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ARTIFICIAL INTELLIGENCE FOR FAULT ISOLATION IN WIND ENERGY CONVERSION SYSTEMS

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Abstract. *Global wind capacity installation grows steadily each year in an effort to harness wind power and generate clean electricity from renewable energy sources. A trend in offshore wind turbine installations presents new challenges for operation and maintenance teams in order to improve reliability and minimize downtime. The identification and classification of faults in wind energy conversion systems are crucial factors in extending the lifespan of wind turbines by detecting and isolating faults based on failure modes. Geared drivetrain systems in offshore wind turbine facilities are being replaced by direct-drive systems, where the rotor and multi-pole synchronous generators are coupled together. Due to the harsh environment, the generator experiences the highest downtime, while the pitch control system exhibits the highest failure rates. Thus, this study aims to develop an intelligent decision-making system to classify the types of faults present in the pitch control system. The dataset was generated using AMESim software, simulating both healthy and faulty signals. The variables used in the fault modeling included pitch angle, rotor speed and active power. The pitch system was modeled using a PI controller, while the permanent magnet synchronous generator was represented using the dq0 representation of the three-phase system. Four different types of faults were simulated within the wind energy conversion system, comprising three faults in the speed sensor and one in the pitch actuator. In terms of artificial intelligence, a knowledge-based approach was developed using object-oriented programming and compared to three machine learning algorithms: random forest, gradient boosting and k-nearest neighbor. All four faults were effectively identified and isolated by the rule-based system, demonstrating an accuracy of 95%, slightly lower than the machine learning algorithms. Thus, the knowledge-based system proved to be proficient in fault detection and explanation, comparable to ML models. However, the fact that a knowledge-based system has the ability to explain its solutions, that approach fosters the exploration of new avenues in diagnosing faults in wind turbines.*

Keywords: *wind turbine, fault isolation, knowledge-based systems, pitch control.*

1. INTRODUCTION

Wind energy conversion systems have contributed to the growth of wind energy installed capacity worldwide. In 2021, new wind turbine onshore and offshore installations accounted for 93.6GW of global nominal capacity. The strategic market sector of the Global Wind Energy Report estimates that 557GW will be installed over the next five years worldwide (GWEC, 2023).

The growing trend toward greater global nominal capacity has opened the way for manufacturers to deploy double-digit megawatts wind turbines (Bensalah *et al.*, 2022). Gearless or hybrid drivetrain, larger wind turbine blades and low-speed multipole permanent magnet synchronous are some of the configurations adopted by wind turbine manufacturers.

Among wind turbine manufacturers, rated power has achieved higher values due to larger wind turbine blades. Two companies have manufactured blades with sizes of 115m and 107m, capable of generating 14MW each (Siemens Gamesa Renewable Energy, 2023; General Electric Renewable Energy, 2023). Another Danish manufacturer developed a rotor diameter of 236m, with a blade length of 115.4m, capable of reaching a rated power of 15MW using a three-stage gearbox and permanent magnet synchronous generator (Vestas, 2022). On the other hand, a Chinese wind turbine manufacturer is developing a model with a hybrid drivetrain and a blade length of 118m to reach an impressive 16MW (Mingyang Smart Energy, 2022).

Despite such improvements in power generation, availability, reliability and serviceability are key performance indicators for maintaining these large assets during normal operating conditions for power production acquired from wind energy. Hence, conditional maintenance based on mathematical models plays a significant role in achieving high global performance indicator standards (Zonta *et al.*, 2020).

Cho *et al.* (2018) proposed a model for diagnosing faults in the pitch system of offshore floating wind turbines oper-

