EUROPEAN MECHANICAL SCIENCE

Research Article

e-ISSN: 2587-1110

Hydraulic fault detection of wind turbine generators using artificial neural networks

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Abstract: In the current context where fossil resources are diminishing globally, and carbon emissions are increasing daily, the importance of green energy, particularly wind energy, is growing significantly. The increasing of wind turbines will not only reduce the carbon footprint but also decrease dependence on external resources. To increase the installed capacity of wind turbines, it is crucial to reduce not only installation costs but also operational costs. The largest proportion of operational costs is service, and maintenance costs. One of the most critical approaches to reducing service, and maintenance costs is preventive maintenance activities. The objective of preventive maintenance activities is to minimize or ideally eliminate production losses through scheduled turbine shutdowns before failures occur. In this study, artificial neural network-based algorithms that predict potential hydraulic failures during the operational period were utilized. For this purpose, data from the turbine SCADA system over a period of two years, considering the equipment, and sensors connected to hydraulic systems, were compiled. The study was conducted using the WEKA program, comparing Multilayer Perceptron (MLP), Radial Basis Function Classifier (RBF Classifier), SMOreg (Support Vector Machines for Regression) algorithms. Result of the study, the MLP algorithm was applied with a percentage split of 66% for training, and 33% for testing, achieving a prediction accuracy of 96.32%

Keywords: Artificial Neural Networks, Faults Detection, Predictive Maintenance, WEKA, Wind Turbine

1. Introduction

Since wind energy is one of the most important sources of clean energy, it has gained global support in recent years. Renewable resources are utilized to reduce the carbon footprint, and achieve carbon neutrality. Wind turbines are often exposed to harsh environmental conditions because they are typically installed in remote areas, far from residential zones. Consequently, wind turbines frequently experience malfunctions. The most common malfunctions include electrical failures, control system issues, and sensor defects. Under these conditions, fault diagnosis in wind turbines is crucial in terms of operational, and maintenance costs. Moreover, timely fault diagnosis, and maintenance can significantly reduce major financial losses. To minimize turbine downtime, lower operational, and maintenance expenses, and extend service life, machine learning-based fault diagnosis is recommended.

In this study, the hydraulic failures of a wind power plant located in Konya between 2020, and 2022 were analyzed. The variables considered for failure included hydraulic oil temperature, wind speed, hydraulic unit pressure, yaw brake pressure, internal ambient temperature, external ambient temperature, active power data, and blade angles. Additionally, the fundamental characteristics of artificial neural networks (ANN) were discussed, and a model capable of predicting hydraulic failures using ANN was developed, and its performance evaluated.

1.1. Fundamental Components and Failures of Wind Turbines

Wind turbines primarily consist of a gearbox, generator, converter, yaw systems, pitch systems, hydraulic systems, control systems, and auxiliary systems. Experts, and researchers recommend conducting failure analysis

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Cite this article as:
Döndüren, A. T., Yağcı, M. (2024). Hydraulic fault detection of wind turbine generators using artificial neural networks. *European Mechanical Science*, *8*(4): 331-340. https://doi.org/10.26701/ems.1577643

History dates:
Received: 04.11.2024, ***Revision Request***: 27.11.2024, ***Last Revision Received***: 03.12.2024, ***Accepted***: 19.12.2024

on various components such as power systems, mechanical systems, drive systems, generators, and gearboxes, as these are the most studied for efficient fault diagnosis. Data-driven real-time fault diagnosis is performed using data mining technologies in wind turbines. By observing useful data, and classifying the system as either faulty or normal conditions. The SCADA system contains both real-time data, and recorded historical [1].

Real-time monitoring of wind turbine conditions allows for overcoming these defects. Through turbine condition monitoring technology, parameters such as vibration, temperature, pressure, and electrical data tracks. Comparing these results with predefined optimal values enables the early detection of electrical, and mechanical failures [2].

