Nadziranje hidro generatora pomoću strojnog učenja za rano otkrivanje kvarova u HE Dubrovnik

Machine Learning-Driven Hydrogenerator Monitoring for Early Fault Detection in HPP Dubrovnik

Hossein Foroozan[a,*], Ozren Orešković[a], Božidar Filipović-Grčić[b], Ivan Krnić[c], Ivan Kolić[c], Nikola Mijalić[c]

[a] Veski d.o.o., Zagreb, 10000, Croatia
[b] University of Zagreb Faculty of Electrical Engineering and Computing, Zagreb, 10000, Croatia
[c] HEP d.d., Dubrovnik, 20000, Croatia
*Corresponding author: hossein.foroozan@veski.hr

INFORMACIJE O ČLANKU

Kategorija:
Izvorni rad

Ključne riječi:
Hidrogenerator
Nadzor prema stanju
Strojno učenje
Rano otkrivanje kvarova
Otkrivanje odstupanja u ponašanju

SAŽETAK

Hidroenergija je jedan od ključnih izvora čiste energije u svijetu. Budući da su mnoge hidroelektrane u pogonu već desetljećima, sve veća pozornost usmjerava se na njihovu pouzdanost i dugoročnu održivost. Ovaj rad daje osvrt na rastuću potrebu za prediktivnim i učinkovitijim strategijama održavanja, s naglaskom na primjenu naprednih sustava nadzora i dijagnostike, nadograđenih modulima za strojno učenje u svrhu rane detekcije kvarova, odnosno odstupanja od uobičajenog ponašanja agregata. Opisani sustav koristi povijesne podatke za uspostavu referentne razine normalnih radnih uvjeta – kako za mehaničke (npr. vibracije), tako i za električne parametre (npr. parcijalna pražnjenja). Procesne, električne i mehaničke veličine poput radne i jalove snage, temperature statora i ležajeva, protoka itd. koriste se kao ulazni podaci za definiranje modela. Algoritam strojnog učenja u stvarnom vremenu nadzire odstupanja izlaznih mjernih vrijednosti (vibracije, parcijalna pražnjenja) od očekivanih vrijednosti koje generira model. Te očekivane vrijednosti dobivene su učenjem na skupu podataka iz referentnog razdoblja koje su odabrali domenski stručnjaci. Nakon toga slijedi analiza korelacije podataka kako bi se identificirali najvažniji parametri za treniranje modela, validacija točnosti modela i, po potrebi, uključivanje dodatnih podataka. Sustav je instaliran u HE Dubrovnik, gdje se pokazao korisnim za rano prepoznavanje promjena u ponašanju agregata. Implementacija ovakvog sustava značajno doprinosi povećanju pouzdanosti postrojenja.

ARTICLE INFORMATION

Category:
Original research paper

Keywords:
Hydrogenerator
condition-based monitoring
Machine Learning
Early Fault Detection
Abnormal Behavior Detection

ABSTRACT

Hydropower remains a key global source of clean energy. However, many plants have been operating for decades, raising critical concerns regarding reliability and sustainability. In response to the growing need for more efficient and predictive maintenance strategies, this paper introduces an advanced monitoring and diagnostic system enhanced by a machine learning-based module for early fault detection and the identification of behavioral deviations. The proposed system leverages historical data to establish a baseline for normal operational conditions of both mechanical (vibration) and electrical (partial discharge) parameters. Operational, electrical and mechanical metrics such as active and reactive power, stator temperatures and flow are used as inputs to the model. Meanwhile, the system monitors deviations in outputs—partial discharge and vibration—against expected behavior. To implement this solution, domain experts first define a reference period representing normal operation. Then, correlations between various parameters are analyzed to identify the most relevant features, train the model, and validate its performance using additional data. The system has been deployed at the HE Dubrovnik hydropower plant, proving its effectiveness in detecting early change and monitoring behavioral deviations. This implementation is contributing to enhanced overall plant reliability.

1. Introduction

Hydropower plants convert the hydraulic potential energy of water into electrical energy [1]. Hydropower is a major part of global energy mix and accounts for roughly 16% of the world's electricity production, making up about 60% of all renewable energy output [2]. Given this pivotal role in energy generation, enhancing the performance, efficiency, and reliability of hydropower plants is essential. In this regard, using advanced monitoring systems for early fault detection is essential to ensure their continued reliability and efficiency in the face of growing energy demands [3]. These days, with the advancement of technology, especially in the fields of artificial intelligence, augmented reality, cloud processing, and big data, various industries are increasingly benefiting from these innovations and improving their products or services. With these advances, traditional monitoring systems in hydropower plants no longer follow today's technological capabilities.

Advanced diagnostic and monitoring technologies now offer new opportunities for improved maintenance of these critical assets. Conventional maintenance strategies are mostly reactive or based on predetermined calendars. In these systems unexpected failure can lead to operational disruptions and great economic losses. Conventional protection systems are reactive to fault, meaning they usually detect faults only after predefined thresholds are exceeded. In addition, traditional monitoring and diagnostic systems are used in predictive manner, but still the responsibility for diagnosis and response falls on human operators—introducing risks of delay or error.

Artificial intelligence and machine learning now enable the analysis of vast operational datasets, identifying trends and forecasting conditions by learning from past performance. By applying machine learning (ML) algorithms, hydropower plants can not only improve the precision of their maintenance routines but also greatly extend the operational life of their assets. This study explores how a standard monitoring and detection system can be enhanced through the integration of a machine learning-based early fault detection module. In this regard, first, the paper initially reviews the related works in this field, followed by an explanation of the methods employed. Finally, the effectiveness of these methods is demonstrated through their application in a real-world setting in Dubrovnik hydropower plant.