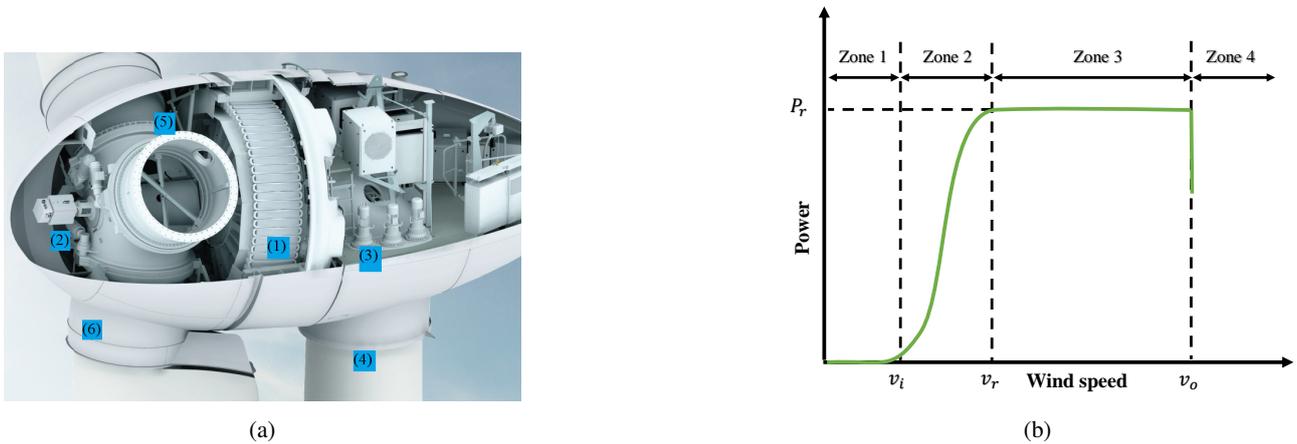


Figure 1: (a) Enercon direct drive wind energy components: 1 – annular synchronous generator, 2 – pitch control unit, 3 – yaw drive, 4 – tower, 5 – hub, 6 – rotor blade (Enercon Wind Energy Systems, 2022) and (b) wind turbine different control zones for maximum power extraction.

ating at a constant speed. The authors classified three types of faults: bias (PSB), fixed output (PSF), and actuator stuck (PAS). They performed fault detection, isolation, and control. Detection was achieved using residuals, which represent the difference between the healthy value estimated by Kalman filters and the measured value. Fault isolation was performed using an algorithm that correlates the pitch angle trend, the standard deviation of the nacelle angle, and pitch angle operational limits. Fault-tolerant control was implemented by reconstructing the correct output and replacing the measured fault at that instant. The authors created scenarios to detect single and multiple faults, as well as the structural aspect of the turbine.

Korkos *et al.* (2022) also addressed fault diagnosis in the pitch control system. They implemented an adaptive neuro-fuzzy inference system. The authors pre-processed SCADA data, including the labeling process. They extracted the most frequent events related to pitch control from maintenance logs and alarms. Here, three of the nine most frequent events mentioned in the article are: hydraulic cylinder replacement, bearing replacement, and hydraulic oil error injection. These three events accounted for 77% of the faults in the study. The authors used a hybrid neural network and fuzzy inference model, which allowed training based on historical data and connected logical rule-based sentences with the data. The algorithm took inputs such as power, the three blade pitch angles, and rotor speed, all in relation to wind speed and accompanied by a fault label. The maximum accuracy achieved by the authors was 87%.

Given the previous literature, the objective of this work is to develop a knowledge-based system to detect and isolate faults in the pitch control system. To achieve this, the study employs a dynamic model-based approach to reproduce both healthy and faulty signals. The decision-making system employs rule-based reasoning and propositional logic. After the coding process, the rules were evaluated on the training dataset and compared to three machine learning algorithms.

2. THEORETICAL BACKGROUND

This section introduces the fundamental principles of wind energy conversion systems and, within the realm of predictive maintenance, an artificial intelligence approach for diagnosing faults in the pitch system of wind turbines.

2.1 Wind energy conversion systems: components and power control

Wind energy conversion systems (WECS) are a collection of components that work together to convert the kinetic energy of wind into mechanical energy, which is then used to generate electricity (Akorede, 2022). Figure 1 shows the main components inside the wind turbine nacelle.

Figure 1a displays a gearless wind turbine with an annular generator featuring multiple poles and low angular speed, along with permanent magnets on the rotor's surface. Blade pitch control is achieved through an electromechanical actuator composed of modules. An electric pitch drive, attached to a planetary gearbox, drives a pinion connected to an annular gear, rotating the blades to the required position. A power supply module is responsible for power distribution and battery charging, as well as servo controllers to adjust the blade pitch angle in response to the sensor demand signal (Hau, 2013).

Wind turbines can operate in a wide range of wind speeds, from 3 m/s to 25 m/s. The pitch angle and rotor speed are adjusted to meet power demand and maintain wind turbine availability. Figure 1b shows the control zones of the wind energy conversion systems, which take into account the wind speed and the generated power.

Wind turbines operate in four different zones based on wind speed. In zone 1, the turbine is disconnected from the grid because the wind speed is too low to generate power. In zone 2, the rotor starts generating electricity as the blades come out of inertia. The system uses different algorithms to extract the maximum amount of wind power within the range below the rated wind speed (El-Shimy, 2014). In zone 3, the pitch control system keeps the rotor speed constant and adjusts the pitch angle of the blades to maintain the rated power. In zone 4, the operator shuts down the wind turbine to protect the components from structural overloading and mechanical failures (Zhang *et al.*, 2023).

