efficiency of turbine operation. Such a system also reduces maintenance costs, allowing timely response to identified problems.

Further research could involve the implementation of ANFIS in real operating conditions to evaluate its effectiveness and reliability for long-term projects. Additionally, it would be worth exploring the application of ANFIS to other types of renewable energy, such as solar panels or hydroelectric power plants, for monitoring and controlling their operation. Moreover, studying the performance of ANFIS in real-time scenarios could provide valuable insights into its adaptability and responsiveness under dynamic conditions.

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## References

1. IRENA. *Renewable Energy Statistics 2024*; International Renewable Energy Agency: Abu Dhabi, United Arab Emirates, 2024. Available online: https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2024/Jul/IRENA_Renewable_Energy_Statistics_2024.pdf (accessed on 5 September 2024).
2. Fatahian, H.; Fatahian, E.; Mohamed-Kassim, Z. Wind Turbine Standards. In *Encyclopedia of Renewable Energy, Sustainability and the Environment*, 1st ed.; Elsevier: Amsterdam, The Netherlands, 2024; pp. 427–436. [CrossRef]
3. Bhattacharjee, S. Wind Power Technology. In *Sustainable Fuel Technologies Handbook*; Dutta, S., Hussain, C.M., Eds.; Academic Press: Cambridge, MA, USA, 2021; pp. 123–170.
4. Dubchak, L. Modern renewable energy sources and methods for detecting their defects. *Comput. Syst. Inf. Technol.* **2024**, *2*, 21–26. [CrossRef]
5. Du, Y.; Zhou, S.; Jing, X.; Peng, Y.; Wu, H.; Kwok, N. Damage detection techniques for wind turbine blades: A review. *Mech. Syst. Signal Process* **2020**, *141*, 106445. [CrossRef]
6. Kong, K.; Dyer, K.; Payne, C.; Hamerton, I.; Weaver, P.M. Progress and Trends in Damage Detection Methods, Maintenance, and Data-driven Monitoring of Wind Turbine Blades—A Review. *Renew. Energy Focus* **2023**, *44*, 390–412. [CrossRef]
7. Memari, M.; Shakya, P.; Shekaramiz, M.; Seibi, A.C.; Masoum, M.A.S. Review on the Advancements in Wind Turbine Blade Inspection: Integrating Drone and Deep Learning Technologies for Enhanced Defect Detection. *IEEE Access* **2024**, *12*, 33236–33282. [CrossRef]
8. Phan, N.M.L.; Tung, D.N.; Thanh, T.N.; Vu, N.T.-T. ANFIS Wind Speed Estimator-Based Output Feedback Near-Optimal MPPT Control for PMSG Wind Turbine. *J. Control Autom. Electr. Syst.* **2023**, *34*, 588–598. [CrossRef]
9. Raouf, I.; Lee, H.; Kim, H.S. Mechanical fault detection based on machine learning for robotic RV reducer using electrical current signature analysis: A data-driven approach. *J. Comput. Des. Eng.* **2020**, *9*, 417–433. [CrossRef]

