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Anomaly detection method based on the deep knowledge behind behavior patterns in industrial components. Application to a hydropower plant

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A B S T R A C T

This paper describes a new methodology that aims to cover a gap detected in the area of detection of anomalies and diagnosis of industrial component behaviors: there is a need of robust procedures compatible with dynamic behaviors and degradations that evolve over time. The method proposed is based on the creation of behavior patterns of industrial components using well-known unsupervised machine learning algorithms such as K-means and Self-Organizing maps (SOMs) as a starting point. An algorithm based on local Probability Density Distributions (PDD) of the clusters obtained is used to enhance the characterization of patterns. The joint use of these algorithms facilitates a new way to detect anomalies and the surveillance of their progress. The paper includes an example of an application of the method proposed for monitoring the bearing temperature of a turbine in a hydropower plant showing how this method can be applied in behavior and maintenance assessment applications. The results obtained prove the advantages and possibilities that the proposed methodology has on real world applications.

1. Introduction

Prognostics and health management (PHM) of industrial systems has been one of the leading research areas over the last decades due to the remarkable advances in the field of the Internet of Things (IoT) (Sisinni et al., 2018). The aim of health management is to collect (relevant) data from various sensor sources and carry out the necessary processing including the extraction of key features, fault diagnosis and prognosis, etc. in which a wide range of Artificial Intelligence (AI) algorithms can be applied (Khan and Yairi, 2018). Different approaches are proposed in the literature about PHM carried out through behavior/failure patterns based on mathematical models and AI techniques (Diez-Olivan et al., 2019). Health management can be addressed from multiple points of view depending on its application: prediction/prognosis of the remaining useful life (Stetter, 2020); reliability and failure detection (Vieira and Sanz-Bobi, 2013), component degradation assessment (Alaswad and Xiang, 2017), normal behavior assessment (Gil et al., 2018), etc.

This paper proposes a new approach in the field of health management based on behavior patterns. A behavior pattern is a characterization of the response of the system under specific working conditions (Zhao et al., 2020). Detecting deviations between the expected and the real behavior is the initial step in the detection of failures, anomalies, etc. Among the multiple AI algorithms that can be found in the literature (Khan and Yairi, 2018; Diez-Olivan et al., 2019; Ahmed et al., 2019), this study proposes the use of a specific type of unsupervised learning algorithms, in particular two clustering algorithms: K-means, for their short training times; and Self Organizing Maps (SOMs) characterized for their capability of organizing vast and complex data sets without loosing visibility of the data mapping process (Khan and Yairi, 2018), this means that the mapping process is not a black box method, allowing the user understanding and visualizing the multiple steps taken along the clustering process. Another advantage of using unsupervised clustering algorithms is their capability of clustering features without a previous knowledge about the dataset to be clustered. These two properties are essential in behavior patterns.

In comparison to other studies in the literature, behavior anomalies and failures are frequently detected through statisti-

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cal indicators (Vieira and Sanz-Bobi, 2013; Gil et al., 2018; Rauber et al., 2015; Gonzalez et al., 2015; Liang et al., 2019); this paper proposes an additional indicator based on Probability Density Functions (PDFs), also Probability Density Distributions (PDDs), as part of the reference behavior pattern. This contribution improves significantly the characterization of the component behavior and the detection of failures and anomalies.

Literature in PHM and Condition Based Maintenance (CBM), typically focuses on providing an overview of multiple approaches in behavior assessment (Tautz-Weinert and Watson, 2017; Gil et al., 2018); health monitoring (Zhao et al., 2019; Kang et al., 2019); strategies in CBM (Olde Keizer et al., 2017); degradation assessment (Alaswad and Xiang, 2017), etc. but they do not make any allusion about possible strategies in maintenance quality assessment. This paper aims to assess system behaviors, but also quantify the effectiveness and quality of the maintenance tasks carried out in the system. The proposed strategy in maintenance quality assessment focuses on evaluating the behavior of a component before and after it goes through a maintenance task allowing for an assessment of the efficacy of such maintenance task regarding a previous normal reference behavior.

In order to illustrate the efficacy and usefulness of this novel methodology for anomaly detection in industrial components, this paper sets forth a case study of the Bergenshalvøens Kommunale Kraftselskap's (BKK) Nygard plant located north-east of the city of Bergen. This hydropower plant is in the Modalen river system, located together with several dams and three other hydropower plants (BKK, 2019). Nygard is a pumped storage power plant with two different operating modes:

- Pumping mode: Nygard is pumping from the reservoir Stølsvatnet up to the reservoir Skjerjevatnet.
- Power generation mode: Water is taken from the reservoir Skjerjevatnet through Nygard power plant and Steinsland power plant. This means that the water is not discharged back to Stølsvatnet, but directly after going to the Nygard power plant it passes to the Steinsland power plant and discharges into the (not regulated) lake Steinslandsvatnet and further downstream to the connected rivers and lakes in the Modalen valley.

