Efficiency Monitoring of a Cooling Water Pump based on Machine Learning Techniques.

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ABSTRACT

This paper presents a method for efficiency monitoring of two circulating water pumps working in a combined cycle power plant for cooling the steam coming from a water-steam turbine. The method is based on monitoring the performance of the pumps over time using machine learning techniques that try to discover patterns in the data observed from the pumps. This permits the maintenance staff to assess the possible degradation of the pumps and evaluate the effect of the corrective and preventive maintenance implemented. Some examples of real cases will be presented in the paper to illustrate the method proposed.

1. INTRODUCTION

Detection of the performance degradation of any industrial component is a crucial point to keep the quality of service and operation as expected. The anomaly detection as soon as possible with respect to the expected normal performance is a key knowledge for application of a data-driven, efficient prognostics and health management program (PHM) as is inferred from references (Zio, 2022), (Maior, Araújo, Lins, Moura &. Droguett, 2023), (Chavan & Yalagi, 2023) , (Ochella, Shafiee & Dinmohammadi, 2021), (Nassif, Talib, Nasir & Dakalbab, 2021), and (Calvo-Bascones, Sanz-Bobi & Welte, 2021). These references are based on machine learning techniques as the main tools to reach their PHM objectives. They have been applied to discover patterns from data on the pump performances. When the patterns observed are different from those observed in previous periods of time, it can suggest a degradation in their performance. However an intelligent connection guiding the methods of degradation detection and connecting with maintenance strategies has not been explored intensively in the current state-of-the art. There is no doubt that the development of advanced maintenance techniques, such as condition-based maintenance (CBM) and predictive maintenance (PdM), has led to significant improvements in the health monitoring of industrial components (Moleda, Małysiak-Mrozek, Ding, Sunderam & Mrozek,D. 2023). These techniques employ real-time data and advanced algorithms to predict failures and schedule interventions before critical breakdowns occur. Nevertheless, despite these developments, evaluating the actual effectiveness of maintenance actions remains a challenge. Currently, numerous existing methods do not provide an accurate quantitative assessment of the impact of maintenance on equipment health, limiting their ability to optimize resources and improve system reliability and availability (Sinha, 2015) and (Liu, Balieu & Kringos, 2022). A review of the literature on maintenance effectiveness reveals that, despite the multitude of methodologies that have been proposed, many of them have not demonstrated efficacy in real-world applications. This is primarily due to oversimplifications and a lack of consideration of key factors in certain operating conditions (Costa & Cavalcante, 2022). Furthermore, communication and collaboration between operational and maintenance departments are often insufficient or non-existent, which can result in a lack of coordination and suboptimal decision-making. Thus, in this context, there is a clear necessity to develop more robust and applicable methods that can accurately and practically evaluate maintenance effectiveness (Bengtsson & Lundström, 2018). One recent review of the state-of-the-art application of machine learning methods to water pumps can be found in (Sunal, Dyo & Velisavljevic, 2022). The most part of the existing publications in this review are oriented toward detecting particular types of failure modes. Even

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though these methods obtain promising results, there are a few, for example (Orhan, 2024), oriented to monitoring and anomaly detection of the efficiency of circulating water pumps of power plants, and this paper tries to contribute to covering the gap in this point. This paper has two main contributions to the current state-of-the-art. The first one is the development of a method based on machine learning techniques for automated continuous monitoring of the health degradation of a hydraulic pump that supplies essential information about its condition to the maintenance staff. The second contribution, which is more difficult to find in scientific literature, is the evaluation of the effect of maintenance applied in the condition of the pump. Information for the maintenance crew about whether the maintenance carried out by external companies improves the condition of a component treated or not does not exist in most industries. The maintenance is accepted as correctly applied, and usually, there are no instruments about the quality of the work in the context of the life of the component. Usually, after maintenance, if everything is working, it is accepted that the maintenance was effective; how much is not discussed, and this is the core of the second main contribution of this paper. The method used for its development and the results obtained are presented with a real case.

The paper is organized as follows: Section 2 describes the foundations of the study. Section 3 shows the application of the method used. Finally, Section 4 presents the more relevant conclusions reached.

2. FOUNDATIONS OF THE METHOD PROPOSED

The methodology proposed tries to cover the following objectives:

- Characterization of the behavior curve of the water pumps by the power-flow curves observed.
- Characterization of performance patterns of the pumps over time, with the use of Machine Learning techniques.
- Detection of anomalies or degradation of the behavior expected for the different working conditions of the pumps.
- Study of the effects of maintenance on the operation of water pumps. The idea is to evaluate how maintenance actions affect the operation of the water pumps and their efficiency. This will make it possible to suggest recommendations for a better efficient operation of water pumps and the early identification of performance degradation.