2.2 Predictive maintenance methods

According to Sikorska *et al.* (2011), fault diagnosis in wind turbines can be classified into three categories: fault detection, fault isolation, and fault identification. Fault detection refers to detecting and reporting an anomaly in a system. Fault isolation involves classifying the specific fault in the system where an anomaly occurred. Fault identification refers to identifying the mode of failure in the component.

As stated by Zonta *et al.* (2020) and Montero Jimenez *et al.* (2020), the process of fault diagnosis in wind turbines can be approached through different methods. The authors discuss these methods either individually, in a hybrid way, or with multiple approaches. When considered individually, diagnostic methods are broadly divided into three classes: model-based, knowledge-based, and data-driven. Model-based methods are further divided into mathematical models, probability distribution, hidden Markov models, Kalman filters, particle filters and Golay filters. Knowledge-based methods are divided into fuzzy logic or expert systems, while data-driven methods encompass different types of machine learning approaches for fault classification.

3. DEVELOPMENT OF A PREDICTIVE MAINTENANCE METHOD FOR FAULT ISOLATION

The next sections address the development of a knowledge-based method for fault diagnosis and a data-driven approach to verify the method. The process of developing a method for fault diagnosis using a knowledge-based system, based on the work of Liebowitz (1992), encompasses four stages: development of dynamic modeling for data acquisition, development of a representative knowledge model, coding process, and evaluation of the developed system.

3.1 Dynamic modeling for data acquisition

Data acquisition was achieved by using a mathematical model-based approach to generate a dataset. The dataset composition modeling was based on aerodynamic, torsional, and electrical equations from wind energy conversion systems. The modeling begins with the determination of the mechanical power on the rotor blades through the wind speed. The angular velocity on the rotor blades is transmitted via the power train to the generator, which takes as input the speed on the generator shaft, converts it into three-phase voltage and current, and determines the active power. Figure 2 presents the dynamic model represented by blocks in AMESim 17. The PI controller acts as an electromechanical actuator, adjusting the blade pitch angle to a setpoint according to the wind speed and the turbine operating region. The collected signals were wind speed, rotor angular speed, active power, and pitch angle.

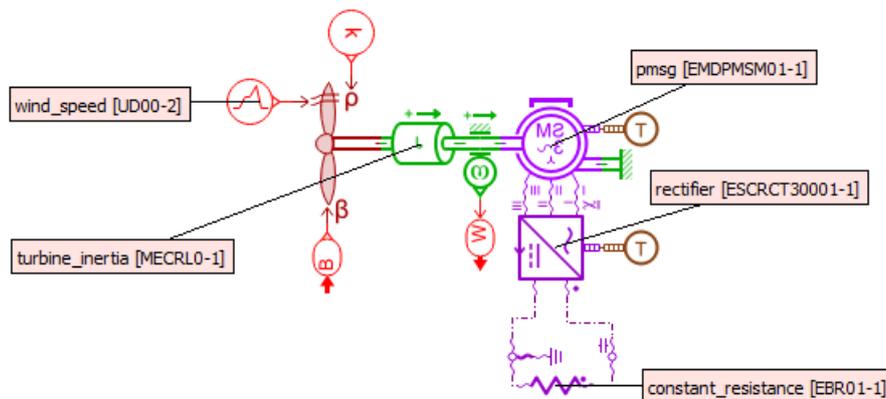


Figure 2: Dynamic model based on a 2MW wind turbine represented in blocks in AMESim.

Changes in the angular speed sensor and the PI controller lead to abnormal behavior in the wind turbine, disrupting its normal operational state and causing it to enter a faulty state. Three sensor failures and one PI control failure are sufficient to reproduce a fault scenario in the pitch controller, then generate faulty signals for the knowledge base of the fault diagnosis model. Therefore, Eq. (1) presents the acquired signal from the pitch controller's accelerometer. In the following equation, X_s represents the measured signal, $a(t)$ is a variable for signal amplification, and $b(t)$ is an additive

variable to the measured signal.

$$X_s(t) = X_s(t)a(t) + b(t) \quad (1)$$

The dynamic modeling of the pitch control system is accomplished using a PI controller. The controller adjusts the blade pitch angle to maintain the turbine at the rated speed ($\omega_{rated} = 18rpm$) in the static state of the model, thereby keeping the power output constant. Equation (2) presents the iterative calculation of the controller's pitch angle, where the manipulated variables are the proportional time constant, K_p , and the integral time constant, K_i (Lan *et al.*, 2018).

$$\beta(t) = K_p(X_s(t) - \omega_{rated}) + K_i(t) \int (X_s(t) - \omega_{rated})dt \quad (2)$$

To represent a high degree of robustness in the system and understand the behavior of the data over time, several simulations were developed through sensitivity analysis. In order to capture the signature faults and the normal behavior of the wind turbine, both in the optimization zone and constant rotor speed zone, seven wind speed levels were used: 6, 7, 8, and 9 m/s (representing wind speeds in the optimization zone) and 13, 14, and 15 m/s (representing wind speeds in the constant speed zone).