2. Literature Review

In this section, a literature review with focusing on the use of machine learning for predictive maintenance and early fault detection in hydropower plants is provided. In this regard, first, the main related technologies are introduced, followed by a summary of key studies in the area.

Advanced sensors, processors, computing and communication infrastructure, advanced databases, and cutting-edge AI models are the key technologies for predictive maintenance and early fault detection. A decade ago, limited data processing capabilities and the complexity of training ML models were major challenges. Advancements in cloud computing have provided powerful and scalable infrastructures and leading companies like Microsoft, Amazon, and Google play a key role in this field [4]. On the other hand, with the progress in the field of Internet of Things and the improvement of communication infrastructure and sensor technologies, today more data is recorded from different parts of the power plant. With the rapid progress in artificial intelligence in recent years, there has been growing interest in analyzing this data more effectively to enhance early fault detection methods. The integration of ML into Condition-Based Maintenance (CBM) systems marks a turning point in predictive maintenance strategies. On the other hand, with the progress in the field of Internet of Things and the improvement of communication infrastructure and sensor technologies, today more data from different parts of the hydropower plant is available. With new ML algorithms we can handle larger and more complex datasets that offers deeper insights into equipment behavior. According to a recent study by Epochai [5], AI training capacity might quadruple every year through 2030, potentially reaching a staggering 2e29 floating point operations (FLOPs). However, this growth comes with some challenges, like owner and energy supply and chip manufacturing.

One of the pioneers in applying Artificial Intelligence for real-time diagnostics of power generation systems is introduced by Gonzalez et al. (1986). They developed an expert system for fault diagnosis of turbine-generators from sensor data and inference rules [6]. Liu et al., as cited in [7], reviewed AI techniques for fault diagnosis in rotating machinery. The paper explores different methods including k-nearest neighbor, Naive Bayes, Support Vector Machine, Artificial Neural Networks and Deep Learning and discusses their theoretical background and industrial applications. Afridi et al. in [8] highlight the important role of AI in predictive maintenance for renewable energy systems. The paper examines the current predictive maintenance frameworks, and focusing on how AI helps to improve system efficiency and deal with issues related to data quality and security. Fera and Spandonidis have developed an AI and IoT-based framework that can detect corrosion in hydropower plant conductors. It has more than 80% accuracy and a low false alarm rate of 5%, showing the effectiveness of machine learning in predictive maintenance [9]. Bernardes et al. [10] present a systematic review about using ML methods for enhancing energy production in different modes of hydropower operations. The paper highlights supervised learning in improving predictions of river flow and reservoir management [10]. Bütüner et al. [11] developed an ML model for anomaly detection in hydropower plants. In this model they focus on oil circulation system of the hydraulic governor.

The shift from scheduled to predictive maintenance in hydropower plants represents a major transition supported by technological developments and research. Jiang et al. [12], discuss a predictive maintenance system for hydropower plants that uses Multi-Agent Systems (MAS) and Neural Networks (NN) for automating maintenance tasks to reduce downtime and costs and improve equipment reliability with real-time monitoring. Ribeiro et al. [13] discuss a predictive maintenance system at Brazil's Itapebi Power Plant that uses digital signal processing to monitor electrical signals in hydrogenerators. Also, required equipment is mentioned in details in the paper. Their work focuses on signal monitoring without using AI or ML. Betti et al. [3] proposed a new Key Performance Indicator (KPI) based on a Self-Organizing Map (SOM) neural network, tested with a year's worth of data from two Italian hydropower plants to improve their operational efficiency and maintenance planning. Jin et al. [14] introduced a predictive maintenance model that uses LSTM neural networks along with time-temperature rate analysis, applied to a decade of data from a 56 MW plant, focusing specifically on detecting anomalies in bearing temperature.

Some scientific literature refers to the integration of real-time monitoring, data systems, sensors, diagnostics, and simulation models as a "digital twin" [15], [16]. GE defines a Digital Twin as a virtual representation of a physical asset, system, or process, designed to monitor, prevent, predict, and optimize performance through real-time analytics to create business value [15]. This definition of a digital twin aligns well with the methodology and outcomes of this research. In the next part, the method is introduced and then the results of its use in a real system are presented and analyzed.

3. Methodology

Hydropower plants play an important role in the global energy mix by providing renewable, clean, and sustainable electricity [1]. These systems are complex, made up of multiple subsystems that each come with their own engineering and operational challenges. Figure 1 shows a schematic of the main components of a typical hydropower plant [11].

Monitoring of a complex system like a hydropower plant in real time means measuring, storing, and analyzing many different values with minimum delay. In addition to these steps, for early fault detection, this data should be compared with historical data to detect any unusual changes or patterns in order to find problems in the system before they turn into serious faults.
Modeling of such a system is required to analyze and predict its behavior. At the highest level, modeling techniques can be classified into three distinct categories: data-based, physics-based, and hybrid models [17]. Data-based models, or black-box models, use historical and real-time data to identify behavioral patterns by combining statistical methods, machine learning, and artificial intelligence. In this modeling approach, it is essential to carefully prepare and filter the data. Inputs and outputs used in the models should be analyzed and validated by experts, and the selection of training and testing sets is particularly important. This method is used in the present research. For Physics-based modeling we need deep knowledge of system dynamics for detailed analysis. Also, this type of models faces significant challenges related to uncertainty management and efficient real-time processing. These models are also known as white-box models. Hybrid models combine the benefits of both data-driven and physics-based methods. These grey-box models are valued for their broader applicability, especially in digital twin systems. However, they are quite complex and only work when both the physical model and corresponding data are already available. Updating or adapting them to other hydropower plants is usually not feasible.
In this paper, after defining and understanding the problem, various data is collected from the monitoring system. The data is following a process through cleaning, normalization, and feature engineering to get it ready for analysis. Once preprocessed, the data is divided into training, validation, and testing sets. A suitable algorithm is then chosen, the model is trained, and its settings (hyperparameters) are adjusted. The model's performance is checked using the validation and test sets and any mistakes are reviewed by domain experts to improve the results. After the testing process, the model is integrated into the monitoring system environment. The overall process is illustrated in Figure 2.