1.2. Artificial Neural Networks and Their General Characteristics

Artificial Neural Networks (ANN) were first developed by Rosenblatt under the name "perception." The purpose of ANN is to ensure accurate classification of data by determining optimal parameter values. After each iteration (epoch), the error rate is updated, and these rates are distributed across the weight parameters, allowing the values assigned to each node to be refreshed [3].

ANN is a machine learning method inspired by the structure of biological neurons. In the input layer of the network, the input values are defined, and the data then passes through multiple layers. The data moves through various nodes, referred to as neurons, in each layer, where its numerical value is calculated, and compared with the previous value. The goal of this comparison is to minimize the difference, aiming to bring the error closer to zero, thereby enabling the network to learn. The performance of the network is measured using accuracy functions. Structurally, the network consists of three fundamental layers: an input layer, hidden layer, and an output layer.

Artificial neural networks (ANN) are mathematically composed of inputs, weights, a summation function, an activation function, and output layers. Inputs are the data provided for the network to learn. The weight value represents the multiplication of the input data by a factor. The magnitude of the weight does not indicate the importance of the data. The summation function is used to combine information from the inputs for computation. The activation function aids in determining the outputs. Activation functions such as Linear, Step, and Sigmoid are commonly used [4].

The Sigmoid function is the most widely used activation function, limiting the data between 0, and 1. The Tanh function, which restricts data between -1, and 1, often provides better performance than the Sigmoid function due to its directional change in processing [5].

By multiplying the inputs with the weights, the NET inputs are obtained. The term "NET" is an abbreviation for "Network." Various methods exist for calculating the NET value. The calculation using the summation method can be seen in the following equation [6].

$$NET = \sum_{i=1}^{n} x_i . w_i \tag{1}$$

From this, it can be understood that the data from the first to the nth value are multiplied by their respective weights, and summed to obtain the NET inputs. The X values represent the inputs, while w represents the weights. The same calculation method does not need to use throughout the entire ANN model. The NET value obtained in artificial neurons is then passed through the activation function. The activation function processes the NET value, and converts it into the output. Increasing the number of neurons in the hidden layer may make the ANN system more complex, but it also leads to better outputs [6].

Prediction studies using artificial neural networks have been applied across various fields in literature. One study, which aimed to predict solar radiation data using artificial neural networks, and machine learning, employed daily/hourly solar radiation data from the provinces of Bursa, and Çanakkale for the years 2015-2019. The study involved prediction using artificial neural networks, and classification analysis using a machine learning algorithm [4].

In a study aimed at predicting the production data of a solar power plant, the goal was to develop the plant's feasibility software. This study developed the Solar Power Plant Feasibility Software by predicting the production data of solar, and wind power plants, both renewable energy sources, based on meteorological, and geological data. To achieve production forecasting, advanced feed forward back propagation Artificial Neural Networks (ANN), the Adaptive Neuro-Fuzzy Inference System (ANFIS), and the deep learning model Long Short-Term Memory (LSTM) were employed, due to their success in predicting with nonlinear models, a key application of artificial intelligence [7].

Aiming to forecast wind speed, and guide planned operations, various artificial neural networks, and models were compared. In the study, short-term wind speed forecasting was performed using ANN methods with data obtained from a station in Yalova, Turkey. The analysis aimed to predict wind speed one hour ahead, allowing for interventions in sudden failures, and maintenance planning [8].

Additionally, a study was conducted on identifying, detecting, and locating faults in power transmission lines using ANN. In this study, feed forward neural networks, convolutional neural networks, and generalized regression neural networks were employed [9].

A comprehensive fault detection system for wind turbines is presented, utilizing sensors in the process. Specifically, the model is designed with a lightweight, highly efficient structure, and employs ensemble-based artificial neural networks, achieving a fault detection rate of 96.5%. The robustness of this model has been validated through various numerical simulations. Additionally, it has been compared with other methods, and the operating model has been found to exhibit higher accuracy [10].

They have worked on artificial neural network-supported early fault detection for bearing failures in wind turbine generators. It is noted that gearbox failures cause significant downtime in wind turbines, and a large portion of these failures originate from gearbox bearings. Detecting wear, and degradation in gearbox bearings early would enable effective preventive maintenance, which in turn would reduce overall maintenance costs. In this study, a neural network-based monitoring system is proposed using data from the control, and data acquisition system. This application was implemented on 2 MW onshore turbines located in southern Sweden. The results demonstrate that the proposed neural network-based condition monitoring system is capable of detecting severe damage [11].