The example used to illustrate the methodology proposed is oriented to the anomaly detection in the bearings (Liang et al., 2019) of the hydropower plant from the information provided by its Supervisory Control And Data Acquisition (SCADA) system. SCADA systems are still widely used in industry (Boyes et al., 2018), (Kwon et al., 2016) although the transition towards modern IoT systems combined with analytics is more and more consolidated in applications in industry (Sisinni et al., 2018; Lee et al., 2018) and society (Andreev et al., 2019).

This paper is organized as follows. Section 3 describes the methodology proposed to compose a behavior pattern and the information self-contained in each of these patterns. This section also includes two different strategies to compare behavior patterns and a description of two indicators used in the assessment of patterns. At the end of this section some strategies used to detect deviations from the reference pattern are also briefly indicated. Section 4 presents a real case-study in which the methodology proposed is applied to a hydropower plant behavior. This section states the type of assessment carried out for this case study. Section 5 presents the results obtained in the behavior assessment, and finally, Section 6 states the conclusions reached from the methodology proposed and its results in the case study of the hydropower plant.

2. Motivation and statement of the problem

After a deep review of the state-of-the-art, this paper describes a new method that attempts to cover an important gap discovered in the field of automatic anomaly detection in industrial components. The implementation of different types of methods and algorithms for anomaly detection in industry is not new, several approaches have been implemented and successfully reported. However there is a lack of guidance to update or adapt an implemented method of anomaly detection once it is running for a long time. It seems that once the method is in operation, it is valid forever. However, most part of industrial components have degradations over time that can be detected as anomalies. This is correct, but once the component is not as good as new, over the pass of time its behavior can be lightly deviated with respect to this expected behavior due to common age degradation, but it is still in good condition to develop its mission. This means that a model for anomaly detection implemented some time ago can successfully alert, for example, to certain degradation observed due to ageing, but once this degradation is reported and the most convenient actions are taken, is the model used for anomaly detection still useful? This is a question that few studies in scientific literature have explored and our proposed method seeks to contribute to. Another advantage proposed is the immediate identification of the variable or variables that could explain the origin of the anomaly detected enhancing the capability to become alert earlier. The next sections will describe the details of the method proposed.

3. Methodology

This section describes the methodology proposed in this paper for anomaly detection. This methodology is divided into two main stages, the preparatory stage and the behavior assessment stage. The preparatory stage starts with the composition of a reference pattern based on a SOM algorithm, an unsupervised algorithm that allows the reduction of data to a set of clusters obtaining groups of similar observations without previous knowledge required. The number of clusters is decided by the application of the Elbow criterion (Ketchen and Shook, 1996; Kodinariya and Makwana, 2013) based on another unsupervised algorithm such as K-means. The cooperation of both algorithms is widely known (Mulliez et al., 2018; Van Laerhoven, 2001). This step will be described in Section 4.3 as part of the application of the methodology in a real case study. Each cluster obtained in the SOM represents an Operation Mode. Operation Modes are behavior patterns defined by variables sharing similar feature values. This and other concepts, will be described in this section. In addition, for each Operation Mode several features are measured, in particular, the methodology includes a special feature based on the computation of local probability density distributions for each one of the Operation Modes. All these features contribute strongly to the novelty of the application and will be described in Section 3.1. This methodology focuses on the study of component behaviors comparing a reference pattern with another pattern or using test observations. The strategy applied is chosen at the end of this first stage.

After the Operation Modes and their characteristics have been defined in the reference pattern, the procedure for anomaly detection starts at stage two. The detection of anomalies can be carried out comparing two behavior patterns as explained in Section 3.2.1; or comparing a reference pattern with discrete observations as described in Section 3.2.2. After the matching process carried out at stage two, discrepancies are quantified numerically at stage three using indicators. The two indicators proposed in this methodology are described in Sections 3.3.1 and 3.3.2. Both indicators can be

