22nd International Conference on Renewable Energies and Power Quality (ICREPQ'24)
Bilbao (Spain), 26th to 28th June 2024
*Renewable Energy and Power Quality Journal* (RE&PQJ)
ISSN 2172-038 X, Volume No.22, September 2024

# E-maintenance in hydropower energy generation: A case study of Enel Colombia

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**Abstract.** Traditionally, maintenance in the hydropower industry has been a labour-intensive and time-consuming process. It often relies on scheduled inspections and manual intervention. E-maintenance in hydropower plants can help to address this challenge by allowing remote monitoring and control of plant equipment, enabling timely detection and diagnosis of potential problems. This paper presents a case study of the implementation of an e-maintenance strategy for hydropower infrastructure at one of the largest generation companies in the Colombian electricity market. A machine learning model, implemented by Enel Colombia, is fed with recorded data on turbine bearing temperature and active power generation to predict problems in hydropower generators. The results show how e-maintenance can reduce operating costs and avoid breakdowns in hydro generation.

**Key words.** E-maintenance, Hydro unit generator, Hydropower energy generation, Machine learning.

## 1. Introduction

The use of hydropower as a sustainable and clean energy source has been a fundamental aspect of global efforts to reduce carbon emissions and combat climate change. Currently, it generates more electricity than all other renewable technologies combined **[1]**. Hydropower generation not only provides a reliable source of electricity but also offers the flexibility necessary to balance the intermittent nature of renewable energy sources like wind and solar **[2] [3]**. However, ensuring the long-term viability and optimal energy production of hydroelectric power plants is essential. In the digital age, cutting-edge technologies have paved the way for a transformative approach known as 'e-maintenance'. This approach leverages the power of data analytics, remote sensing, and automation to revolutionize the management of hydropower energy generation facilities **[4] [5]**.

Traditionally, maintenance in the hydroelectric industry has been a labour-intensive and time-consuming process, often relying on scheduled inspections and manual interventions **[6]**. Moreover, the maintenance of these plants, particularly in the context of integrating renewable energies, presents a range of challenges that need to be addressed. One of the main challenges in maintaining hydropower plants with renewable energy integration is the need to ensure their reliable operation **[7]**. This is an important aspect considering the intermittent nature of renewable energy sources.

E-maintenance in hydropower plants can help address this challenge by allowing for remote monitoring and control of plant equipment, enabling timely detection and diagnosis of potential issues. Remote monitoring and control systems can also allow for preventive maintenance, reducing the risk of unexpected failures and extending the lifetime of the plant.

Furthermore, e-maintenance also can help to optimize maintenance planning, allowing for efficient scheduling of maintenance activities that minimize the loss of profit during maintenance periods by predictive and proactive maintenance strategies. In addition, the non-linear and complicated nature of hydropower-generating units requires a comprehensive condition monitoring system to effectively monitor and supervise these units **[8]**. This condition monitoring system is crucial for reducing fault development, minimizing unnecessary malfunctions, and meeting the increasing demands of functional and maintenance requirements in the hydroelectric industry.

The advent of advanced sensors, Internet of Things (IoT) devices, and real-time data analytics tools has opened new possibilities for monitoring the condition of hydropower plants in real-time. E-maintenance integrates these technologies into a comprehensive framework, allowing for continuous data collection, analysis, and the generation of actionable insights. This enables plant operators to detect anomalies, predict potential failures, and schedule maintenance activities with precision, ultimately leading to increased operational efficiency, reduced downtime, and significant cost savings.

According to IEA, Colombia enjoys a strong natural resource base. Renewable accounted for more than a third of total energy consumption in 2020, thanks to the significant role of hydropower generation. In 2021, renewable energy accounted for 25% of total energy supply in Colombia and for 29% of final consumption **[9]**. However, in recent years, the Colombian electricity system has embarked on an ambitious journey towards energy transition. With the goal of transforming the energy matrix and embracing sustainability, this process has presented numerous challenges that force generation companies to introduce technological innovations in their processes. Moreover, it also offers unprecedented opportunities for the country considering that about 67% of the electric energy comes from hydropower generation.