2. Materials and Methods

In this study, artificial neural network-based algorithms were used to predict potential hydraulic failures that may occur during operation. In this way, possible failures will be addressed during non-windy periods through preventive actions. The aim of preventive maintenance activities is to minimize or, if possible, eliminate production losses by performing turbine shutdowns before a failure occurs.

For this purpose, data from a two-year period was collected through the turbine SCADA system, taking into account the equipment, and sensors connected to the hydraulic systems. Sensors located in relevant areas on the turbine transmit data to the SCADA system via various communication protocols. Data related to the topic has been analyzed, and compiled in the SCADA system. The date, and time of hydraulic failures are recorded as fault logs in the SCADA system. The approach here involves creating datasets based on the assumption that the first 60 seconds before a failure is considered faulty, while the subsequent 60-second interval is considered fault-free.

2.1. Data Sources

Data from hydraulic failures occurring between 2020, and 2022 were used in the models. The variables considered include hydraulic oil temperature, wind speed, hydraulic unit pressure, yaw brake pressure, internal temperature, external temperature, production data, and blade angles. ▶**Table 1** provides a summary of the data included in the study, and their respective units.

2.2. Correctly Classified Examples and Confusion Matrix

Correctly classified examples: This is the percentage of the total number of examples that the model classifies correctly relative to the total dataset. It reflects the overall performance of the classification [12].

$$\text{Accuracy } (\%) = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{TP} + \text{FN} + \text{FP}} \text{x100} \tag{2}$$

Confusion Matrix: A matrix that compiles information about actual, and predicted classifications. This can be seen following ▶**Table 2**.

Correctly classified data refers to the TN (True Negative), and TP (True Positive) components. The performance of the model is proportional to the number of correctly classified data, and indicates the effectiveness of the classification [13]. The terms used in the confusion matrix are defined as follows:

TN (True Negative): The number of correct predictions where an example is truly negative.

FP (False Positive): The number of incorrect predictions where an example is predicted to be positive.

FN (False Negative): The number of incorrect predictions where an example is predicted to be negative.

TP (True Positive): The number of correct predictions where an example is truly positive.

2.3. Classification Accuracy, Sensitivity, Specificity, and F-Measure

Sensitivity, and specificity are commonly used statistical methods for interpreting, and explaining the results of data testing. Classification sensitivity, and specificity are determined using the equations shown below.

$$Sensitivity\ (\%) = \frac{TP}{TP + FN} x100 \tag{3}$$

Table 1. Variables of Data

Variables	Unit
Hydraulic Oil Temperature	Degree Celsius
Wind speed	m/sec
Hydraulic Unit Pressure	bar
Yaw Brake Pressure	bar
Temperature	Degree Celsius
Ambient Temperature	Degree Celsius
Production	kW
Blade Degree-1	Degree
Blade Degree-2	Degree
Blade Degree-3	Degree

Table 2. Confusion Matrix

		Predicted Values	
		Negative	Positive
Actual Values	Negative	TN (True Negative)	FP (False Positive)
	Positive	FN (False Negative)	TP (True Positive)

https://doi.org/10.26701/ems.1577643

$$\text{Specificity (\%)} = \frac{TN}{TN + FP} x100 \tag{4}$$

$$Error\ Rate\ (\%) = \frac{FN + FP}{TN + TP + FN + FP} x100 \tag{5}$$

Sensitivity: The ratio of true positives to all data predicted as positive. It measures the model's ability to correctly classify positive examples. A high sensitivity ratio indicates that there are few false negatives [13].

Specificity: The ratio of true negatives to all data predicted as negative. It measures the model's ability to correctly classify negative examples. A high specificity ratio indicates that there are few false positives [13].