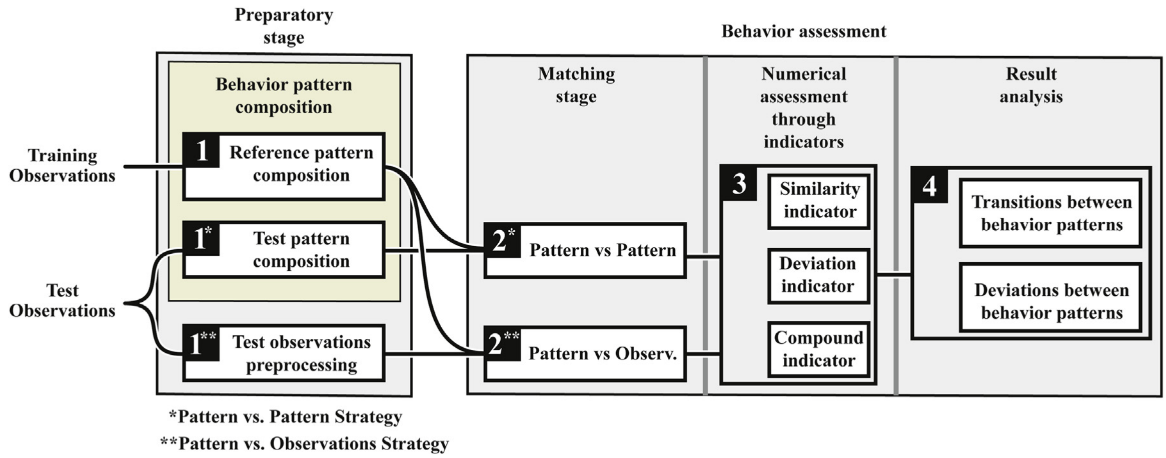


Fig. 1. Stages of the methodology proposed for anomaly detection based on behavior patterns.

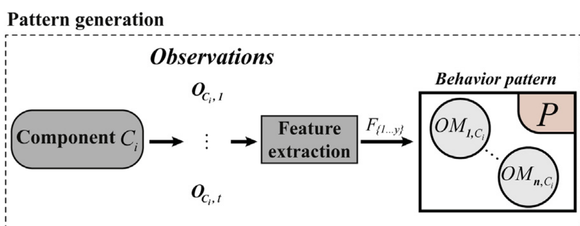


Fig. 2. Scheme of the procedure proposed for the generation of patterns from the measured variables of a component.

used jointly to enhance the detection of anomalies as described in Section 3.3.3.

The stage four of the methodology is the analysis of the results obtained. Two analysis are proposed. The first, based on the assessment of transitions between patterns of behavior, described in Section 3.4. The second, based on the assessment of deviations quantified numerically through the indicators previously proposed, described in Section 3.5.

The stages of the methodology proposed are represented in Fig. 1.

Section 4 describes how this methodology has been implemented in the assessment of certain components in a turbine of a hydropower plant and Section 5 describes the results obtained and how they can be interpreted showing the true potential of this novel methodology.

The behavior of an industrial component is defined by the *Observations* (Os) collected during the operation of the component. Similar Os lead to the definition of *Operation Modes* (OM) understood as the most predominant Os within a particular component behavior.

In the context of this paper each Os and OM are defined by the group of features used to characterize the behavior of the component. Once the OMs of a component are identified, they make up the component behavior pattern. Detecting changes in the OMs (changes in the behavior) gives rise to multiple applications such as failure identification, component degradation quantification or the detection of changes in *OC*s.

In order to explain the methodology proposed, it is necessary to state the elements involved in this approach. The *component C* is the element under assessment. Components are defined by C_i or C depending on the number of components under assessment.

A scheme of the procedure proposed is shown in Fig. 2. The variables shown in this figure are:

- C_i: Component to be studied. E.g. Bearing cooling unit, particle filter, transformer, etc.
- $O_{C_i,t}$: Observations of the component behavior collected at time t by sensors or SCADA systems.
- $F_{\{1...y\}}$: Features chosen to define the behavior of the component. The values of the features are obtained from the observations registered. E.g. relative temperature, pressure, voltage, etc.
- OM_{n,C_i}: Operation Modes that define the behavior pattern of component C_i, being n the total number of *OMs*

The first step is the extraction of features from the observations through an unsupervised clustering algorithm followed by the composition of the behavior pattern P of n Operation Modes $OM_{n,Ci}$. Each pattern is made up of the set of clusters obtained determined by the feature values observed over a period of time t.

A behavior pattern can be obtained through different unsupervised learning algorithms such as Self-Organizing Maps (SOM), K-means or any other clustering technique. The following subsections explain the information contained in a pattern and how this information can be extracted and used in the assessment of a component behavior.

3.1. Initial reference behavior pattern

A deviation can only be quantified with regard to a reference value. To detect deviations in patterns, it is necessary to define a reference obtained from normal behavior observations. As said before, one of the strategies proposed to model the behavior of a component is through Self-Organizing Maps (SOMs) (Kohonen, 1982, 2006) proposed by Kohonen as an alternative clustering technique. SOMs have been widely used in the characterization of industrial systems and components behaviors (Li et al., 2018; Khan and Yairi, 2018; Gil et al., 2018).

SOM models allow for classifying the behavior of a component and identifying new *OMs* automatically, adding them or updating the ones already observed. This first step of clustering is not the novelty of the methodology proposed, but it is essential to start its deployment. In order to understand the similarities between a SOM and a behavior pattern, each *OM* can be understood as a neuron within the map.