10. Raouf, I.; Kumar, P.; Kim, H.S. Deep learning-based fault diagnosis of servo motor bearing using the attention-guided feature aggregation network. *Expert Syst. Appl.* **2024**, *258*, 125137. [CrossRef]
11. Deepak, K.; Mandal, R.K.; Verma, V. Power Quality Improvement of a Hybrid Renewable Energy Sources Based Standalone System Using Neuro-Fuzzy Controllers. *Distrib. Gener. Altern. Energy J.* **2023**, *38*, 1815–1838. [CrossRef]
12. Gómez-Barroso, Á.; Alonso Tejeda, A.; Vicente Makazaga, I.; Zulueta Guerrero, E.; Lopez-Guede, J.M. Dynamic Programming-Based ANFIS Energy Management System for Fuel Cell Hybrid Electric Vehicles. *Sustainability* **2024**, *16*, 8710. [CrossRef]
13. Ulutas, A.; Altas, I.H.; Onen, A.; Ustun, T.S. Neuro-Fuzzy-Based Model Predictive Energy Management for Grid Connected Microgrids. *Electronics* **2020**, *9*, 900. [CrossRef]
14. Kumar, T.P.; Karthee, B.N. A Neuro-Fuzzy Controller for Multilevel Renewable Energy System. *Indian J. Sci. Technol.* **2016**, *9*, 1–8. [CrossRef]
15. Aref, M.; Abdelaziz, A.Y.; Geem, Z.W.; Hong, J.; Abo-Elyousr, F.K. Oscillation Damping Neuro-Based Controllers for Augmented Solar Energy Penetration Management of Power System Stability. *Energies* **2023**, *16*, 2391. [CrossRef]
16. Afghoul, H.; Krim, F.; Chikouche, D.; Beddar, A. Tracking the maximum power from a PV panel using a Neuro-fuzzy controller. In Proceedings of the 2013 IEEE International Symposium on Industrial Electronics, Taipei, Taiwan, 28–31 May 2013; pp. 1–6. [CrossRef]
17. Fazlollahi, V.; Taghizadeh, M.; Shirazi, F.A. ANFIS modeling and validation of a variable speed wind turbine based on actual data. *Energy Equip. Syst.* **2019**, *7*, 249–262.
18. Chhipa, A.A.; Kumar, V.; Joshi, R.R.; Chakrabarti, P.; Jasinski, M.; Burgio, A.; Leonowicz, Z.; Jasinska, E.; Soni, R.; Chakrabarti, T. Adaptive Neuro-Fuzzy Inference System-Based Maximum Power Tracking Controller for Variable Speed WECS. *Energies* **2021**, *14*, 6275. [CrossRef]
19. Ali, M.; Afandi, A.N.; Nurohmah, H.; Rukslin, R.; Haikal, M.A.; Djalal, M.R. Optimization of wind-turbine control using the hybrid ANFIS-PID method based on ant colony optimization. *AIP Conf. Proc.* **2023**, *2536*, 030002. [CrossRef]
20. Hossain, M.; Mekhilef, S.; Afifi, F.; Halabi, L.M.; Olatomiwa, L. Application of the hybrid ANFIS models for long-term wind power density prediction with extrapolation capability. *PLoS ONE* **2018**, *13*, e0193772. [CrossRef]
21. Suganthi, L.; Iniyan, S.; Samuel, A.A. Applications of fuzzy logic in renewable energy systems—A review. *Renew Sustain. Energy Rev.* **2015**, *48*, 585–607. [CrossRef]
22. Griche, I.; Messalti, S.; Saoudi, K.; Touafek, M. A New Adaptive Neuro-Fuzzy Inference System (ANFIS) Controller to Control the Power System equipped by Wind Turbine. *ITM Web Conf.* **2022**, *42*, 01011. [CrossRef]
23. Griche, I.; Messalti, S.; Saoudi, K.; Touafek, M.Y. A new adaptive neuro-fuzzy inference system (ANFIS) and PI controller to voltage regulation of power system equipped by wind turbine. *Eur. J. Electr. Eng.* **2019**, *21*, 149–155. [CrossRef]
24. Gökkus, G.G. Anfis-Based Real-Time Power Estimation for Wind Turbines. *Konya J. Eng. Sci.* **2023**, *11*, 136–149. [CrossRef]
25. Griche, I.; Messalti, S.; Saoudi, K.; Touafek, M.Y.; Zitouni, F. A new controller for voltage and stability improvement of multi-machine power system tuned by wind turbine. *Math Model Eng. Probl.* **2021**, *8*, 81–88. [CrossRef]
26. He, S.; Huang, H.; Fan, B.; Huai, X. A novel SC-PI with ANFIS compensation for wind turbine pitch control. *ITM Web Conf.* **2022**, *47*, 03010. [CrossRef]
27. Ata, R. An adaptive neuro-fuzzy inference system approach for prediction of power factor in wind turbines. *Istanb. Univ. J. Electr. Electron. Eng.* **2012**, *9*, 905–912.
28. Aldair, A.A.; Obed, A.A.; Halihal, A.F. Design and implementation of ANFIS-reference model controller based MPPT using FPGA for photovoltaic system. *Renew Sustain. Energy Rev.* **2018**, *82*, 2202–2217. [CrossRef]
29. Kavitha, C.R.; Varalatchoumy, M.; Mithuna, H.R.; Bharathi, K.; Geethalakshmi, N.M.; Boopathi, S. Energy Monitoring and Control in the Smart Grid: Integrated Intelligent IoT and ANFIS. In *Applications of Synthetic Biology in Health, Energy, and Environment*; IGI Global: Hershey, PA, USA, 2023; p. 27. [CrossRef]
30. Moyo, R.T.; Tabakov, P.Y.; Moyo, S. Design and modeling of the ANFIS-based MPPT controller for a solar photovoltaic system. *J. Sol. Energy Eng.* **2021**, *143*, 041002. [CrossRef]
31. Gamage, D.; Zhang, X.; Ukil, A.; Wanigasekara, C.; Swain, A. Design of ANFIS controller for a DC microgrid. In Proceedings of the 2020 3rd International Conference on Energy, Power and Environment: Towards Clean Energy Technologies (ICEPE), Shillong, India, 5–7 March 2021; pp. 1–6. [CrossRef]
32. Gorzalczany, M.B. On some idea of a neuro-fuzzy controller. *Inf. Sci.* **1999**, *120*, 69–87. [CrossRef]
33. Zahedi, F.; Zahedi, Z. A review of neuro-fuzzy systems based on intelligent control. *J. Elect. Electron. Eng.* **2015**, *3*, 58–61. [CrossRef]
34. Zemali, Z.; Cherroun, L.; Hadroug, N.; Hafaifa, A. ANFIS models for fault detection and isolation in the drive train of a wind turbine. *Int. J. Energetica.* **2022**, *7*, 64–70.
35. Rabbi, M.F.; Emon, S.H.; Nishat, E.M.; Tseng, T.L.; Ferdoushi, A.; Huang, C.C.; Rahman, M.F. A novel approach for defect detection of wind turbine blade using virtual reality and deep learning. In Proceedings of the IISE Annual Conference & Expo, New Orleans, LO, USA, 20–23 May 2023; p. 7.
36. Liu, C.; An, A.; Yang, Y. Wind turbine surface defect detection method based on YOLOv5s-L. *Nephrol. Dial. Transplant.* **2023**, *1*, 46–57. [CrossRef]
37. Liu, G.; Si, J.; Meng, W.; Yang, Q.; Li, C. Wind Turbine Fault Detection with Multimodule Feature Extraction Network and Adaptive Strategy. *IEEE Trans. Instrum. Meas.* **2023**, *72*, 3504613. [CrossRef]