In this paper, we present a case study of the implementation of the e-maintenance strategy for the hydropower generation infrastructure within one of the major generation companies in the Colombian electricity market. Through this case study and concrete examples of e-maintenance processes and e-maintenance system inputs and outputs, we aim to illustrate the transformative potential of e-maintenance in optimising hydropower generator performance, improving reliability and contributing to the sustainability of the energy infrastructure. More specifically, we present the following contributions:

1) The e-maintenance concept used by Enel Colombia and the architecture of its system.

2) The analysis developed for a machine learning model implemented by Enel Colombia's to predict problems on hydro generators.

3) The predictive analysis applied to a hydro unit generator based on recorded data of its turbine bearing temperature and active power generation.

## 2. State of the Art on E-Maintenance for Hydropower Plant

Hydropower generation has played a critical role for many decades in the renewable energy landscape, providing clean, sustainable electrical energy as well as contributing to grid stability. However, the reliable and efficient operation of this type of plants requires increasingly effective maintenance strategies. In recent years, the integration of digital technologies and approaches based on the management of large amounts of data, collectively called "e-maintenance", has revolutionized the way maintenance is carried out in the generation industry, including hydroelectric. This state-of-the-art review explores the latest advances in e-maintenance for hydroelectric plants, focusing on the latest technological trends and their practical applications.

### A. Condition Monitoring and Sensors

Condition monitoring helps to track the health of any piece of equipment over its useful life. This strategy is carried out using sensors where can measure, in real time, different types of parameters. Sensor's technology and data analytics helps to improve the condition monitoring for e-maintenance.

*Advanced Sensor Technology*: E-maintenance largely depends on the use of electronic sensors, IoT (Internet of Things) devices and their respective data management. These sensors are used to monitor the health of power equipment and the performance of critical components such as turbines, generators and bearings in the driving part. The latest advances in sensors include the use of fiber-optics, ultrasound, and wireless systems, which allow the management of data in real time and their communication between them with or without a physical connection, allowing greater understanding in the evaluations of their health status **[10]**. As for the IoT, this is considered one of the most important aspects of the digital era of the 21st century. It allows the connection of different measurement and operation devices to the Internet network. Its use in hydroelectric generation systems has achieved improvement in the storage and manipulation of large amounts of sensor data for their respective processing and subsequent preventive maintenance action **[11]**.

*Data based Analytic*: Integrating data from multiple sensors and sources is a hallmark of modern e-maintenance. Several techniques, including Machine learning and AI algorithms, are employed to analyse these data streams, identifying patterns, anomalies, and predictive failure indicators. This allows for the timely detection of issues and predictive maintenance planning **[11]-[12]**.

### B. Predictive Maintenance

Predictive maintenance is a technique that uses data analysis tools and techniques to detect anomalies in operation and possible defects in equipment and processes, so that they can be resolved before failure occurs.

*Prognostics and Health Management (PHM):* PHM techniques have gained importance in e-maintenance of hydropower systems. PHM combines data analytics with physics-based models to predict the remaining useful life of components. It allows operators to schedule maintenance precisely when needed, reducing downtime and minimizing costs **[13]**. These systems integrate advanced sensors with prognoses to monitor the health status of power equipment in real time, and through different techniques allow establishing the best moment to initiate review and maintenance actions, achieving an increase in lifetime of the equipment, and improving its reliability. The PHM system improves the application of condition-based maintenance (CBM).

*Predictive Analytic in Hydropower Plant Maintenance:* Predictive analytics in the context of hydropower plant maintenance has become increasingly precise, thanks to the wealth of historical operational data at our disposal. These data-driven predictive models serve a crucial role in forecasting equipment failures, estimating maintenance expenses, and optimizing maintenance schedules, thereby enhancing overall plant availability **[12]**. Various strategies have been explored to address predictive maintenance in hydropower plants. In a comprehensive study by Afridi et al. **[14]**, the authors conduct an in-depth review of artificial intelligence techniques applied to predictive maintenance in renewable energy systems. The review categorizes these techniques into four main groups of machine learning (ML) algorithms:

1) Classical Algorithms
2) Fuzzy Logic-Based Methods
3) Hidden Markov Models
4) Neural Networks

These diverse approaches all share the common goal of predicting future equipment failures based on labelled datasets, historical time series data comprising multiple variables, or even image datasets. The suitability of each approach is contingent on the specific nature of the maintenance problem they address, whether it involves classification, generative machine learning, or image analysis.