In this paper, first, a period with normal behavior of the hydrogenerator is selected by domain experts and used for training the ML models. In this regard, some critical signals are chosen as outputs to represent the behavior of the system, after which, certain signals are selected by domain experts as initial inputs, and a model is trained to predict the outputs. In the following steps, a correlation between inputs and outputs is analyzed, and the most effective inputs are selected. Several machine learning methods were tested, including XGBoost, LightGBM, and Support Vector Regression, and in the end, a Random Forest Regressor was chosen due to its robust performance, minimal need for preprocessing, and clear feature-importance outputs that support interpretability. This is a supervised learning algorithm that uses an ensemble approach for regression tasks [18]. Ensemble learning means combining the results of several models to make a more accurate prediction than a single model alone [18]. Hyperparameters of the model were adjusted to improve the model's performance.

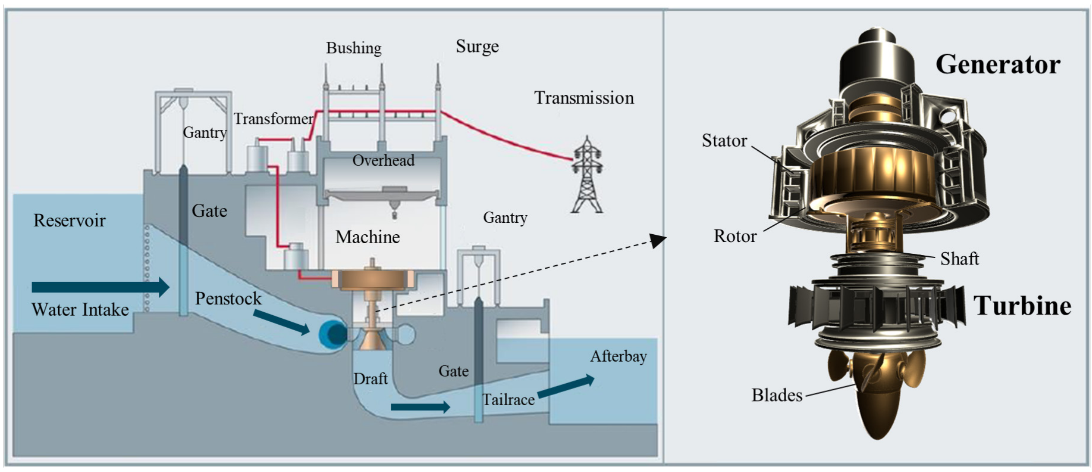

Figure 1 A schematic diagram of the main components of a hydropower plant
Slika 1. Shematski prikaz glavnih komponenti hidroelektrane

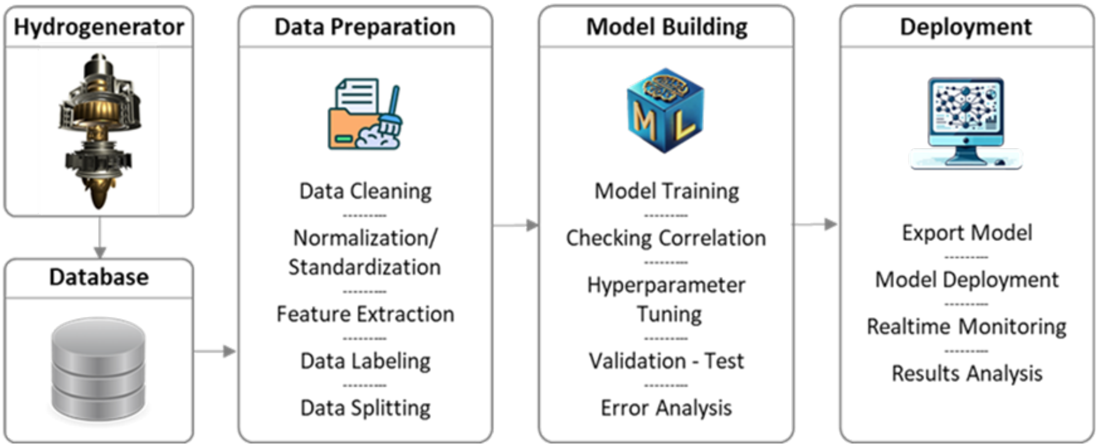

Figure 2 Machine Learning Workflow
Slika 2. Tijek rada strojnog učenja

The depth of the decision trees was also explored to see how well the model could learn patterns from the data. By fine-tuning how the model splits decision points and setting limits for the minimum number of samples needed for each split or leaf, the model was better controlled to avoid overfitting. This method makes it easier to adjust the model based on different operating conditions, limits, or thresholds. Besides tuning for accuracy, other practical aspects, like model size, resource usage, and hardware requirements were also considered, specially to make sure the model runs in real time with little delay. To help with that, the number of features considered at each decision point was limited, which made the model faster to train and quicker to make predictions.

The difference between predicted values and measured values is referred to as the residual value. When this residual value remains within a predefined band, the hydrogenerator is considered to be operating normally. This band is calculated based on residual values observed during the system's normal behavior. A schematic illustration of this concept is shown in Figure 3.