F-Measure: To provide more meaningful comparative results, the F-Measure combines both sensitivity, and specificity. The F-Measure is the harmonic mean of sensitivity, and specificity [13].

$$F\ Measure = \frac{2\ x\ Sensitivity\ x\ Specificity}{Sensitivity + Specificity} \tag{6}$$

2.4. Kappa Statistics

Kappa statistics is a statistical method used to measure the agreement between classifications based on the same category. It is a more reliable measure than a simple percentage calculation. It is a robust method used to test inter-rater or intra-rater reliability. The values can range from -1 to 1, where 0 represents agreement occurring by chance, and 1 indicates perfect agreement. Details are provided in ▶Table 3 [14].

Kappa adjusts for the agreement that could have occurred randomly among similar responses.

$$\varkappa = \frac{P_0 - P_e}{1 - P_e} \tag{7}$$

P_0: The percentage of agreement between observers

P_e: The percentage of agreement between observers due to chance

Table 3. Kappa Coefficient Values Interpretation

Kappa Value	Interpretation
< 0.00	Poor
0.01 – 0.02	Slight
0.21 – 0.40	Fair
0.41 – 0.60	Moderate
0.61 – 0.80	Substantial
0.81 – 1.00	Almost Perfect

2.5. Other Approaches

Mean Absolute Error (MAE): This can be expressed as the average of the absolute differences between the actual values, and the predicted values. A low mean absolute error indicates good performance of the model [13].

$$A = \frac{1}{n}\sum_{i=1}^{n}|x_i - x'_i| \tag{8}$$

Relative Absolute Error (RAE): This is a metric used to measure the performance of a model. It is the ratio of the sum of the model's absolute errors to the sum of the deviations of the actual values from their mean. A low relative absolute error indicates good performance of the model.

$$RAE = \frac{\sum_{i=1}^{n}|x_i - x'_i|}{\sum_{i=1}^{n}|x_i - \bar{x}|} \tag{9}$$

$\bar{x}$: The mean of the actual values

x_i: The actual values

x'_i: The predicted values

n: The number of samples in the data

Root Mean Square Error (RMSE): This is a metric used to measure the performance of a model. It is the square root of the average of the squared differences between the predicted values, and the actual values [13].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - x'_i)^2} \tag{10}$$

A small RMSE indicates that the model's predictions are accurate.

Root Relative Squared Error (RRSE): This metric is the square root of the ratio of the sum of the squared differences between the actual values, and the predicted values to the sum of the squared differences between the actual values, and their mean [13].

$$RRSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - x'_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x}_i)^2}} \tag{11}$$

A small RRSE indicates that the model's predictions are accurate.

2.6. Model Features and Methods Implemented on WEKA

The algorithms used on the datasets include Multilayer Perceptron (MLP), Radial Basis Function Classifier (RBF Classifier), and SMOreg (Support Vector Machines for Regression). The parameter settings in the software are the default settings.

2.7. Multilayer Perceptron

The Multilayer Perceptron (MLP) identifies the relationship between linear or non-linear data. The input layers, output layers, and hidden layers form the core of the MLP classifier. In most cases, a single hidden layer is sufficient for solving the problem. However, additional hidden layers may be added to improve the results, although this will increase data processing time[12].

The input layer processes the input data, while tasks

 https://doi.org/10.26701/ems.1577643

such as prediction, and classification are handled by the output layer. In MLP, a feed-forward structure is established from input to output [15].

All nodes in the network utilize the sigmoid function, which ensures that the data remains within the range of 0 to 1.

$$sigmoid\ (x) = \frac{1}{1+e^{-x}} \tag{12}$$

2.7.1. Parameter settings in MLP

Learning Rate: Determines the speed at which the weights are updated. A high learning rate can lead to instability in the model, while a low learning rate may result in slower learning.

Momentum: Ensures more stable weight updates, and helps the model avoid local minima. A high momentum can accelerate the learning process, but it also increases the risk of instability. On the other hand, a low momentum slows down the learning process but allows for more control over the model.