To achieve all these objectives, a set of tasks was developed as part of the methodology implemented and presented in Figure 1. The methodology proposed is based on previous experiences of the authors such as those published in (Calvo-Báscones, Sanz-Bobi & Welte, 2021) and (Calvo-Báscones, Sanz-Bobi, Brighenti & Ricatto, 2020). First, the behavior of the circulation water pumps was analyzed with data on their performance (Bowman & Bowman, 2021). These two circulation water pumps are in operation in a power combined cycle plant. This plant consists of two combined cycles, each with a steam turbine and two gas turbines. A circulation water pump is a hydraulic pump that takes water from a source and impulses it through a set of pipes to cool the steam coming from the water-steam cycle of a combined cycle plant. The water is moving thanks to the conversion of the electrical energy coming from an electrical motor to mechanical energy by a set of coupled axes and drive blades. The electricity used is converted into water flow and pressure at the output of the pump. The efficiency of the pump relates the consumption of electrical energy with the mechanical energy used for the water circulation (HI, 2013). The correct operation of these pumps is essential for the efficiency of the water-steam cycle of the power plant.

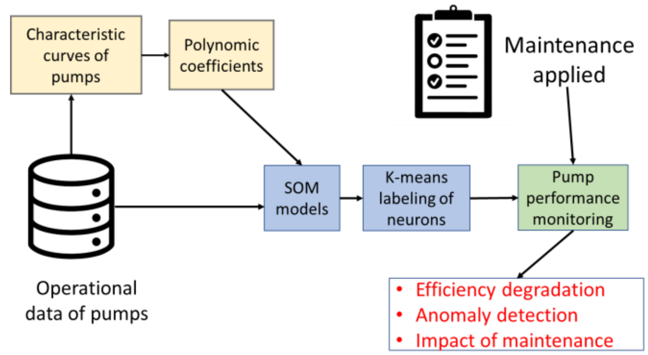

Figure 1. Information flow of the methodology implemented.

The data used for the analysis of the two water pumps includes information on pressure, flow, and current, variables that give an idea of the pump efficiency. This data spans from 2020 to early 2024, with records taken every ten minutes.

A preliminary analysis of the behavior of the water pumps was carried out, which consisted of obtaining their characteristic curves (flow-pressure) over time. At this point, outliers and incorrect measurements were removed.

Using data from the first week that it was available, a characteristic curve was constructed for each pump by a polynomic approximation of the optimal degree. The data used were selected taking into consideration all the working conditions of the pumps. Using the same degree, a polynomic approximation was used to fit the performance curves for the following weeks. By maintaining the same polynomial degree, it is possible to observe if there have really been variations between weeks.

Next, a pattern-discovery strategy was applied using machine learning techniques to create a model able to synthesize the behavior of the water pumps and detect any anomaly or potential degradation. The model developed is based on self-organizing maps (SOM) (Bonaccorso, 2018).

A SOM is a neural network model that maps multi-dimensional input data into a low-dimensional space represented by a number of neurons. The SOM is defined by a set of nodes or neurons that cover the input space of examples in such a way that its information is clustered through the nodes of which the weights represent a pattern of the examples observed after training. The values of the node weights are adjusted during the network training phase using an unsupervised learning algorithm.

The result is that input data that show similar characteristics among them are clustered together and a representative pattern or profile of data inputs is assigned to each cluster through the neuron weights. Thus, data are represented by a finite set of nodes of which the weights are the centers of the clusters found in the examples by the training algorithm. Furthermore, it is a general fact that the SOM training algorithm adjusts the node weights in such a way that neurons will be more concentrated in those areas of the input space with higher density. Each neuron contains all the input data that are clustered around its weights according to their similarity. Each cluster represents a pattern of information.

The SOM model developed is able to create patterns of power, flow, and currents observed in different neurons and calculate the average performance for each of them. The data has been segmented both annually and monthly, and the developed model was applied to each of these time periods.

The SOM model permits the analysis of the pump behaviors over time, and in order to robust its benefits, two different versions of this model were created. The first version uses the values of pressure, flow, and average current of the pump as inputs to the model. The second method additionally includes as input the coefficients of the characteristic curves already obtained.