Once the clusters were obtained, the methodology proposed is focused on the information inside each cluster focusing on the following four main elements:

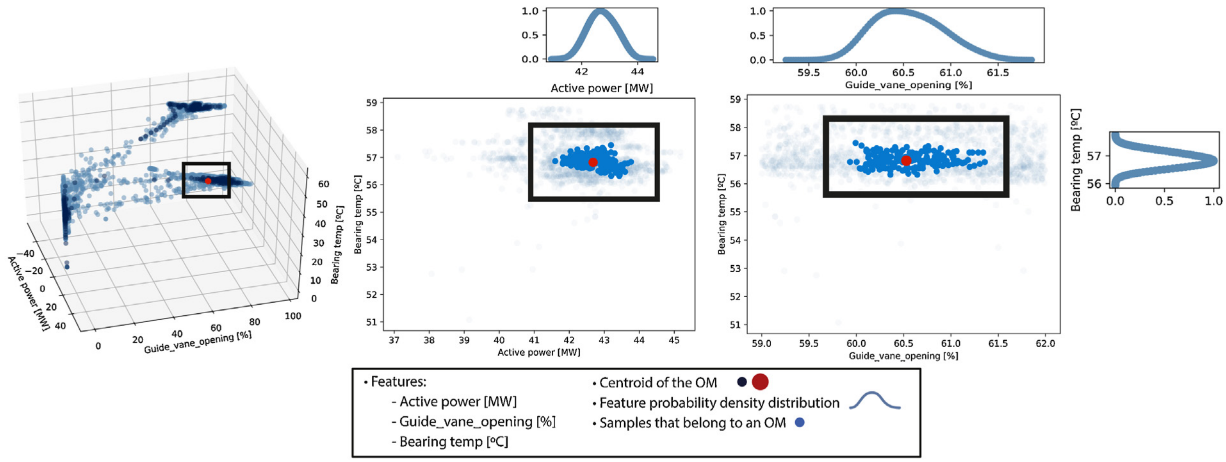


Fig. 3. Main elements that make up a behavior pattern.

- Features: Attributes/variables that define the *OMs* of each pattern. The number of attributes/variables that define the dimensions of each *OM*.
- Centroids: Centroids are the most representative and characteristic values within each *OM*. They are also understood as the “gravity center” of the observations that belong to the same *OM*.
- Feature Probability Density Functions (feature PDF): Provide information about how observations are distributed within each *OM*.
- Statistical Features: Standard deviation explains how much the observations of the same cluster differ from the centroid of the group. The number of hitting samples per *OM*, provides information about which *OMs* are more frequent or more relevant within the overall pattern.

Some of these elements are depicted in Fig. 3 which shows a real example of the hydropower plant behavior modeled through a SOM.

Each *OM* feature PDF is computed through the *Parzen windows* technique, also know as *kernel density estimation* (Parzen, 1962) which states that the probability density function of n observations $\{v_1, \ldots, v_i, \ldots, v_n\}$ of a variable V can be computed as:

$$P_V(v_x) = \frac{1}{n \cdot h} \sum_{i=1}^{n} K\left(\frac{v_x - v_i}{h}\right) \tag{1}$$

where $P_V(v_x)$ is the value that an observation v_x of V has within the PDF; h is the bandwidth estimator obtained according to the rule of thumb stated by Silverman (Silverman, 1986) as:

$$h = \left(\frac{4\hat{\sigma}^5}{3 \cdot K}\right)^{\frac{1}{5}} \approx 1.06\hat{\sigma}n^{-1.5} \tag{2}$$

where K is in both Eqs. (1) and (2) the Gaussian kernel used to compute the probability distribution:

$$K\left(x|\mu, \sigma^2\right) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{3}$$

being $\hat{\sigma}$ the standard deviation and μ the mean value of the n observations of V.

In the next step, the PDF is computed along an uniformly spaced vector $\overline{E}$ of size d from $PDF_{F,\min}$ to $PDF_{F,\max}$, where $PDF_{F,\min}$ and $PDF_{F,\max}$ are the values in which the probability distribution goes below the probability threshold T_p. T_p allows for the definition of the length of the tails of the PDF for feature F in a general manner. The maximum value of the PDF is normalized to 1 to permit the comparison of maximum probability values between features. See Fig. 4.

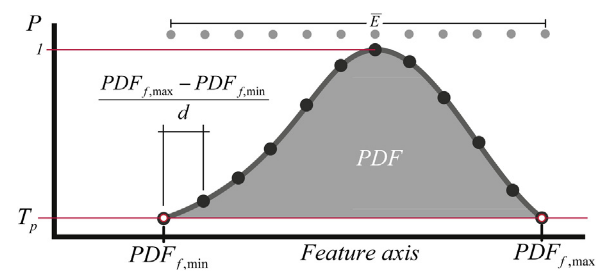


Fig. 4. Maximum and minimum values of the PDF.