Furthermore, some researchers have proposed improved input indicators to enhance the accuracy of predictive maintenance. For instance, in a study by Betti et al. **[15]**, the authors delve into the concept of condition-based monitoring, introducing a novel key performance indicator. Their findings demonstrate that this new indicator outperforms traditional multi-variable monitoring approaches, indicating a promising avenue for more effective maintenance strategies in hydropower plants.

### C. Remote Monitoring and Control

E-maintenance allows for remote monitoring and control of hydropower plants. The e-maintenance does not control the plants only monitoring. Operators can access real-time data and remotely manipulate equipment, reducing the need for on-site personnel and improving safety in hazardous environments **[11]**. This is considered a potential improvement in maintenance types and strategies, due to the possibility of having expertise centres located far from the plants, reducing the costs derived from having those personnel in the hydropower plants.

### D. Digital Twins

The concept of digital twins has garnered significant attention in the field of e-maintenance. By creating digital replicas of physical assets, operators can simulate various operational scenarios, evaluate the impact of maintenance decisions, and optimize plant performance **[12]**. These digital replicas span across diverse domains, including civil infrastructure, as exemplified by dam digital twins **[16]**, as well as various equipment types, such as wind turbines **[17]**, and hydropower generators. Machine learning techniques have also been explored within the context of digital twins **[17]**.

### E. Cybersecurity

Securing Data and Infrastructure: As e-maintenance relies on digital connectivity and data exchange, cybersecurity is essential. The state of the art includes robust cybersecurity measures, encryption protocols, and intrusion detection systems to safeguard critical infrastructure from cyber threats **[18]**.

## 3. E-maintenance process

The digital maintenance process developed by Enel Colombia involves different work teams that combine information technologies with human resources. Among these technologies, the processing and visualization of a large volume of data and real-time measurements stand out. However, the greatest added value in the whole process is provided by the people involved through their knowledge and experience of the electricity generation processes. Figure **1** shows the e-maintenance diagram, which is explained below.

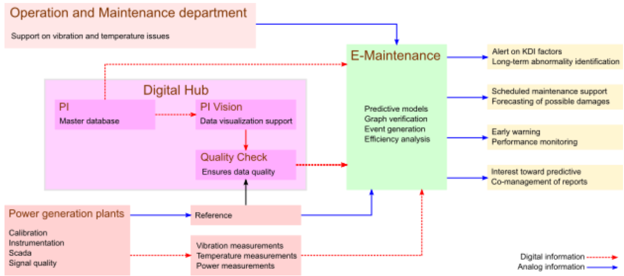

Fig. 1. Enel Colombia's e-maintenance process diagram

### A. Operation and Maintenance department

It comprises the work group that provides technical support in the mechanical, electrical, and control issues to identify if the measurements are adequate and in consequence warning signals are correct. At this stage, it is important experience and knowledge of the work team in addition to the knowledge of the power generation process. That is, the team can identify, for example, if the oil temperature behaviour of a certain equipment is adequate for that equipment.

### B. Digital Hub

This working group is charged with the systems' basic components, which are: recording, storing, and analysing data, ending with visualizing the data.

*1) Recording data:* To maintain proper system functionality, continuous monitoring is necessary to identify any potential failures or errors. For this, it is necessary to record the parameters of the asset by using monitoring sensors that are connected to a Supervisory Control and Data Acquisition (SCADA) system. The data recorder includes electrical and mechanical variables such as voltage, current, active power, reactive power, temperature, electrical frequency, rotational speed, and switch position.

*2) Storing and analysing data:* The accuracy of failure predictions in a predictive system relies on relevant, sufficient, and high-quality data sources. For predictive maintenance, such data sources include maintenance historical records, operational data, and metadata for monitored assets. Maintenance historical records contain information about repair activities, replaced components, and experiences of failure. These events expose degradation patterns and serve as crucial data for developing an effective predictive model.