Furthermore, to correctly compare the performance and efficiency of the water pumps between different time intervals, a reference time has been defined in each case. This reference time corresponds to the first year in the annual study and the first month of the first year in the monthly pump study.

The neuron weights of the SOM were labeled according to the performance within they represent using a K-means algorithm that suggested a number of clusters (Bonaccorso, 2018). These clusters correspond to levels of performance.

The temporal evolution of the percentage of neurons corresponding to each performance group was studied and represented. This is a new and powerful method to observe how the efficiency of the pumps is evolving over time, identifying periods of better or worse performance that can suggest rescheduling the planned maintenance and observing the effectiveness of the maintenance applied.

Finally, the evolutions of the pump performances were complemented by the times when maintenance tasks were applied. The results are very important for the evaluation of how maintenance tasks impact the efficiency and performance of the pumps.

3. APPLICATION AND RESULTS

After a preprocessing procedure for cleaning the available data, the first step of the method implemented is the creation of a model by a polynomial approximation of the characteristic curves of the pumps based on the water flow and power measured. This step gives a quick overview of the pump life over time, which helps in the next steps of the method. The first complete week of clean data that is available and represents all the working conditions of the pumps was selected as the reference week. A polynomial model is fitted and the optimum degree is obtained. In both pumps, an optimum degree of 13 was the result. If, in the next weeks, the pump is working such as in the reference period, the coefficients obtained for the same polynomial degree should be of a similar value; if not, an unexpected change of performance could be present. As an example, Figure 2 shows some of the values observed of the coefficients over time, where each point corresponds to a week in the x-axis and its value in the y-axis. In this figure, it is observed that around week 150, all the coefficients have a dynamic lightly different than in previous weeks, alerting for possible degradation of the pump performance.

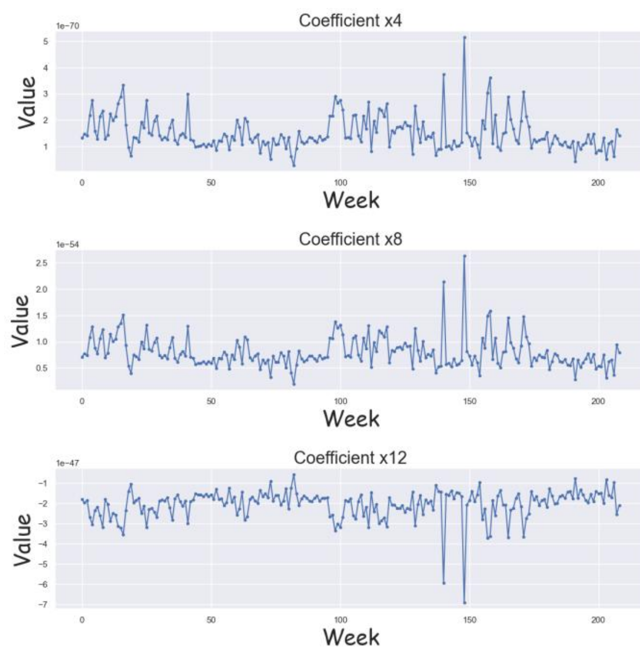

Figure 2. Evolution over time of some coefficients (x4, x8 and x12) obtained by the polynomial model.

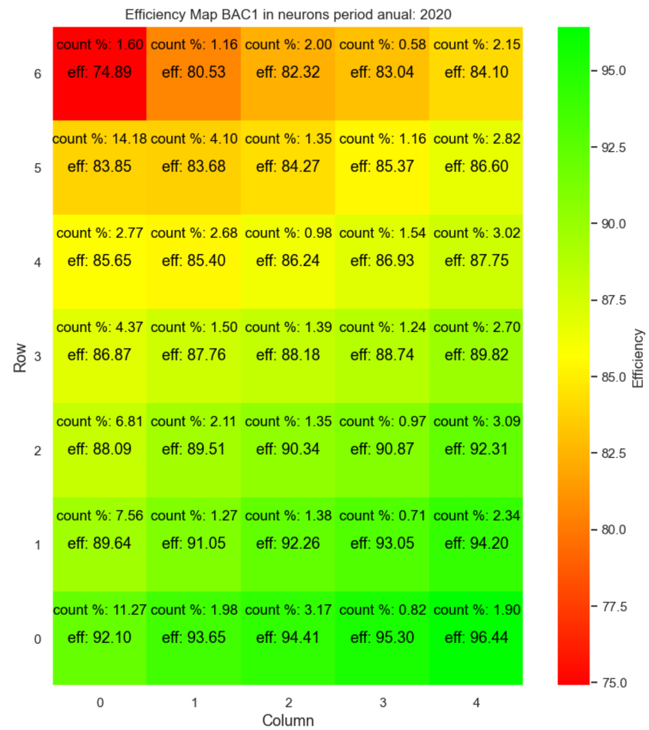

Figure 3. Evolution of the performance of the pump in the reference year.