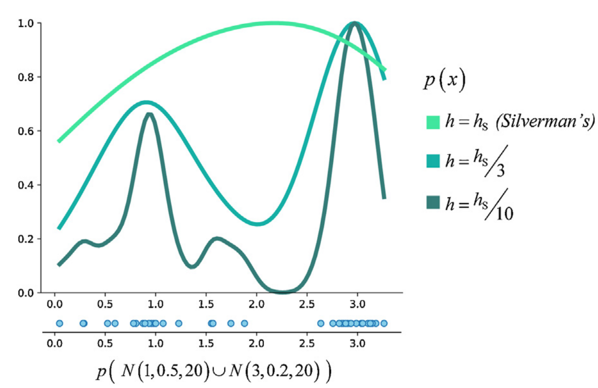


Fig. 5. Probability density functions for different bandwidth values, where h_S is the bandwidth obtained using the rule of thumb of Silverman.

Fig. 5 shows how the PDF varies depending on the value of h applied. Where h is the value obtained through the rule of thumb of Silverman stated in Eq. (2). Small values of h provide a more detailed representation of the PDF, however if the values of h are too small they might lead to over-fitting issues. The example of the PDF shown in this figure corresponds to the union of two normal distributions: $N(\mu = 1, \sigma = 0.5, n = 20) \cup N(\mu = 3, \sigma = 0.2, n = 20)$ shown as blue dots. Function tails (not shown in the figure) are monotonically decreasing curves with a horizontal asymptote in $P = 0$.

The elements above mentioned make up a behavior pattern. Each pattern can be compared with other patterns or directly with a set of observations. These two methodologies based on the assessment of patterns are some of the novelties proposed in this article.

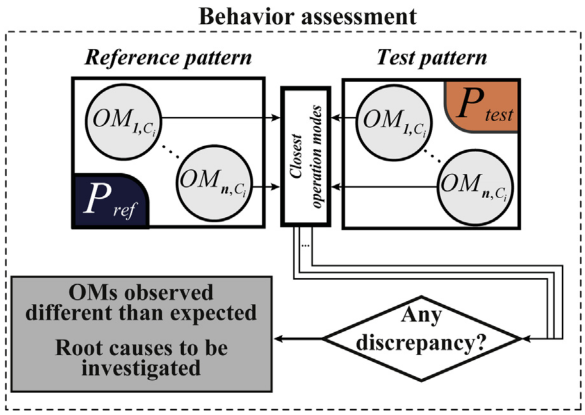


Fig. 6. Strategy followed in the behavior assessment "Pattern vs. Pattern". A reference and a test pattern are matched regarding the OMs to be compared.

Section 3.2 is entirely devoted to the explanation of these two types of assessment methods.

3.2. Behavior assessment

This section covers two of the main contributions of this paper. After computing a behavior pattern, it is necessary to know and understand how they can be used to get the most from the information self-contained in each pattern. In Section 3.1 pattern elements have been presented. In this section, such elements will be matched and compared according to a novel methodology that tackles this assessment from two different points of view. The first one, focused on the assessment and comparison of two different behavior patterns, presented in Section 3.2.1. The second one, focused on the assessment of a set of observations comparing them with a reference behavior pattern, presented in Section 3.2.2. These two strategies are not complementary. The assessment of patterns is based on the study of their features using two indicators: similarity and deviation, explained in detail in Section 3.3. The implementation of one strategy instead of the other depends on the type of application defined by the user. Both strategies are described in detail including the main advantages and disadvantages of each strategy. For a clear understanding, the algorithm steps are summarized at the end of the sections of both strategies.

3.2.1. Strategy 1 – behavior assessment "Pattern vs. Pattern"

This method focuses on comparing two behavior patterns. A scheme of this approach can be seen in Fig. 6. Deviations are quantified comparing the *OM*s of both patterns. Reference patterns are made up of feature values obtained from normal behavior observations. Test patterns are made up of feature values obtained from the observations under assessment.

Each *OM* in the test pattern is compared with their nearest *OM* in the reference pattern based on the Euclidean distance between *OM* feature centroid values. Fig. 7 shows an example in which a reference pattern (behavior in 2011) and a test pattern (behavior in 2012) are matched. The features that define both patterns are: active power [MW] (power generated or consumed by the hydropower plant), percentage of the guide vane opening [%] (related to flow rate) and temperature of the bearings of the turbine [°C] (related to the working conditions of the bearings). Through these three features the behavior of the hydropower plant turbine can be characterized. This figure shows two working modes: (A) in which the hydropower plant is pumping water back to the reservoir (consuming power), and (B) in which the hydropower plant is generating power releasing water through the turbine. For a better visualization of the information, the values of the OMs centroids are represented using their Bearing temperature [°C] and Guide vane opening [%].