Also, it is necessary to check the accuracy of the data, that they correspond to the correct format, and that they are taken in the correct time window. This task is done by the Quality check group.

The data are then placed in an internal cloud where they can be consulted, making it possible to trace the historical behaviour of each of the parameters of the generation units and thus analyse their behaviour. That is, if any variable changes its behaviour gradually, it is possible to detect it by comparing it with the historical data stored in the cloud.

*C. Power generation plant*

On the other hand, the automation of all generation units by a system for SCADA allows measurements and data capture in real-time, these data may include variables such as vibrations, temperature, and power. These data are sent to the e-maintenance application.

*D. E-Maintenance*

It is a digital platform applied to predictive maintenance that uses algorithms with artificial intelligence and Machine Learning. The system monitors and analyses data from the generation units to predict their behaviour and anticipate critical problems or increase performance through predictive models related to the damages produced in the generation units.

Using the stored historical process data, it is possible to develop predictive statistical models. These statistical models predict the ideal values of the variables of the generation units from the real-time measurement data by comparing them with the statistical models for the normal operating state of the units.

The statistical models identify possible abnormal conditions and trigger alarms, therefore a reliable and extended historical database is required to properly "train" the models on all possible operating conditions of the generating units.

## 4. E-maintenance system architecture

Creating a computational infrastructure to gather and analyse data from several power generators across geographically scattered sites is a major challenge. Engineers must consider, at each site, the monitoring infrastructure, the communication infrastructure, the cost of training and maintaining predictive models, the computational infrastructure, and the availability of knowledgeable human resources. To address these challenges, we propose a globally interconnected architecture structured in layers.

Figure 2 depicts the main components of the proposed architecture. In the first layer, at the bottom of the figure, we have a set of sensors connected to the electric generation infrastructure (i.e., hydropower generators, solar generators, or wind turbines). Those sensors send information signals to Programmable Logic Controllers (PLC) that communicate with SCADA systems. Those SCADA systems serve as control systems and data acquisition components. The SCADA systems are connected to country/regional on-premises data centers through an Operational Network. The on-premises clusters serve as local data storage and analytical facilities. Local control rooms are also connected to the whole system through the operational network. There, in the data centers, local engineers monitor the power generating systems and the current state of operation. The results of predictive analyses are also presented in the control rooms for local engineers to take the corresponding actions.

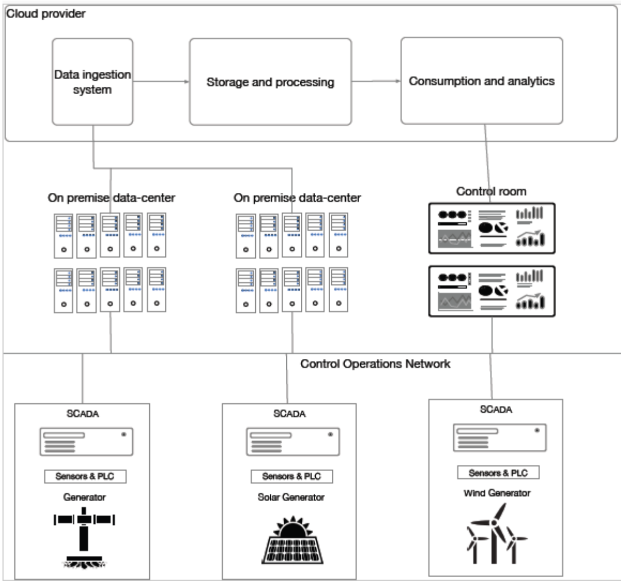


Fig 2. General architecture of data analytic system

The third layer, the top layer in the figure, depicts the global data analysis infrastructure where the trained models gather data and predict maintenance events. First, the data ingestion system gathers information from several generating sites in different countries across the world, cleaning the raw data and preparing it for analysis. Then, the Storage and Processing Facilities input the data into predictive intelligent models that generate alerts when maintenance events are detected. The results are finally prepared and presented to final users across the company. All the infrastructure is deployed and maintained in the cloud.