Wind speed determination is based on various works on fault diagnosis in wind turbines (Cho *et al.*, 2018; Lan *et al.*, 2018; Badihi *et al.*, 2015; Zemali *et al.*, 2023), considering their respective power optimization and constant speed zones.

For each intensity, four sensor faults were modeled: fixed value in the sensor, offset value, a trend at the sensor's reading, and a delay in the actuator response. The description of each fault is presented in Tab. 1 (De Kooning *et al.*, 2021; Silva *et al.*, 2012). The faults were inserted throughout the simulation. The simulation duration was 600s, with a convergence time step of 1s. All four faults were introduced starting from 250s, and the boundary condition is given in Tab. 1. The healthy proportional and integrative constants of the PI controller were given according to the work of Badihi *et al.* (2015).

Table 1: Fault description and initial conditions on accelerometer.

Fault type	Fault description	Fault conditions
Sensor fixed	The sensor remains at a fixed value even in rotor speed variation.	$t < 250 \Rightarrow a(t) = 1, b(t) = 0$ $t \geq 250 \Rightarrow a(t) = 1, b(t) = 13$ $0 < t < 600 \Rightarrow K_i = 0.04$
Sensor offset	The signal presents an amplification on its output.	$t < 250 \Rightarrow a(t) = 1, b(t) = 0$ $t \geq 250 \Rightarrow a(t) = 1, b(t) = 2$ $0 < t < 600 \Rightarrow K_i = 0.04$
Sensor drift	A progressive change in signal over time.	$t < 250 \Rightarrow a(t) = 1, b(t) = 0$ $t \geq 250 \Rightarrow a(t) = 1, b(t) = \frac{4t}{175} - \frac{26}{7}$ $0 < t < 600 \Rightarrow K_i = 0.04$
Actuator delay	A delay to meet the angle of attack demand.	$0 < t < 600 \Rightarrow a(t) = 1, b(t) = 0$ $t < 250 \Rightarrow K_i = 0.04$ $t \geq 250 \Rightarrow K_i = 0.002$

More details about the dynamic equations of the wind turbine and the fault signatures are available in the work of Branco and Silva (2023), where the pre-fault and post-fault behaviors are discussed through the residual approach of digital twins. In terms of datasets, 28 combinations were generated, with three fault signatures in the wind speed sensor of the pitch controller and one signature in the actuator. Each dataset consists of healthy and faulty segments. Healthy segments belong to the majority class in the healthy class, while faulty segments behave differently for each type of fault. The datasets, comprising wind speeds of 7, 8, 13 and 14m/s, were utilized for training and feature extraction, while the datasets with wind speeds of 9 and 15m/s served as test data.

3.2 Knowledge representation

Knowledge refers to information about a particular domain that is used to solve problems. To solve problems that require knowledge, it is necessary to represent that knowledge in a computer. A language for knowledge representation is used to formalize human knowledge in a way that a computer can perform inferences (Poole and Mackworth, 2017).

According to Giarratano and Riley (2004), knowledge can be expressed in the form of rules, oriented-object modeling, semantic networks, or logic. In this work, knowledge representation was adopted using a rule-based approach and propositional logic. These forms of knowledge representation favor an approach closer to human reasoning and are effective in inducing knowledge in the inference machine.

Rule-based representations allow for the explicit and understandable expression of knowledge using an “If-then” structure. This structure is similar to how human experts express their knowledge when making decisions (Russel and Norvig, 2021).

In this stage, it is also necessary to understand the behavior of faults statistically in order to extract the implicit knowledge within the faults and express them in numerical form. Therefore, control limits for faults were determined, based on the slope of the fault curve or the mean and standard deviation (Nan *et al.*, 2008; Montgomery, 2009).

The fault types have specific control limits, where if a value falls within a control limit, the system isolates a fault and identifies its specific type. A fault is triggered if, after checking the values within a sliding window, the value falls within one of the proposed fault control limits in Tab. 2 (Encalada-Dávila *et al.*, 2021; Zemali *et al.*, 2023).