Some of the advantages of this method are:

- This method is more robust against outliers. Samples that are less representative in a behavior are also less representative in the pattern.
- In those cases where the number of observations under assessment is significantly large, working with patterns instead of samples implies a reduction in the volume of information that has to be stored and processed in the assessment.
- This strategy allows for differing deviated *OM*s from real new *OM*s depending on the location of the *OM* of the pattern under assessment taking into account the PDFs of the reference pattern. Sharp deviations in *OM*s centroids can be due to a fault in the system or a change in the operation strategy. This assessment is based on the indicators stated in Section 3.3.
- This methodology allows for the comparison of two behavior patterns with different numbers of *OM*s.

Some disadvantages of this method are:

- Building a pattern for each new set of observations implies longer running times than comparing directly new observations with a reference pattern.
- To detect small deviations in the behavior, the number of *OM*s has to be big enough to provide a detailed characterization of the behavior. An excessive number of *OM*s could, on the other side, lead to over-fitting issues in the pattern.

The corresponding algorithm of this strategy is summarized in Algorithm 1.

Algorithm 1.

Input: Reference pattern $OM_{ref,f,M}$, Test pattern $OM_{test,f,N}$, Total number of OMs in ref pattern (M), Total number of OMs in test pattern (N), health index threshold for each feature (τ_f)

Output: List of deviations in each of the OM of the reference pattern, global behaviour deviation of the test pattern

for *each* $OM_{test,f,n}$ $(n \in N)$ **do**
  initialize $C_{OM_{test}f,n}$ from $OM_{test,f,n}$;
  initialize list of $C_{OM_{ref}f,m}$ from all $OM_{ref,f,m}$;
  find the closest $C_{OM_{ref}f,m}$ to $C_{OM_{test}f,n}$ using Euclidean distance;
  initialize $C_{OM_{ref}f,m}$, $\sigma_{OM_{ref},f,m}$ and $p_{ref,f,m}$ from closest $OM_{ref,f,m}$;
  for *each* $f \in$ *behaviour features* **do**
    compute similarity index $S_{f,n}$ $(C_{OM_{test}f,n}, p_{\mathrm{ref,f,m}})$;
    compute deviation index $D_{f,n}(C_{OM_{test}f,n}, C_{OM_{ref}f,m}, \sigma_{OM_{ref},f,m})$;
    define W_S and W_D of the health index;
    compute health index $H_{f,n}(S_{f,n}, W_S, D_{f,n}, W_D)$;
    compare health index with τ_f;
  end
  add to list $H_{f,n}$;
  add to list $H_{f,n} < \tau_f$;
end
list all $OM_{test,f,n}$ with a $H_{f,n} < \tau_f$ to assess local behaviour deviations;
compute $\overline{H_{f,n}}$ to assess global behaviour deviation;

3.2.2. Strategy 2 – behavior assessment “Observations vs. Pattern”

This strategy aims to assess the observed behavior of a component comparing the feature values of the observed samples with their closest reference *OM*. Distances between observation features and *OM*s are measured through the Euclidean distance. Given N as the total number of *OM*s in the reference pattern, n as the index of the *OM* which an observation belongs to, F_{OM_n} the feature values of the closest *OM* centroid, and F_{obs} the feature values of the observation to be matched; the matching equation can be defined as:

$$OM_n : n = \underset{n \in N}{arg\min} \left(\left\| F_{OM_n} - F_{obs} \right\| \right) \tag{4}$$

An schematic representation of this approach is shown in Fig. 8.

An example of this approach is shown in Fig. 9, in which it can be seen how the observations are matched to their closest *OM* within the reference behavior pattern. For a better visualization of the information, the values of the OMs centroids are represented using their Bearing temperature [°C] and Guide vane opening [%].

The advantages of this method are:

- This approach does not require building a test pattern to be compared with the reference one. Therefore, observations can be assessed individually.
- Matching process (samples ↔ OMs) is remarkably fast.

The main disadvantage of this approach is that it is less robust regarding outliers and rare values. When observations are characterized in a pattern, rare values are filtered out preserving those feature values that are more representative.