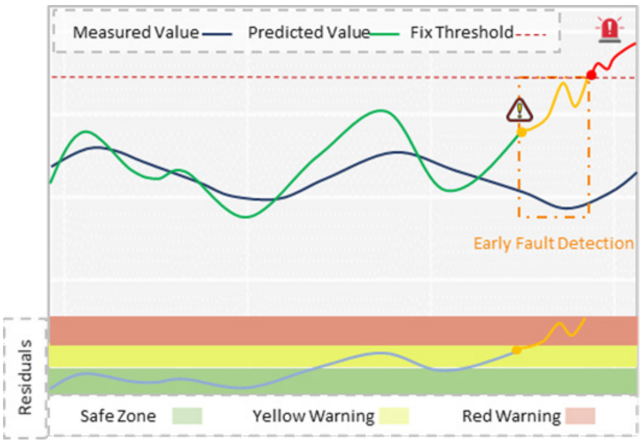

Figure 3: Normal Behavior Modeling with Residual Values and warning Bands
Slika 3. Modeliranje normalnog ponašanja s rezidualnim vrijednostima i zonama upozorenja

When the residual value exceeds the safe band, a warning is displayed in the system. The alarm thresholds are defined based on the type and range of signal values during the system's normal behavior and are categorized into three levels: normal (green), orange, red. The range outside these bands, but before reaching the conventional alarms and fixed thresholds, represents the concept of early fault detection.

In this normal behavior modeling approach, each output sample is generated not only using the corresponding current input data but also by incorporating information from the preceding five input samples. In the next sections, the model is trained and applied to the Dubrovnik Hydropower Plant in Croatia as a case study, and the results are presented and analyzed.

4. A case study

The method is tested in real-time as an add-on to a conventional monitoring system installed on the hydropower plant Dubrovnik in Croatia.

The technical specifications of the power plant are provided in Table 1.

Table 1 Technical Specifications of the Hydropower Plant Dubrovnik in Croatia
Tablica 1. Tehničke specifikacije hidroelektrane Dubrovnik u Hrvatskoj

Machine	Unit B
Hydroelectric Power Plant type	High-pressure diversion plant
Machine type	Vertical suspended machine with three guide bearings
Generator type	IM 8425 (IEC 60034-7)
Turbine type	Francis with vertical shaft
Nominal Power, MW	113,166
Nominal discharge, m^3/s	45
Nominal Net Head, m	269,652
Nominal generator rating	140 MVA
Nominal generator voltage	14 400 V
Nominal speed, RPM	300
Nominal design air gap, mm	32
Step-up transformer voltage ratio	14,4 kV/ 220 kV

The model is set to predict the partial discharge

(PD) peak magnitude (Qm+[1]), the total PD activity (NQN[2]) and vibration parameters of a maximum shaft displacement, Smax, obtained continuously by a monitoring system, since machine commissioning in 2013. Smax is obtained by formula (1):
Besides the shaft displacements (proximity probes)

$$S_{max} = max\sqrt{(SigX)^2 + (SigY)^2} \tag{1}$$

and bearing vibrations (accelerometers) on all three generator guide bearings in two perpendicular directions (X and Y) the monitoring system consists of four air gap sensors, installed on the top of the stator core, at equidistant angles (90°). Also, one magnetic flux sensor is installed at position of 0°, next to the air gap sensors.
The monitoring system is connected and integrated into the SCADA system from which process parameters are obtained. These, among other, include bearing segment, core, clamping finger and winding temperatures, unit's electrical and hydraulic parameters, flow, pressure in penstock and spiral casing. All of these are very important for the dynamical state diagnostics as the vibrations can vary significantly with regime change. All processing parameters are being written into the system's diagnostic common database along with the data from the measurement system sensors. The mentioned process quantities are used in the prediction model as valuable inputs parameters, that are correlated in various combinations throughout the historical records with the observed outputs. For this particular case study, at the first step, the following inputs are selected:
Stator core temperature, Stator winding temperature, Flow, Pressure in penstock, RPM, Active Power (P), Reactive Power (Q), Maximum bearing segment temperatures on all three guide bearings and also thrust bearing.

In the next step, before training and fine-tuning the model, the correlation between selected signals is analyzed and the best signals are selected. The results are shown in Figure 4.

Subsequently, the model is trained based on the most correlated signals, and the hyperparameters are tuned. The model's performance is evaluated using the validation and testing sets, and any errors are analyzed with domain experts for further refinement. Finally, the model is deployed and integrated with the current monitoring system and updated as new data becomes available. For training the model to detect normal behavior of Smax signals, one year of normal data—from June 2022 to June 2023—was used for initial training and evaluation in this study. The model was then tested with data from July 2023 to August