Hidden Layers: Refers to the number of hidden layers, and the number of neurons in each layer. Fewer hidden layers make the model more interpretable, and reduce the risk of overfitting. However, with fewer hidden layers, the model may be insufficient for capturing non-linear relationships, making it less capable of detecting complex patterns, and reducing the likelihood of accurate predictions.

Training Time: Specifies the number of iterations required to train the model. A short training time may prevent the model from fully learning the data, while a long training time can lead to overfitting.

2.8. Radial Basis Function Classifier

The Radial Basis Function Classifier (RBFC) is a feed-forward model used in artificial neural networks. The structure of the RBFC consists of an input layer, a hidden layer, and an output layer. The input layer is where the data is collected, and the calculations take place in the hidden layer [16]. The connection weights between the hidden layer, and the output layer can be determined more quickly, and independently of local minima compared to the Multilayer Perceptron (MLP). The hidden layer utilizes a Gaussian function, and the distance between the input vector, and the center vector of the hidden layer is calculated using this function [17].

$$\varphi(x) = \exp\left(-\frac{\|x-c\|^2}{2\sigma^2}\right) \tag{13}$$

φ(x): Output

x: Input vector

c: Center vector of the RBF

σ: Standard deviation

$\|x-c\|^2$: Represents the Euclidean distance

2.8.1. Parameter settings in RBFC

Number of Functions: This parameter determines the number of Gaussian functions in the model. As the number increases, the complexity of the model also increases, which may lead to overfitting.

Scale Optimization Option: Specifies the scale optimization option. Option 1 sets a single factor for the entire model, while Option 2 assigns a separate scale for each Gaussian function.

2.9. Sequential Minimal Optimization

SMO is a machine learning algorithm associated with Support Vector Machines (SVM) available in WEKA. SVMs are used for classification, and regression problems.

2.9.1. Parameter settings in SMO

C (Complexity Parameter): Balances model flexibility, and error rate. A high C value offers a more flexible model but increases the risk of overfitting, whereas a low C value reduces the risk of overfitting but may result in more errors.

Kernel Type: Used to determine the relationship between data points. Various options are available in WEKA.

Epsilon Parameter: Represents the tolerance value between the actual value, and the predicted value. The smaller the epsilon, the more precise the model becomes.

Tolerance: Defines the tolerance used during the optimization process.

2.10. K-Fold Cross Validation in MLP, RBFC, and SMO

The dataset is divided into K parts. K-1 parts are used for training, while the remaining part is used for testing. The test set is rotated each time, ensuring that the model is trained K times [4].

The evaluations of K-fold cross-validation in this study for K=4, 10, and 24 can be seen in ▶**Table 4**.

2.11. Percentage-Based Data Splitting in MLP, RBFC, and SMO

The program allows the data was split into training, and test sets based on percentages. Different scenarios where 50%, 66%, and 80% of the data are allocated to the training set have been compared can be seen in ▶**Table 5**.

Table descriptions can be seen ▶**Table 4**.

3. Research Findings and Discussion

A comprehensive comparison of the program results has been conducted, and the top 3 most important parameters of the best-performing algorithm, based on the J48 decision tree, have been identified. The points where the algorithm made errors are presented as part of the program output.

The hydraulic unit oil temperature, hydraulic unit pressure, and yaw brake pressure are identified as the most important criteria, as shown in ▶**Figure 1** based on the J48 decision tree classification method.

▶**Figure 2** illustrates that the classification errors in the WEKA program indicate approximately 38 degrees, and 60 degrees as the range where predicted data for the hydraulic unit oil temperature generates errors.

▶**Figure 3** shows that the classification errors in the WEKA program indicate that the predicted data for hydraulic unit pressure generates errors within the range of approximately 162 bar to 220 bar.

▶**Figure 4** demonstrates that the yaw brake pressure predictions generate errors within the range of approximately 223 bar to 228 bar, as indicated by the classification error outputs from the WEKA program.