Table 2: Fault feature extraction.

Fault type	Features
Sensor fixed value	Standard deviation and mean
Sensor offset value	Standard deviation and mean
Sensor drift value	Mean curve slope or primitives
Pitch control delay	Standard deviation and mean

Object-oriented programming in Python was used to develop the knowledge base. This high-level programming language offers various standard libraries. These libraries encapsulate a set of functions, classes, and methods that can be used during programming and incorporate different values into object attributes (Python, 2023). Figure 3 presents a basic algorithm for pitch control detection and diagnosis faults.

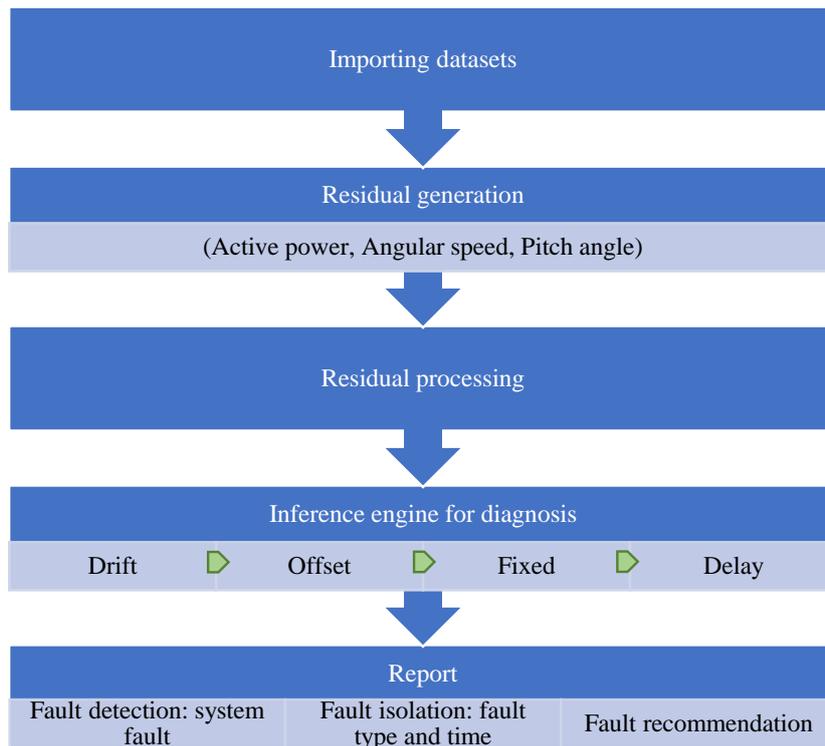


Figure 3: A schematic diagram for fault detection and diagnosis in pitch control system.

After knowledge acquisition, the files are imported into the program in the form of value matrices. There are three matrices that contain residuals of active power, angular velocity, and pitch angle. Signal processing is performed to extract meaningful samples within a time interval without losing precise information over long intervals. Therefore, the means and standard deviations of wind speed and residuals were obtained every 60 seconds.

The algorithm initially evaluates whether there are trends in the data. Detecting trends takes into account the first and second-order derivatives of the data. The first derivative indicates whether there is an increasing or decreasing trend, while the second derivative indicates whether there is a change in concavity or stabilization (Nan *et al.*, 2008). The offset, fixed, and delay faults have distinct control limits and exhibit different behaviors for the three evaluated residuals.

The faults are classified according to the wind intensity affecting the wind turbine. Faults related to a delay in the actuator in the pitch controller are not noticeable in the optimization zone or when the wind speed is less than 12m/s. Therefore, this fault was excluded from the subsequent training and testing process.

3.3 Coding process

The KnowledgeEngine class is designed as an inference engine for fault diagnosis on accelerometers. Within that class, the encapsulation of various user-defined functions facilitates the expansion of the algorithm for new cycles and code organization. The functions are instantiated by associating the object with one of the attributes within the class. The value of the attribute is the dataset obtained in the knowledge acquisition stage. By creating the class as an inference engine, other objects can inherit its attributes, enabling straightforward rule chaining verification in the training dataset. Figure 4 presents the blocks of functions in the code.