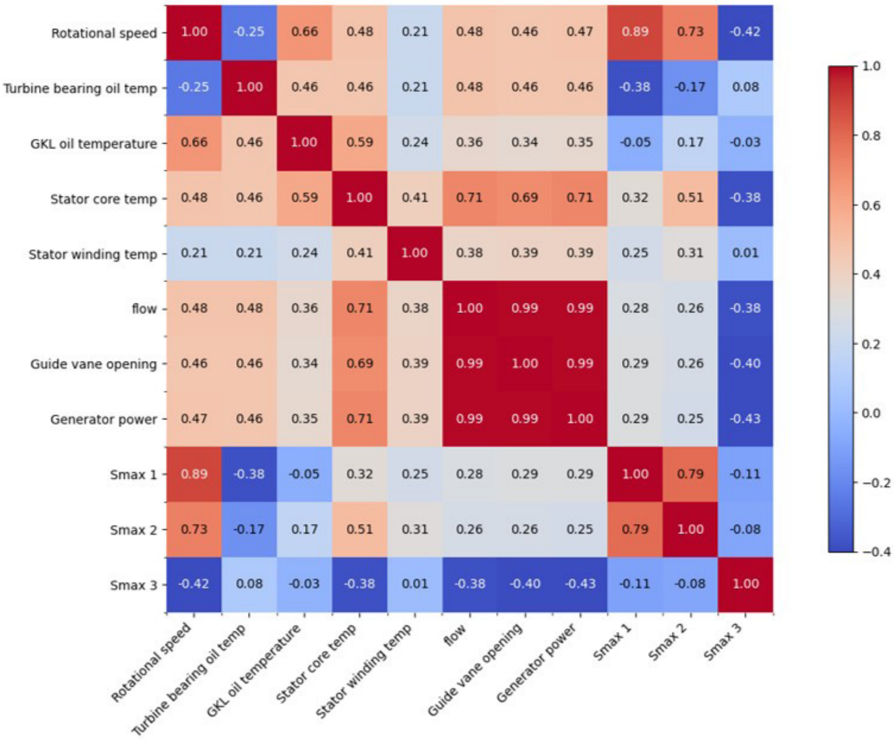

Figure 4 Machine Learning Workflow
Slika 4. Tijek rada strojnog učenja

[1] According to IEC 60034-27-1 Qm is largest magnitude associated with a PD pulse repetition rate of 10 pulses per second (pps), which can be directly inferred from a pulse magnitude distribution chart.
[2] NQN -Normalized Quantity Number - represents the area beneath the curve, on pulse magnitude chart, representing number of pulses per second weighted by the magnitude of the pulses. NQN is a partial discharge quantity that is proportional to the total partial discharge measured by a PD sensor.

2024.

For training the model to detect the normal behavior of partial discharge Qm+ (PD) signal and total PD activity (NQN) on phase B, similar steps were followed to select the most relevant signals. Then, normal data from January 2021 to September 2022 was used for training and evaluating the model, while data from October 2022 to June 2024 was used for testing. The results are discussed in the next section.

5. Results

In this section, the results of deploying the model on a unit of Dubrovnik hydropower plant are presented. The model's low latency, providing outputs in a few milliseconds, enabled its full integration into the existing infrastructure for real-time monitoring and predictive alerting.

It's important to note that these warnings for the early fault detection system differ from conventional alarms and thresholds based on standards for monitoring and protection. The color warnings and alarms do not imply that there is an error or damage in the generator. For example, for Smax signals, the standard conventional alarms and thresholds in the monitoring system are compared with measured and predicted values in Figure 5. The results show that the behavior of unit is normal and well within safe limits. This method detects changes in behavior, compared to the normal historical data and helps in identifying and tracking any changes at early stages.

The results are sent to domain experts for further investigation of a possible root cause. In the following, the results of the models for Smax signals and PD +Qm signals are presented in detail.

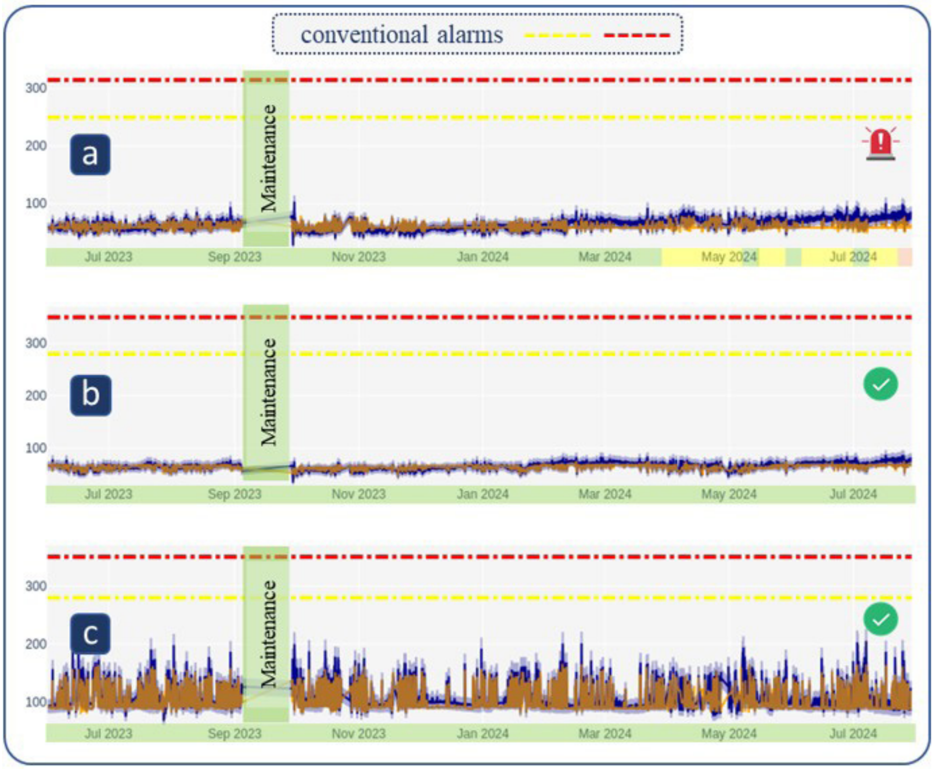

Figure 5 Comparison of Early Fault Detection Warnings with Conventional Alarms. a) Smax_1, b) Smax_2, c) Smax_3.
Slika 5. Usporedba ranih upozorenja na kvarove s konvencionalnim alarmima. a) Smax_1, b) Smax_2, c) Smax_3.

As discussed previously, this model is utilized for the prediction and analysis of Smax signals on all three guide bearings and also partial discharge.

Three levels of warning are defined in this system, green shows normal behavior, yellow shows medium warning and red shows what is considered as an abnormal behavior from the early fault detection system. These ranges help quantify the degree of deviation from the normal behavior.