4. Results and Discussions

Data from the turbine SCADA system, collected between 2020, and 2022, were evaluated using artificial neural networks, and other algorithms. The algorithms employed include Multilayer Perceptron (MLP), Radial Basis Function Classifier (RBF Classifier), and SMOreg (Support Vector Machines for Regression). The parameters of the algorithms were processed using their default settings in the WEKA program. The algorithms were executed with a percentage-based data split, and K-fold cross-validation approaches. For the percentage-based data splitting, ratios of 50%, 60%, and 80% were selected, while K values of 4, 10, and 24 were chosen for the K-fold cross-validation approach, with results recorded accordingly. The results were evaluated, and compared using statistical measures such as Kappa Statistic, Mean Absolute Error, Root Mean Square Error, Relative Mean Absolute Error, and Root Relative Square Error, as well as criteria including Sensitivity, Specificity, Error Rate, and F-measure. The findings

Table 4. K-fold cross-validation in this study for K=4, 10, and 24 with MLP, RBFC, SMO

Algorithm / K Fold	Kappa	MAE	RMSE	RAE [%]	RRSE [%]	Accuracy [%]	Sensitivity [%]	Specificity [%]	Error Rate [%]	F Score [%]
MLP / K=24	0,812	0,117	0,240	23	48	90,63	91,85	89,47	9,38	90,64
MLP / K=10	0,875	0,100	0,222	20	44	93,75	94,49	93,03	6,25	93,76
MLP / K=4	0,775	0,149	0,285	29	57	88,75	88,43	89,08	11,25	88,75
RBFC / K=24	0,45	0,36	0,41	74	82	72,50	70,93	74,32	27,50	72,59
RBFC / K=10	0,51	0,36	0,4	73	81	75,63	72,36	80,00	24,38	75,99
RBFC / K=4	0,475	0,36	0,4	73	81	73,75	70,21	78,79	26,25	74,25
SMO / K=24	0,008	0,495	0,704	99	140	50,42	50,65	50,31	49,58	50,48
SMO / K=10	0,016	0,491	0,701	98	140	50,83	51,02	50,70	49,17	50,86
SMO / K=4	0,079	0,460	0,678	92	135	53,96	53,85	54,08	46,04	53,96

Kappa: Kappa statistics are a statistical method
MAE: Mean Absolute Error
RMSE: Root Mean Square Error
RAE: Relative Absolute Error
RRSE: Root Relative Squared Error

Accuracy: Correctly classified examples
Sensitivity: Measures the model's ability to correctly classify positive examples
Specificity: Measures the model's ability to correctly classify negative examples
Error Rate: Incorrectly classified examples
F-Score: Harmonic mean of sensitivity, and specificity

Table 5. Training Set Ratio in this study for 80%, 66%, and 50% with MLP, RBFC, SMO

Algorithm / Training Set Ratio	Kappa	MAE	RMSE	RAE [%]	RRSE [%]	Accuracy [%]	Sensitivity [%]	Specificity [%]	Error Rate [%]	F Score [%]
MLP / 80%	0,89	0,116	0,225	23	45	94,79	92,31	97,73	5,21	94,94
MLP / 66%	0,925	0,087	0,168	17	33	96,32	96,67	95,89	3,68	96,28
MLP / 50%	0,749	0,163	0,287	33	57	87,50	86,51	88,60	12,50	87,54
RBFC / 80%	0,62	0,343	0,383	69	77	81,25	82,98	79,59	18,75	81,25
RBFC / 66%	0,452	0,356	0,392	71	78	72,39	80,00	65,91	27,61	72,27
RBFC / 50%	0,442	0,392	0,422	78	84	72,08	73,91	70,40	27,92	72,11
SMO / 80%	0,012	0,5	0,707	99	141	50,00	52,63	49,35	50,00	50,94
SMO / 66%	0,185	0,43	0,66	86	131	56,44	85,19	50,74	43,56	63,59
SMO / 50%	0,151	0,43	0,66	85	130	57,08	73,17	53,77	42,92	61,99