38. Liu, X.; Yang, L.; Zhang, Z. Short-Term Multi-Step Ahead Wind Power Predictions Based On A Novel Deep Convolutional Recurrent Network Method. *IEEE Trans. Sustain. Energy* **2021**, *12*, 1820–1833. [CrossRef]
39. Dhiman, H.; Deb, D.; Muyeen, S.M.; Kamwa, I. Wind Turbine Gearbox Anomaly Detection Based on Adaptive Threshold and Twin Support Vector Machines. *IEEE Trans. Energy Convers.* **2021**, *36*, 3462–3469. [CrossRef]
40. Pu, Z.; Li, C.; Zhang, S.; Bai, Y. Fault Diagnosis for Wind Turbine Gearboxes by Using Deep Enhanced Fusion Network. *IEEE Trans. Instrum. Meas.* **2021**, *70*, 102123. [CrossRef]
41. Tong, L.; Fan, C.; Peng, Z.; Wei, C.; Sun, S.; Han, J. WTBD-YOLOv8: An Improved Method for Wind Turbine Generator Defect Detection. *Sustainability* **2024**, *16*, 4467. [CrossRef]
42. Alhamrouni, I.; Abdul Kahar, N.H.; Salem, M.; Swadi, M.; Zahroui, Y.; Kadhim, D.J.; Mohamed, F.A.; Alhuyi Nazari, M. A Comprehensive Review on the Role of Artificial Intelligence in Power System Stability, Control, and Protection: Insights and Future Directions. *Appl. Sci.* **2024**, *14*, 6214. [CrossRef]
43. PIRC. ANFIS MPPT Controller for Wind Energy System. *MATLAB Central File Exchange.* 2024. Available online: https://www.mathworks.com/matlabcentral/fileexchange/59511-anfis-mppt-controller-for-wind-energy-system (accessed on 8 September 2024).
44. Jang, J.-S.R. ANFIS: Adaptive-Network-Based Fuzzy Inference System. *IEEE Trans. Syst. Man Cybern.* **1993**, *23*, 665–685. [CrossRef]
45. YOLO Annotated Wind Turbine Surface Damage. Available online: https://www.kaggle.com/datasets/ajifoster3/yolo-annotated-wind-turbines-586x371 (accessed on 5 September 2024).
46. Dubchak, L.; Sachenko, A.; Wolff, C.; Vasylkiv, N.; Bernas, Z. Classification of wind turbine defects based on the SqueezeNet neural network. In Proceedings of the 2024 IEEE 19th International Conference on Computer Science and Information Technologies (CSIT), Lviv, Ukraine, 16–19 October 2024.
47. Zhang, Z.; Al-Bahrani, M.; Ruhani, B.; Ghalehsalimi, H.H.; Ilghani, N.Z.; Maleki, H.; Ahmad, N.; Nasajpour-Esfahani, N.; Toghraie, D. Optimized ANFIS models based on grid partitioning, subtractive clustering, and fuzzy C-means to precise prediction of thermophysical properties of hybrid nanofluids. *Chem. Eng. J.* **2023**, *471*, 144362. [CrossRef]
48. The Membership Functions. Available online: https://www.wikiwand.com/uk/articles/%D0%A4%D1%83%D0%BD%D0%BA%D1%86%D1%96%D1%8F_%D0%BF%D1%80%D0%B8%D0%BD%D0%B0%D0%BB%D0%B5%D0%B6%D0%BD%D0%BE%D1%81%D1%82%D1%96 (accessed on 20 September 2024).
49. Chumachenko, D.; Sokolov, O.; Yakovlev, S. Fuzzy Recurrent Mappings in Multiagent Simulation of Population Dynamics Systems. *Int. J. Comput.* **2020**, *19*, 290–297. [CrossRef]
50. Pasieka, M.; Grzesik, N.; Kuźma, K. Simulation Modeling of Fuzzy Logic Controller for Aircraft Engines. *Int. J. Comput.* **2017**, *16*, 27–33. [CrossRef]
51. Roshchupkina, N.; Sachenko, A.; Roshchupkin, O.; Kochan, V.; Smid, R. Multisensors signal processing using ANFIS. In Proceedings of the 2013 IEEE 7th International Conference on Intelligent Data Acquisition and Advanced Computing Systems (IDAACS), Berlin, Germany, 12–14 September 2013; pp. 315–318. [CrossRef]
52. Vasylkiv, N.; Dubchak, L.; Sachenko, A. Estimation method of information system functioning quality based on the fuzzy logic. *CEUR Workshop Proc.* **2020**, *2631*, 40–56.