Both strategies provide analogous results, but their applications are different. Comparing a pattern with single observations has a great potential in time series assessments, on the other hand, com-

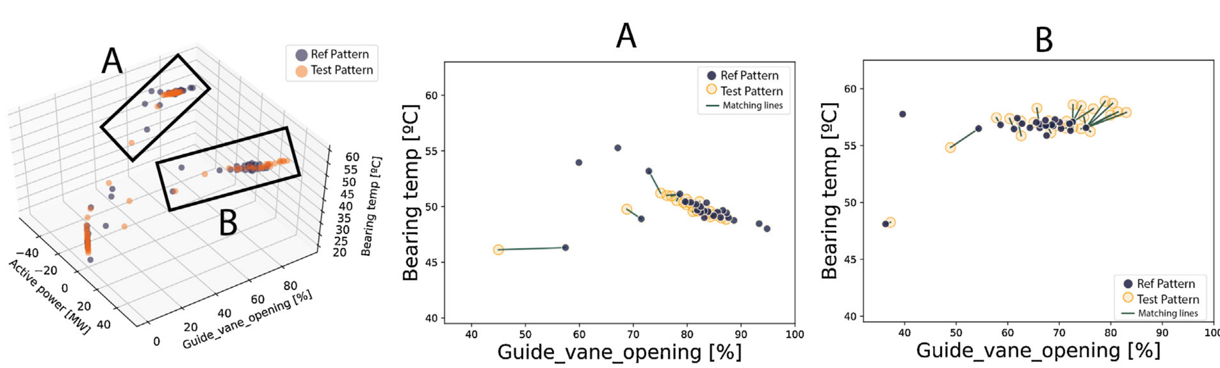


Fig. 7. Example of a behavior assessment “Pattern vs. Pattern”. Two behavior patterns are matched and compared. (A) hydropower plant consuming power (pumping water back to the reservoir); (B) hydropower plant generating power.

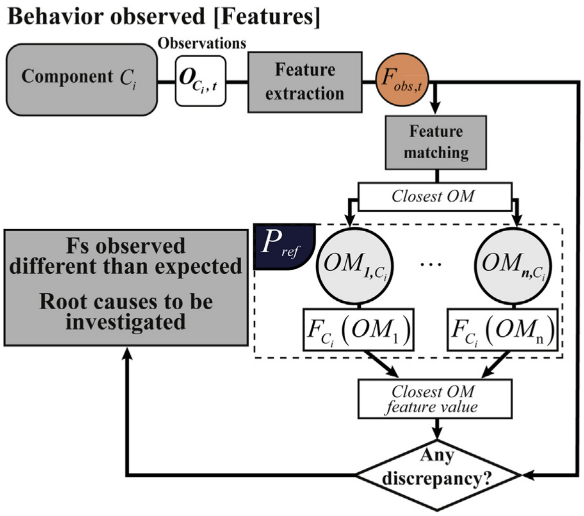


Fig. 8. The strategy followed in the behavior assessment "Observations vs. Pattern". Observation values are matched to their closest reference OMs from the reference pattern to be compared.

paring two patterns offers a greater visibility of those failures that have a global effect on the system behavior with a greater extent in time and deviation from their reference value.

An assessment "pattern vs. pattern" is intended mainly for off-line applications such as trend and evolution analysis, etc. whereas an assessment "observations vs. pattern" is more suitable for on-line/monitoring applications.

The corresponding algorithm of this strategy is summarized in Algorithm 2.

Algorithm 2.

Input: Reference pattern $OM_{ref,f,M}$, List of new observations $O_{f,n}$, Total number of OMs in ref pattern (M), Total number of new observations N, health index threshold (τ_f)

Output: List of deviations for each new $O_{f,n}$, global behaviour deviation of the set of new observations

for *each* $O_{f,n}$ $(n \in N)$ **do**
- initialize list of $C_{OM_{ref}f,m}$ from all $OM_{ref,f,m}$;
- find the closest $C_{OM_{ref}f,m}$ to $O_{f,n}$ using Euclidean distance;
- initialize $C_{OM_{ref}f,m}$, $\sigma_{OM_{ref},f,m}$ and $p_{ref,f,m}$ from closest $OM_{ref,f,m}$;
- **for** *each* $f \in$ *behaviour features* **do**
  - compute similarity index $S_{f,n}$ $(O_{f,n}, p_{\mathrm{ref,f,m}})$;
  - compute deviation index $D_{f,n}(O_{f,n}, C_{OM_{ref}f,m}, \sigma_{OM_{ref},f,m})$;
  - define W_S and W_D of the health index;
  - compute health index $H_{f,n}(S_{f,n}, W_S, D_{f,n}, W_D)$;
  - compare health index with τ_f;
- **end**
- add to list $H_{f,n}$ samples;
- add to list $H_{f,n} < \tau_f$ samples;

end

list all $OM_{test,f,n}$ with a $H_{f,n} < \tau_f$ to assess behaviour deviations for each observation;

compute $\overline{H_{f,n}}$ to assess global behaviour deviations;

3.3. Behavior indicators

Behavior indicators aim to quantify numerically the level of similarity or discrepancy between behavior patterns and/or observations. The strategies proposed in Section 3 aim at matching patterns or observations with their reference pattern. Once the matching process is complete, discrepancies are quantified. This section covers the third step of the methodology. The novelty in this part of the methodology resides in two powerful indicators used jointly to quantify discrepancies:

1 Similarity (similarity value and average similarity). This indicator is explained in detail in Section 3.3.1
2 Deviation/distance from *OM* feature centroid. This indicator is explained in detail in Section 3.3.2.