5.1 Smax Behavior analysis

The analysis reveals that the model's outputs for Smax signals 1 and 3 align with the historical data, that indicate normal behavior of the system. To make the analysis of the results easier, in addition to the defined safe band for the residual signal, the same safe range around the main signal has also been displayed. In the results, the blue band is defined as the safe band around the measured value. This band

is calculated based on the signal behavior during normal periods in the training step. The results show that the model’s outputs, for Smax_2 and Smax_3 are normal, and the system's behavior closely aligns with historical data, indicating normal operation. The results are presented in Figure 6.
The results of the model for Smax_1 signal are presented in Figure 7 and indicate abnormality in certain parts of the data. These alarms are reported by the monitoring system and are sent to domain experts for further analysis. The absolute difference between predicted values and measured values is named as a residual value in section 'd' of Figure 7. These bands are calculated based on residual values

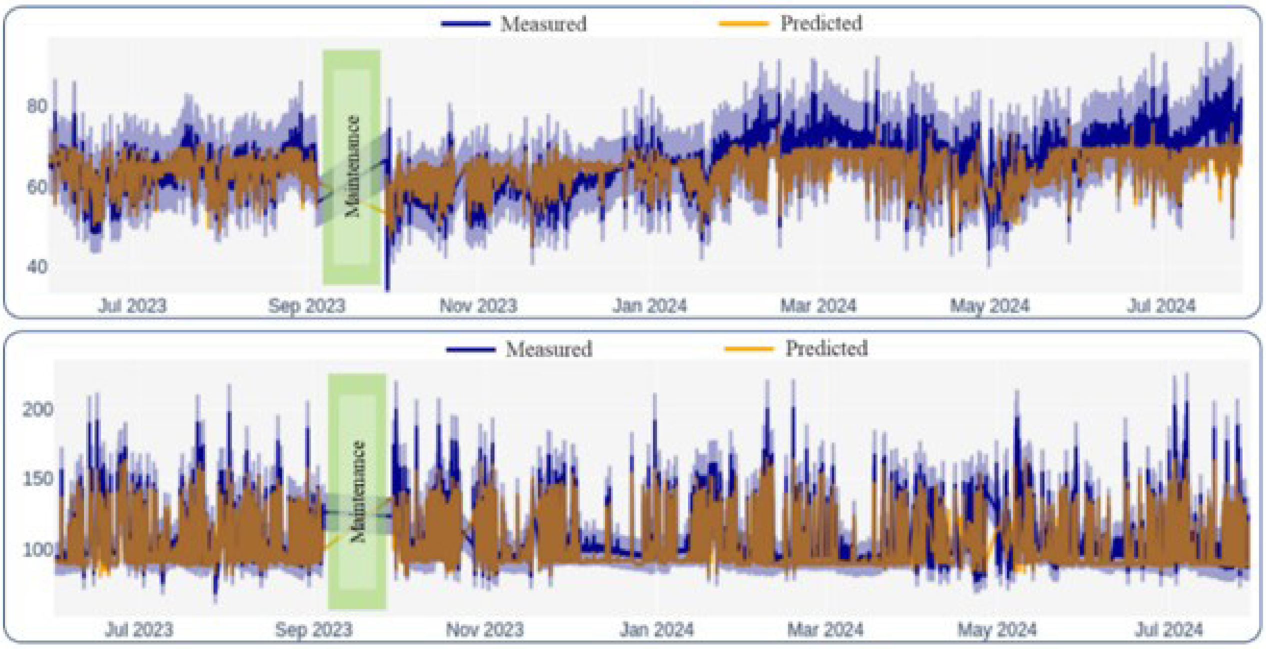

Figure 6: Normal behavior of the Unit: a) Smax_2, b) Smax_3.
Slika 6. Normalno ponašanje agregata: a) Smax_2, b) Smax_3.