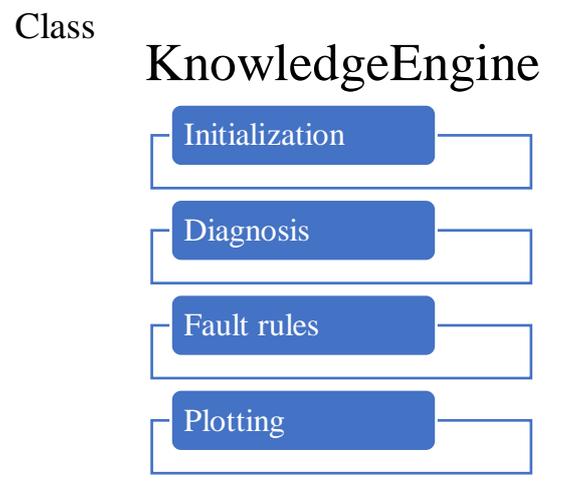


Figure 4: Schematic sequence of the fault isolation code for wind turbine sensors.

The “initialization” method serves as the class constructor, getting instantiated whenever the class is used. In this method the datasets are loaded and assigned to arrays. It also serves as a code presentation screen for the user. The “Diagnosis” method works in conjunction with the “Fault rules” method. When the “Diagnosis” method is instantiated by the user, it checks for each function that contains a different fault in the “Fault rules” method and matches the rules with the instances declared by the user outside the class.

The “plotting” function, when instantiated by the user, generates plots of the active power, angular velocity, and pitch angle for both the overall model and the virtual model. It is also possible to generate plots of the residuals of power, angular velocity, and pitch angle.

3.4 Code evaluation

The rule verification was performed based on a data window of 60 seconds and 120 seconds. The objective is to evaluate a quantity of data in two analyses and determine whether it is possible to detect faults within this interval window. The choice of the interval was made due to the simulation time of the dynamic modeling and the data aggregation in seconds. In the works of Cho *et al.* (2018) and Korkos *et al.* (2022), the authors present the data on an hourly scale with a time step of one hour.

To verify each rule created in the knowledge engine, the confusion matrix was used to assess how many times the algorithm correctly classified each of the faults in the training dataset. Rules triggering were evaluated according to the type of fault encountered. Performance evaluation plays a vital role in fault classification studies. Generally, true positive (TP) and true negative (TN) represent the number of positive and negative samples that have been correctly classified, while false positive (FP) and false negative (FN) denote the number of misclassified instances (Khazaei *et al.*, 2022). Two main metrics for fault isolation were used in this paper. Precision measures positive instances that were correctly predicted from the total predicted instances in a positive class. Recall is the proportion of positive instances correctly predicted. Accuracy is a metric that measures the performance of a model by evaluating the ratio of correct classifications to the total number of instances evaluated (Hossin and Sulaiman, 2015).

Precision measures how much the model is able to correctly classify a type of failure in relation to a misclassification

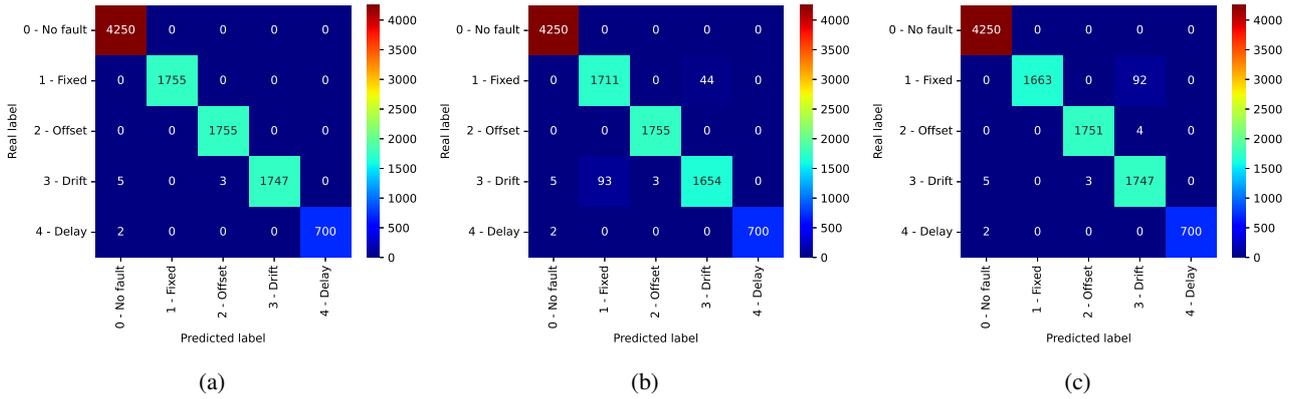


Figure 5: Confusion matrix for (a) random forest classifier, (b) gradient boosting and (c) KNN applied to the training set.

of the same failure. Recall measures how much the model is able to correctly classify a type of failure in relation to another poorly classified failure.