The next step of the method implemented is the creation of two models to characterize the pump behaviors over time-based on machine learning techniques and, in particular, based on SOM. The objective of these models is the identification of patterns of performance and their evolution over time.

The models developed are similar, and the difference is in the inputs used. One model utilizes the variables observed power, flow, and average current data, while the second one also adds as inputs the coefficients of the characteristic curves already described. The first ones use a map of 7x5 neurons and the last ones are based on a map of 2x2 neurons. These architectures were defined after an iterative process of trial and test.

The models were created for annual and monthly periods of time. A reference period is always defined, enabling the measurement of changes in pump performance relative to this period.

After training the model for the reference year, the resulting model is presented in Figure 3. The terms Row and Column are used as indexes to refer in a unique way to any neuron in the figure. Each square corresponds to a neuron, and the legends inside each neuron correspond to the percentage of examples or cases falling into the neuron and, according to them, the average efficiency observed for the pump in each neuron. Also, each neuron has a color that corresponds to the degree of mean efficiency observed in the data that it covers. In Figure 3, the predominant color is green, which corresponds to high efficiency.

This representation can be extended to a monthly basis to observe how the colors of the neuron map are changing or not the colors, meaning there is a degradation or not in the pump behavior. Figures 4a and 4b show an example of two consecutive months where the green color is losing representation in Figure 4b, meaning a possible degradation in the pump performance.

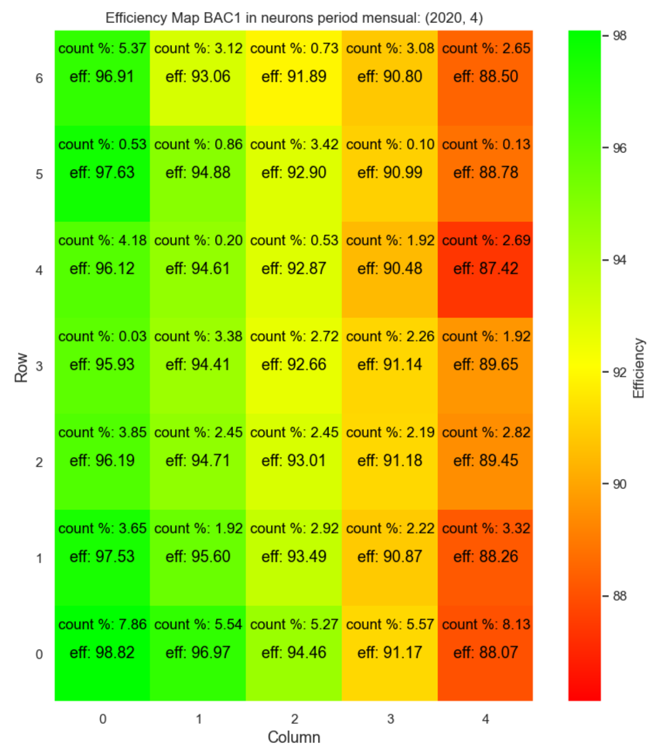

Figure 4a. Evolution of the performance of the pump in two consecutive months. Month I.

In order to improve the interpretation of the neuron maps, five categories or performance groups were proposed to qualify the efficiency observed on them for the pumps (very low, low moderate, good, and excellent). Figure 5 presents the monthly evolution of the percentage of these categories in the SOM map. It is interesting to observe an important pick on the left side of the figure corresponding to a poor efficiency of the pump and also other picks of excellent behavior in the right part of the figure. This information is valuable to qualify the general condition of the pump, and this can guide a rescheduling of the planned maintenance in the future. Another important benefit of the proposed method is the evaluation of the impact of the planned maintenance on the current condition of the pump. It is always supposed that after a maintenance intervention, the condition of the pump should be improved, but there are no precise instruments to evaluate this hypothesis. The method proposed here can help at this point because the qualification of the pump efficiency before and after maintenance can be observed.