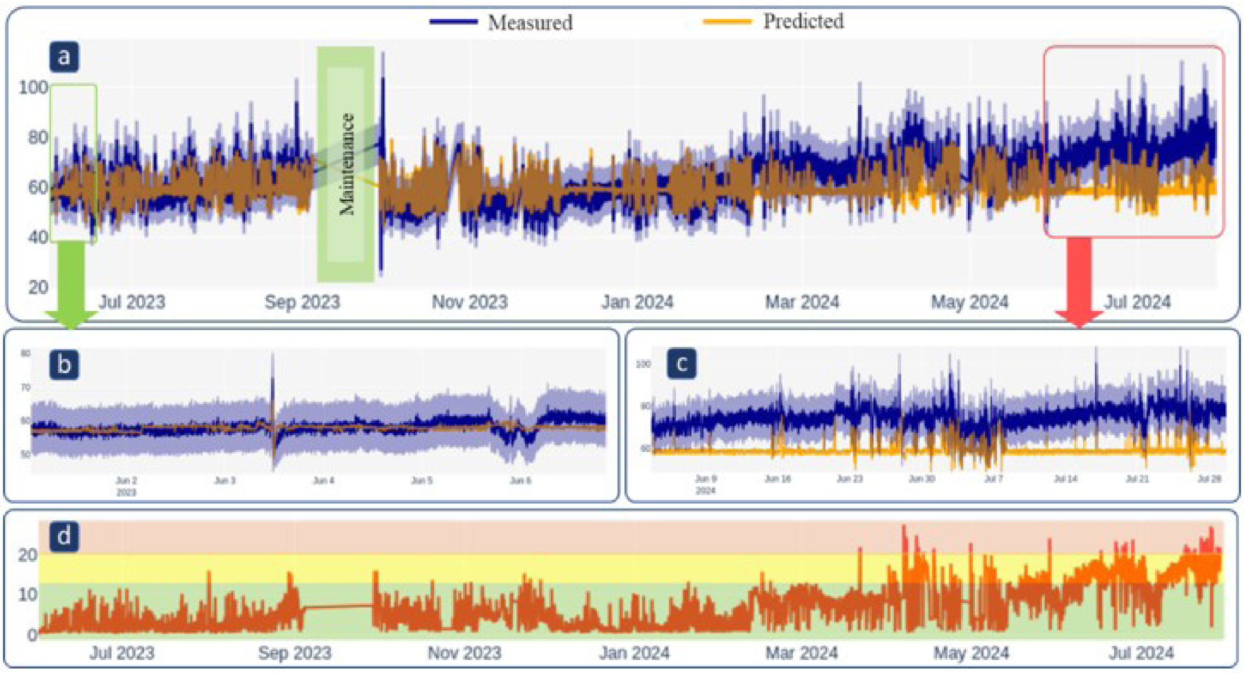

Figure 7 Abnormal behavior of the Smax_1: a) Overview. b) Normal behavior. c) Abnormal behavior. d) Residual values with warning levels.
Slika 7. Nenormalno ponašanje Smax_1: a) Pregled. b) Normalno ponašanje. c) Nenormalno ponašanje. d) Rezidualne vrijednosti s razinama upozorenja.

observed during the system's normal behavior in the training step. When this residual value remains within a predefined green band the hydrogenator is considered to be operating normally.

As depicted in Figure 7b, the system's output remains within this safe range. However, towards the end, as illustrated in Figure 7c, the output exceeds the predefined band and requires further investigation by domain experts. According to Figure 7d, this trend is also evident in the residual values, which represent the absolute difference between the predicted and actual values. It should be mentioned that the trained model discussed in this research for Smax signal is exclusively used in operational mode. In this mode, the model performs satisfactorily, achieving the desired accuracy in output predictions.

5.2 Partial discharge behavior analysis

The test results for the PD +Qm on phase B signal show that it initially exhibited normal behavior, similar to the trained normal data. However, over time, it slightly deviated from the ideal state, triggering a yellow warning in the early fault detection system.

As seen in the results, the warning level in the second signal is higher, and these findings are sent to domain experts for further analysis. The stator core and stator winding temperature signals are shown in Figure 10. The measurements indicate a gradual temperature increase and a correlation with the outcomes obtained from the ML model.

6. Conclusion

The implementation and analysis of the machine learning-based CBM system at the Dubrovnik hydropower plant in Croatia show that this method works effectively. This method allows for the identification of potential system errors and issues earlier than traditional systems and before reaching predetermined limits and conventional alarms.

This model, in addition to Smax signals and PD +Qm signals, can be used for the analysis of other outputs and signals of the system, and finally, by merging these models, a more reliable system can be achieved.

However, there are some challenges. This approach requires deep knowledge to correctly identify what counts as normal or abnormal behavior during the training phase and It's important to handle errors and avoid training the model with abnormal data.

As mentioned earlier, this research uses a data-driven model. In the future, this could be improved by using hybrid models that combine data-driven and physical approaches. This would help keep the model accurate during both steady and changing conditions, predict more outputs, and improve how data is combined in the end. Overall, this work is a meaningful step toward better data analysis and moves us closer to building a digital twin of the system.

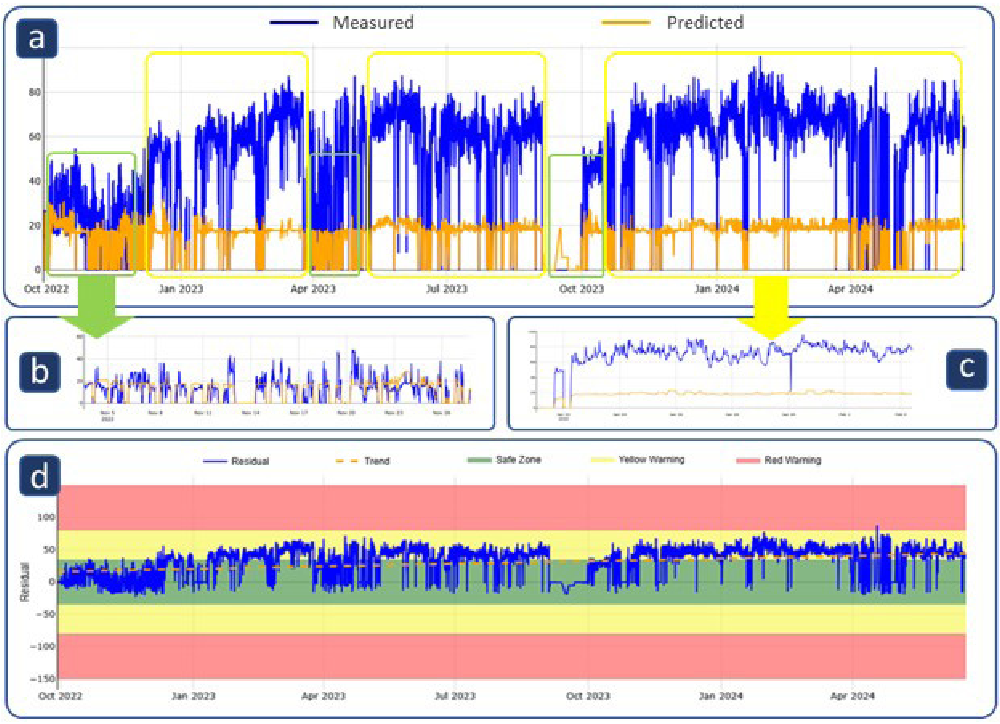

Figure 8 Behavior of first PD signal a) Overview, b) Normal behavior, c) Yellow warning, d) Residual values
Slika 8. Ponašanje prvog PD signala: a) Pregled, b) Normalno ponašanje, c) Žuto upozorenje, d) Rezidualne vrijednosti