## 5. Results

This section presents the results of the e-maintenance system implemented to monitor hydropower unit generation. The focus is on analysing data related to bearing oil temperature, bearing metal temperature, and active power to support predictive maintenance.

*A. Bearing temperature*

Monitoring the temperature of bearings in a hydroelectric unit is critical to identifying potential problems and is an important part of overall plant e-maintenance, it can be measured either by means of oil or by means of metal. Figure 3 shows the temperature behaviour degrees Celsius of turbine bearing metal of hydro unit generator under analysis, where it can be noted two period, comparison, and analysis. During the comparison period, the temperature exhibited normal behaviour. In the analysis period, which began after January 2023, the turbine bearing metal exhibited the same pattern as before, and there was no abnormal behaviour.

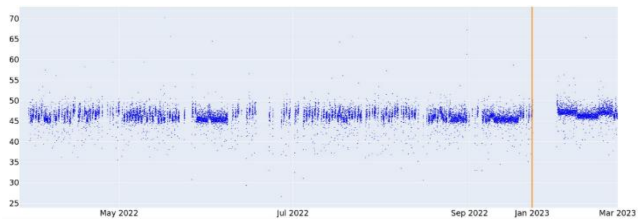


Fig 3. Behavior of turbine bearing metal temperature (°C) of hydro generation unit

Figure 4 displays the temperature behaviour in degrees Celsius of the turbine bearing oil of the hydro unit generator during the analysis and comparison periods. It is worth noting that the bearing oil temperature exhibited deviations from the normal operating temperature range during the analysis period. An anomaly was observed, indicating a potential issue that requires attention.

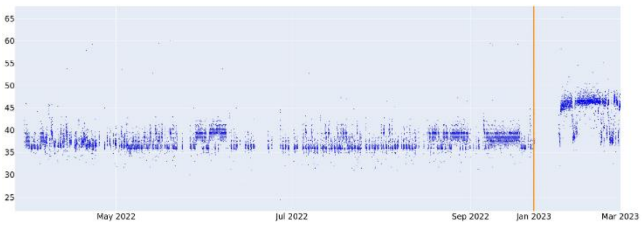


Fig 4. Behavior of turbine bearing oil temperature (°C) of hydro generation unit

### B. *Active Power*

Active power monitoring helps to evaluate the electrical performance of the hydro unit generator. Figure 5 presents an example of active power monitoring. In this case, the behaviour of active power depends on the available water resources. Normal behaviour was observed during the analysis period. This information allows for an analysis of whether the alarm triggered by the turbine bearing oil temperature aligns with the active power generated by the hydro generation unit.

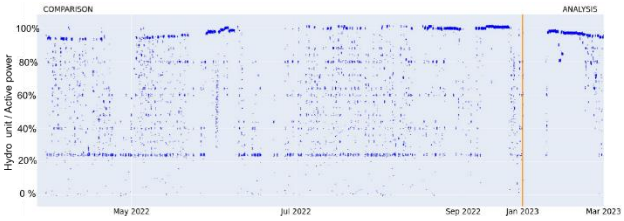


Fig 5. Recorded data of generator unit active power

### C. *Machine learning analysis*

The data provided for turbine bearing metal and oil temperatures, as well as active power generation, are used to feed the machine learning predictive model to analyse potential hydro generator operation issues. In this case, during the analysis period, the AI algorithm will provide a Key Diagnostic Index (KDI) of approximately 2.5, which indicates that an abnormal operation is taking place, as shown in Figure 6.

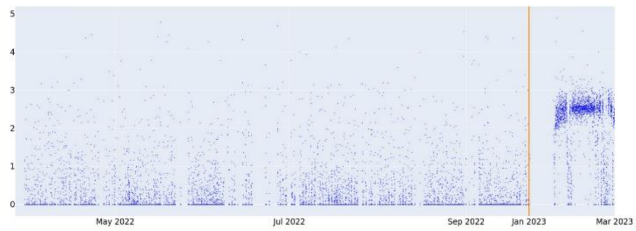


Fig 6. Hydro generator unit index KDI behaviour

### D. *Correlation analysis*

Data correlation makes it possible to analyse how a set of data relates to the behaviour of the hydroelectric unit to predict possible abnormal operation of the unit.