Precision and recall were expressed in Eq. (3) and (4). However, for the sake of comparison with other models, accuracy was adopted and is expressed in Eq. (5). F1-score is another common metric for classification evaluation. It represents the harmonic mean of precision and recall, and is evaluated according to Eq. (6).

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

$$F1 - score = \frac{2}{\frac{1}{precision} + \frac{1}{recall}} \quad (6)$$

4. Model results

This section presents the results of the method for fault isolation on wind turbines, creating confusion matrices and metrics for comparison with the knowledge-based system.

4.1 Knowledge evaluation on training dataset

Three machine learning algorithms were used to verify the rules of the knowledge base. Random forest, gradient boosting, and k-nearest neighbors were used under default hyperparameter conditions in the Python program, without any hyperparameter optimization.

For the use of machine learning algorithms, the dataset was scaled, and the training set containing delay faults for average wind speeds of 6, 7, and 8 m/s was excluded from the analysis. The random forest algorithm was modeled with 100 estimators and two sample splits per leaf. The gradient boosting algorithm had 100 estimators and one sample split per leaf. The KNN algorithm was modeled with 3 neighbor classes, as they showed the best trade-off between accuracy and classification quality, avoiding overfitting and underfitting.

In order to compare the rule-based system, no dataset changing techniques were applied to the training set, such as oversampling or undersampling. Therefore, Figure 5 presents the confusion matrices for the machine learning algorithms.

A common approach at the illustrations of Figure 5 is the occurrence of false negatives at the drift fault, which did not happen in the rule-based system. Similarly, in the rule-based system, few instances with delay fault were classified as “No fault”. In Figure 5b, false positives appeared for the fixed fault, and the precision for the offset fault was 100%. On the other hand, in the KNN algorithm in Fig. 5c, both false negatives and false positives emerged for both fixed and offset faults.

Figure 6 presents the F1-score for both knowledge-based system and machine learning models. The machine learning models have accuracies above 98%. However, the KBS exhibits a high score of 95%, validating it as an excellent fault diagnosis model.

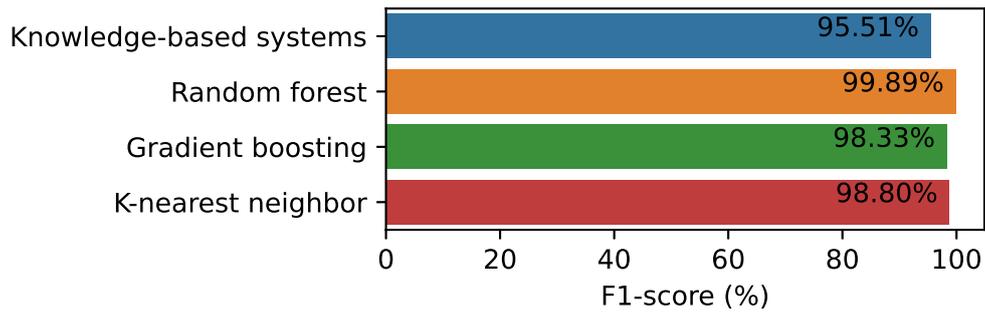


Figure 6: Schematic sequence of the fault isolation code for wind turbine sensors.