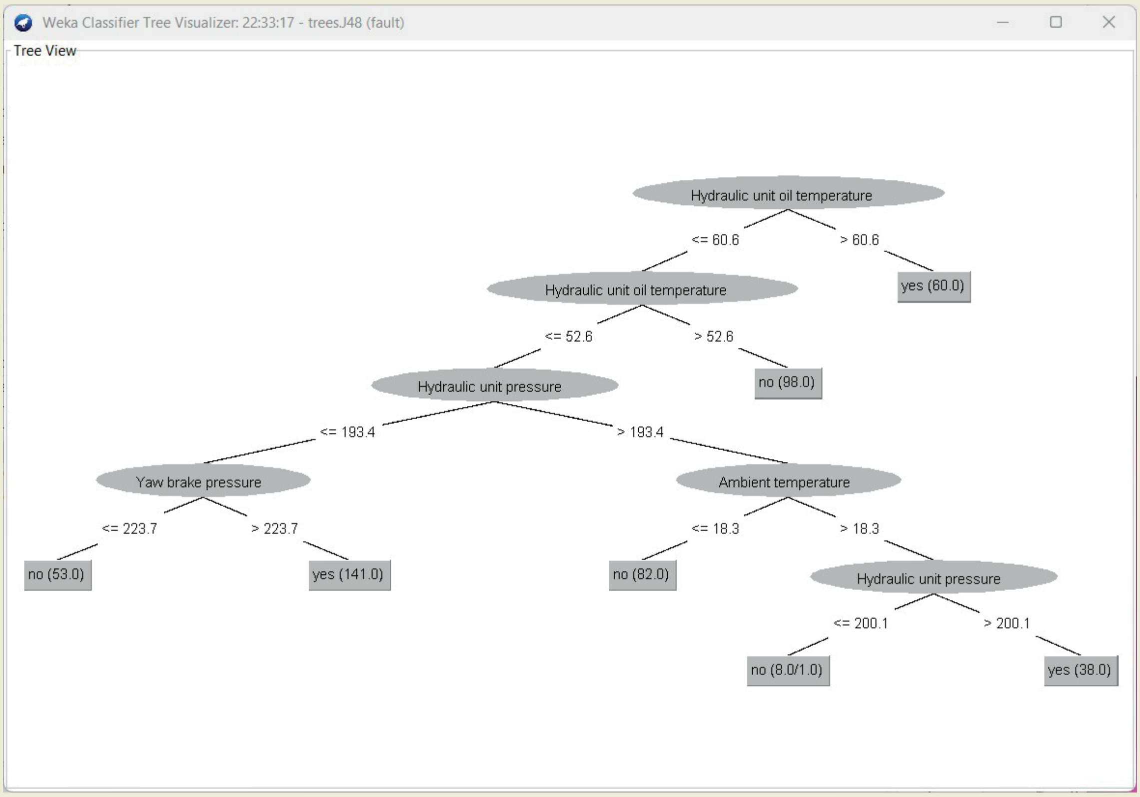

Figure 1. J48 Decision Tree

Figure 2. Relationship between Hydraulic Unit Oil Temperature, and Failure Prediction