Figure 7 shows the comparison and analysis of the correlation between the data of the active power generated and the temperature of the metal in the turbine bearings of the hydro generating unit. From the analysis it can be noted that the behaviour of the metal temperature of the bearings is within the values corresponding to the power delivered by the unit, so the metal does not present any anomaly in this case.

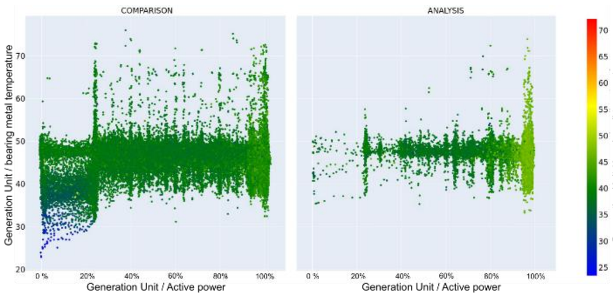


Fig 7. Data correlation between active power generated and metal bearing temperature (°C) of hydro unit generator

The correlation between active power data and turbine bearing temperature is shown in Figure 8. As the generating unit approaches 100% of its generation, the oil temperature tends to be above its operating range. This is an indication of a deterioration in the physico-chemical conditions of the oil and a decrease in its cooling capacity, which can cause deterioration of the bearing metal.

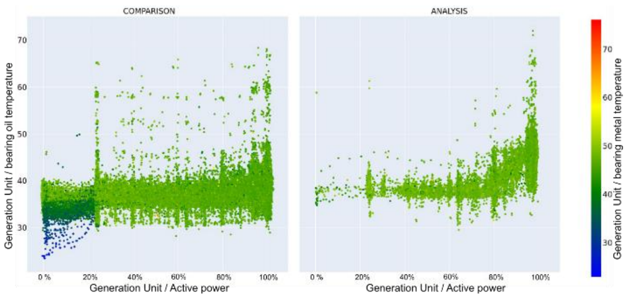


Fig 8. Data correlation between active power generated and oil-bearing temperature (°C) of hydro generator unit

The previous analysis is supported by the correlation of the turbine bearing oil and metal temperature data, as shown in Figure 9. Note how the oil temperature approaches 70 degrees Celsius, confirming possible deterioration of the oil.

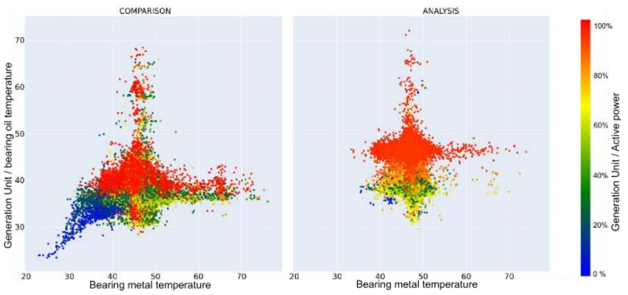

Fig 9. Data correlation between metal bearing and oil-bearing temperatures of hydro generator unit

## 6. Conclusion

The e-maintenance system proved its effectiveness in improving the overall reliability and performance of the hydropower plants. By continuously monitoring turbine bearing temperatures and active power, the system enabled early detection and mitigation of potential issues, minimising downtime, and avoiding costly repairs.

In conclusion, the implementation of e-maintenance in hydropower plants has proven to be a valuable tool for ensuring optimal operational efficiency and preventing unexpected failures. The examples and figures presented highlight the system's ability to detect anomalies in temperature data, and active power, facilitating timely intervention and ultimately contributing to the long-term sustainability of the hydropower infrastructure.

## Acknowledgement

This work was partially funded through the project "Transformación digital de las centrales de generación renovables de EMGESA para el incremento de la confiabilidad y eficiencia de los procesos de operación, mantenimiento y gestión en el marco de la transición y sostenibilidad energética del país" registered in the Colombian Ministry of Science, Technology and Innovation with number 87737.

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