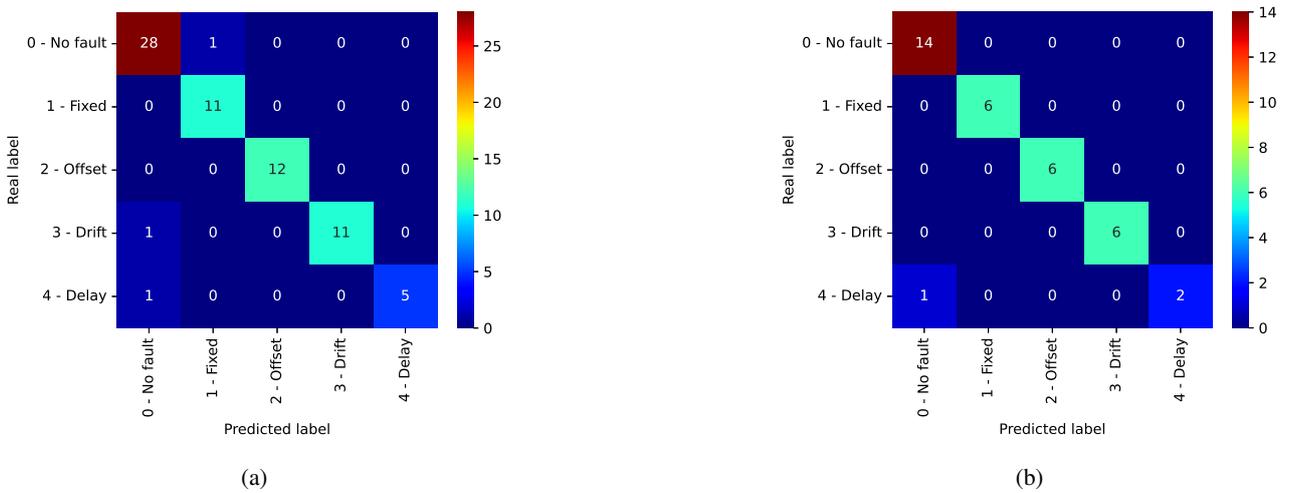


Figure 7: Confusion matrix for the rule-based system test dataset: (a) sampling rate of 60s for test dataset and (b) sampling rate of 120s for test dataset.

4.2 Knowledge evaluation on test dataset

After the training phase of knowledge-based system and machine learning models using a training dataset, the final stage involves using the KBS prototype to verify fault diagnosis for the test dataset. The test set includes both healthy and faulty samples for wind speeds of 9m/s and 15m/s. Figure 7 presents the confusion matrix for the test dataset. In order to compare the two types of sampling, no abrupt changes were observed in the matrices. However, in Fig. 7aa, there are false negatives for the drift, fixed, and delay faults. On the other hand, for the longer 120s sampling in Fig. 7bb, there is only one false negative, which corresponds to the delay in pitch control. Figure 8 compares the accuracies for the two types of sampling, indicating that both are viable options.

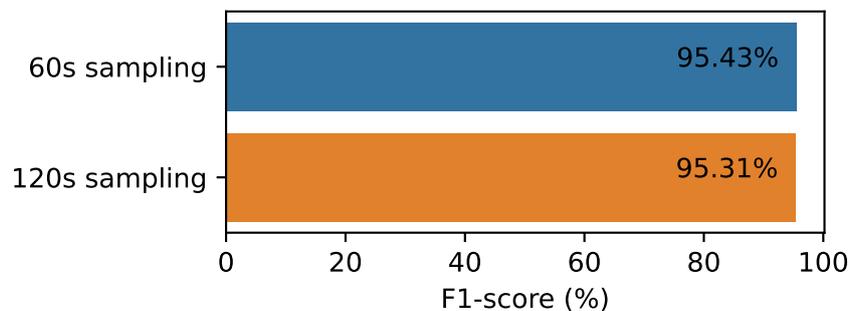


Figure 8: Macro F1-score for knowledge-based systems (KBS) for fault isolation in the test dataset.

The results obtained in this study for the KBS are lower than those of enhanced machine learning models. Korkos

et al. (2022), in their work using the adaptive neuro fuzzy inference system (ANFIS) for pitch control fault detection, achieved accuracies ranging from 97.14% to 98.23% and F1 scores from 75% to 87%. Rahimilarki *et al.* (2022) employed convolutional neural networks to classify pitch control faults. The authors utilized real fault datasets and performed classification on the actuator in three distinct scenarios: single failure, two failures, and four failures. The accuracies achieved for each scenario in their study were 98.37%, 98.87%, and 96.2%.

5. Conclusions

The objective of the study was to isolate faults in the wind turbine pitch system. Four types of faults were selected for this system. Using the expert system development cycle, a rule-based system with propositional logic was developed. The triggering of rules was verified using a confusion matrix and sliding windows throughout the dataset, with varying amounts of data in the windows. Three machine learning algorithms were used to verify the accuracy of the expert system. The knowledge-based system showed an accuracy of 95%, while the machine learning algorithms achieved 98%, proving that expert systems can be as accurate as machine learning algorithms. Finally, with the verified expert system, the remaining dataset was tested to validate the accuracy of the KBS for fault diagnosis. Both the 60s and 120s samples achieved an accuracy of 95%.

It's important to note that the data originates from dynamic sensitivity analyses and doesn't represent real operational data from wind turbines. The origin of the data contributes to the high accuracy of the knowledge-based system prototype. Therefore, it is feasible to evaluate the model with a human expert or real operational data. With the system diagnosis performed and the fault isolated using a knowledge-based system, it is possible to implement system tolerance control by recovering the initial fault value and dynamically modeling the entire wind turbine system. This assists the O&M team in maintaining system reliability within an acceptable range and predicting the optimal intervention time.

The results developed in this study are part of the main author's doctoral thesis, which aims to diagnose faults in wind turbines through digital twins, with the second author serving as the advisor. The next stage of the research involves implementing fault-tolerant control of the pitch system.

6. ACKNOWLEDGEMENTS

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