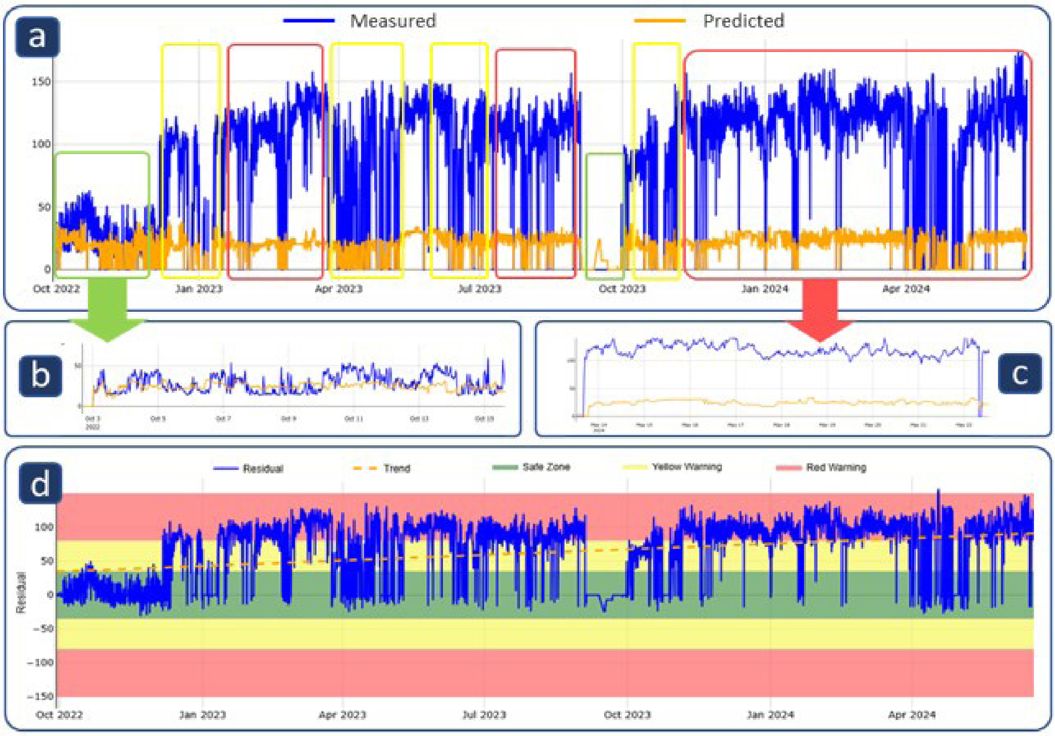

Figure 9 Behavior of second PD signal a) Overview, b) Normal behavior, c) Yellow warning, d) Residual values

Slika 9. Ponašanje drugog PD signala: a) Pregled, b) Normalno ponašanje, c) Žuto upozorenje, d) Rezidual

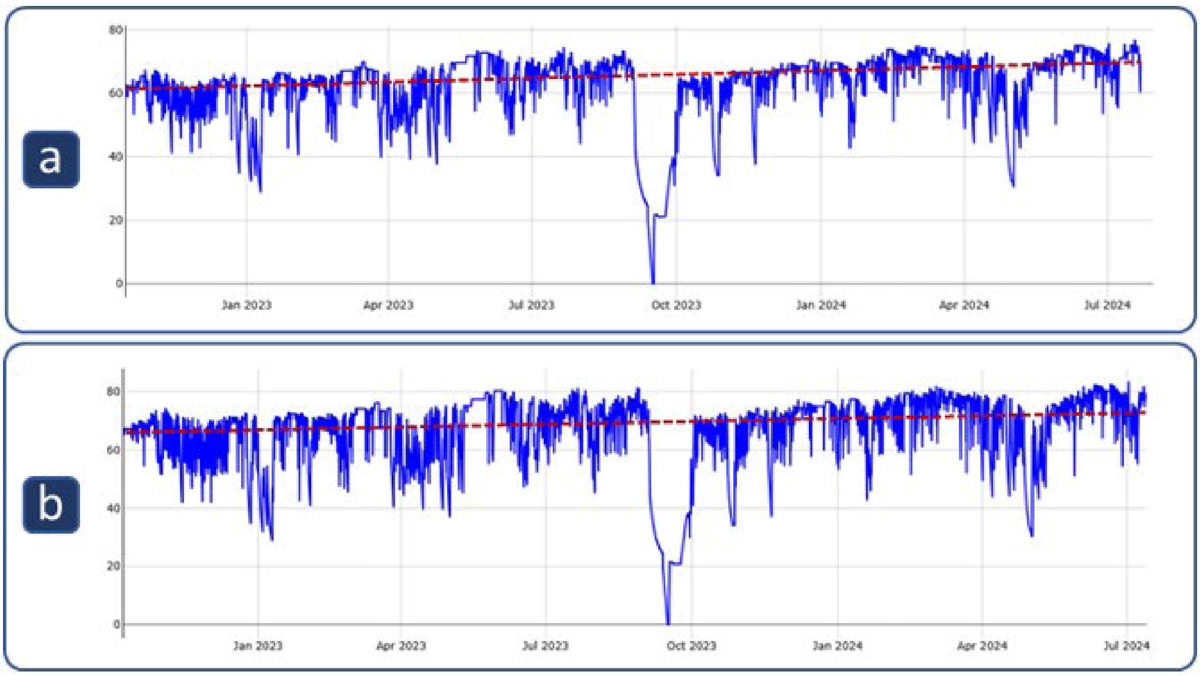

Figure 10 a) Temperature of stator core, b) Temperature of stator winding

Slika 10. a) Temperatura jezgre statora, b) Temperatura namota statora

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