 https://doi.org/10.26701/ems.1577643

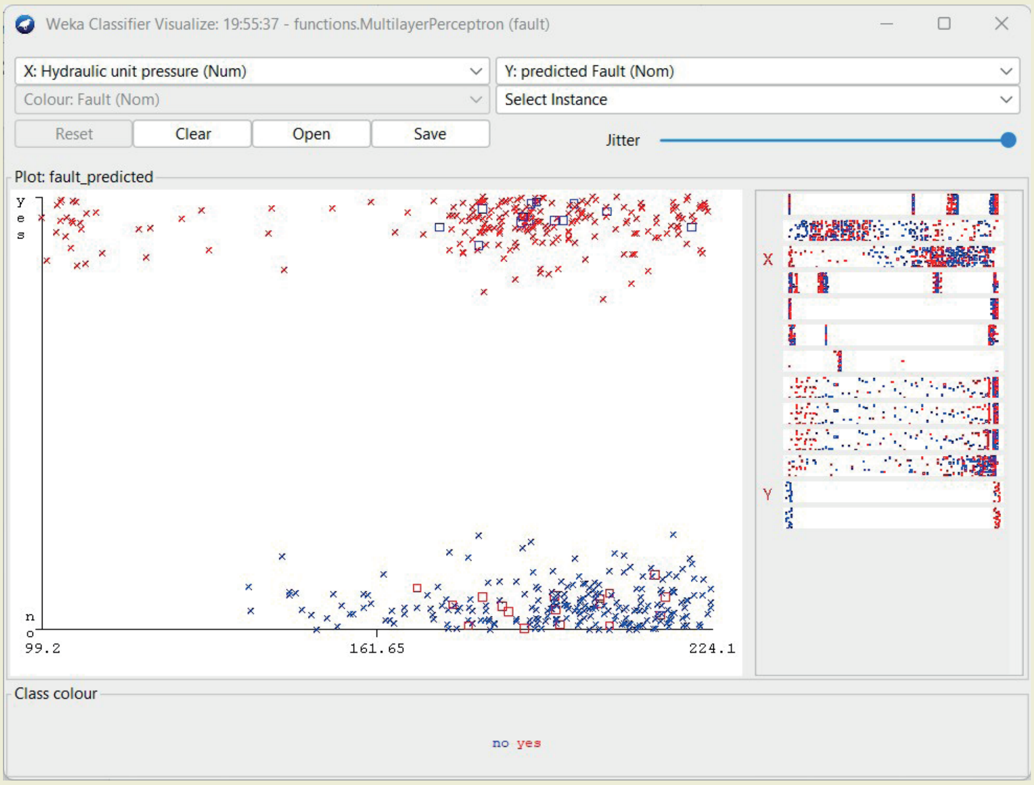

Figure 3. Relationship between Hydraulic Unit Pressure, and Failure Prediction

Figure 4. Relationship between Yaw Brake Pressure, and Failure Prediction

 https://doi.org/10.26701/ems.1577643

indicated that the MLP algorithm, with a distribution of 66% training, and 33% testing, yielded the most successful result with an accuracy rate of 96.32%.

5. Conclusions

The uninterrupted generation of electricity is a critical issue that affects electricity market operations, production, and distribution processes. Additionally, it can lead to significant financial losses for investors. Preventive maintenance to avoid electrical outages is the most economical approach. This study aims to establish preventive maintenance activities by predicting hydraulic failures in advance.

Based on the results of this study, it is recommended to directly integrate the Multilayer Perceptron (MLP) algorithm from artificial neural networks into the SCADA system to test its success rate with real data. This would allow for continuous live reading of data, facilitating the early prediction of failures.

Additionally, forecasting downtime caused by past failures for future months could provide financial insights by establishing predictions between operational costs, and revenue.

To determine the optimal parameter values for the algorithms used in WEKA, the use of optimization algorithms is considered to achieve effective results.

Increasing the diversity, and quantity of data may help uncover different relationships within the dataset. Furthermore, by working with various decision tree algorithms, the most accurate data for failure classification is selected, and incorporated into the algorithm.

Within the scope of preventive maintenance, the failures addressed in this study is evaluated, leading to the creation of preventive activities.

By examining classification errors, the range in which the program makes the most errors identified. The causes of errors within this range will investigate.

Acknowledgments

We would like to thank Necmettin Erbakan University Scientific Research Projects Coordinator ship for supporting this study with project number 23YL19008.

Research ethics

Ethical approval not required.

Author contributions

Conceptualization: Mustafa Yağcı, Tacettin Ahmet Döndüren. Methodology: Tacettin Ahmet Döndüren. Formal Analysis: Mustafa Yağcı, Tacettin Ahmet Döndüren. Investigation: Tacettin Ahmet Döndüren, Resources: Tacettin Ahmet Döndüren. Data Curation: Tacettin Ahmet Döndüren. Writing – Original Draft Preparation: Tacettin Ahmet Döndüren. Writing – Review & Editing: Mustafa Yağcı. Visualization: Tacettin Ahmet Döndüren. Supervision: Mustafa Yağcı.

Competing interests

There is no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

Research funding

Not reported.

Data availability

Not applicable

Peer-review

Externally peer-reviewed.

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