Using results like those presented in Figures 3 and 4, it is possible to observe and measure how effective the maintenance applied was to the pump over time. The number of neurons with a particular type of label gives a good approximation of how effective the maintenance was. If the map of colors is the same as that observed before maintenance, the maintenance was not effective; and when the map obtained after maintenance is close to the best condition observed of the pump, the maintenance was more effective. If, after several maintenance cycles, the map does not change to the best condition observed, the pump is degraded, and therefore, it is possible to plan a replacement or to continue in the degraded state.

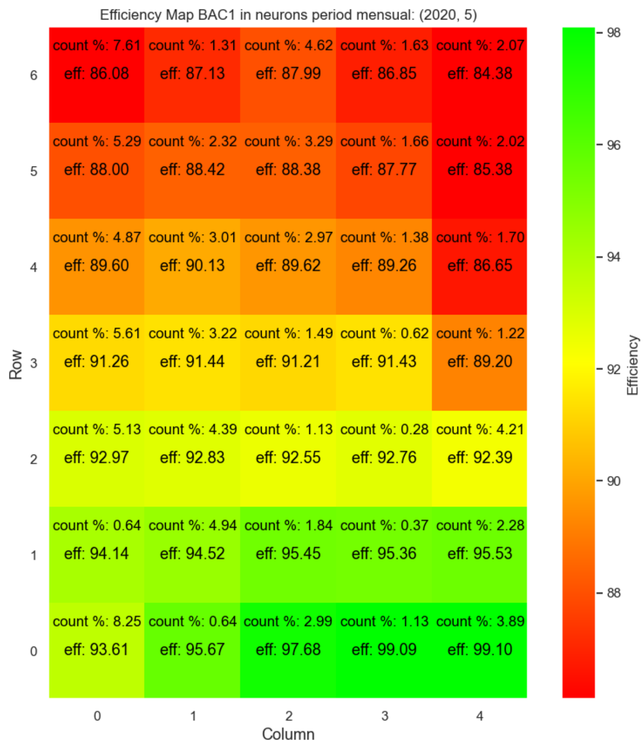

Figure 4b. Evolution of the performance of the pump in two consecutive months. Month II.

Also, Figure 5 includes in vertical lines the time when preventive maintenance was carried out in this pump. It is possible to observe the beneficial impact that maintenance had on the pump, removing the pick of poor performance on the left and keeping the picks of excellent performance after maintenance in the right part of the figure. Light deviation at times is due to the consideration of monthly performance against the exact date of maintenance carried out.

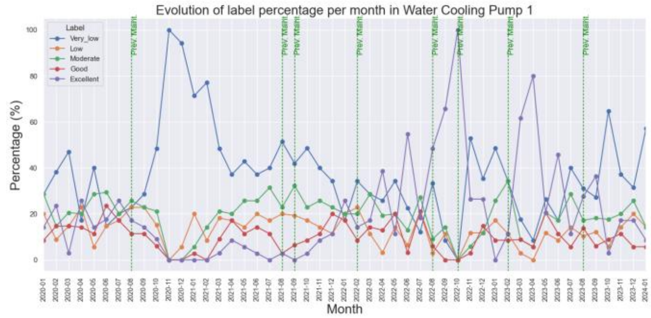

Figure 5. Evolution of quality labels of the monthly pump efficiency and dates of preventive maintenance carried out.

This allows to assert that this is a promising method to monitor the efficiency of the pumps and also the efficacy of the maintenance carried out on them. This is one of the contributions of this paper because the method permits the observation in a graphic and quantitative method of the performance of the pump during its life till maintenance and how it was after it, which is essential information for making the right decisions in maintenance.

4. CONCLUSIONS

This paper has proposed a new methodology based on machine learning techniques for continuous monitoring of the condition of two cooling water pumps belonging to a power plant. First, an analysis of polynomial coefficients for modeling the characteristic curves of the pumps was presented, being useful for a quick view of possible degradation of the pump performances. Once this was obtained, two Self-Organizing Models (SOM) were built to observe typical patterns of behavior of the pumps in their different working conditions. Using reference periods of time, the change in the map contents has been demonstrated to be a good indicator of the life evolution of the pumps over time. Different redundant perspectives were presented in the paper to give a better idea of the pump conditions. Finally, the effectiveness of the maintenance carried out on the pumps has been verified, being the method proposed not only useful for degradation of the pump behaviors, but also as a good tool to know how effective the maintenance was applied. This point opens a feasible way to reschedule the maintenance to be adapted to the moments when it is better to extend the lives of the pumps.

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