These two indicators are frequently used separately in anomaly detection applications but, when combined, it is possible to characterize hidden behaviors that would be misclassified in case that both indicators were applied separately. The advantages of combining both indicators are explained in Section 3.3.3.

3.3.1. Similarity indicator

This indicator makes it possible to quantify how similar an observation is regarding the typical values of the reference *OM* to which it is assigned. This is, for values near to one, an observation is within a range of values with a high density of samples in the reference *OM*. These ranges are determined through the PDFs of the *OM*. The similarity value of an observation $O_{f,n}$ within the PDF of feature *f* of its closest reference *OM* is defined as:

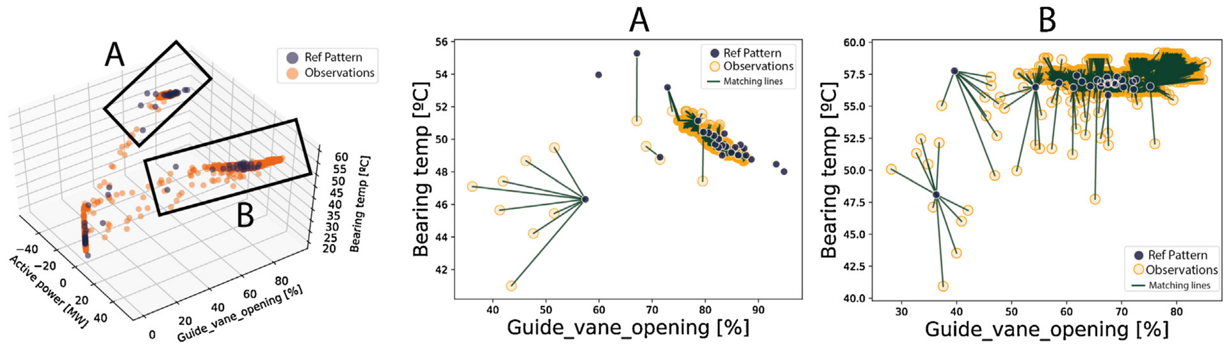


Fig. 9. Example of a behavior assessment "Observations vs. Pattern". A reference pattern is compared with a set of observations. (A) Hydropower plant consuming power (pumping water back to the reservoir); (B) Hydropower plant generating power.

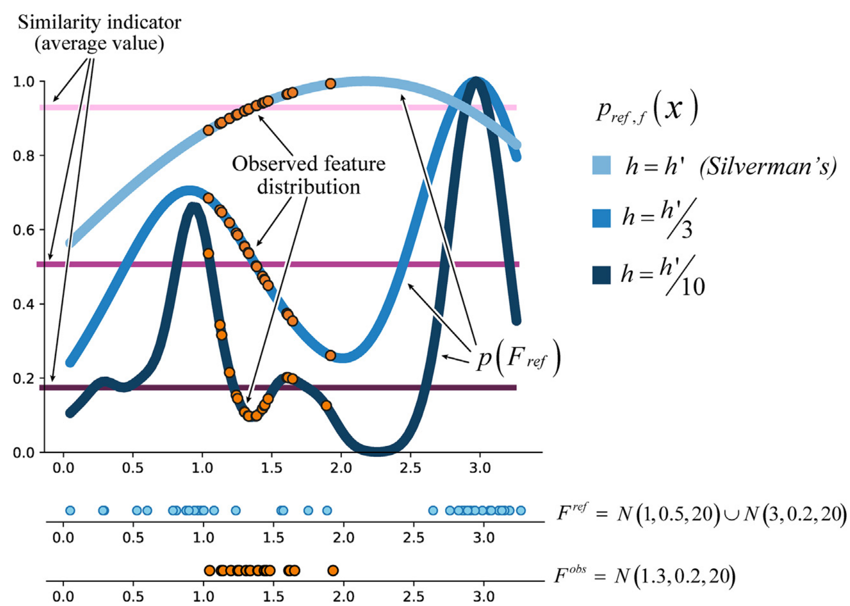


Fig. 10. Assessment of Similarity values regarding the bandwidth h chosen. Three scenarios are shown: Bandwidth obtained through the rule of thumb of Silverman (h'), adjusted bandwidth ($h'/3$), over-fitted bandwidth ($h'/10$).

$$S_{f,n} = p_{\text{ref,f}}\left(O_{f,n}\right) \tag{5}$$

where $p_{ref,f}(x)$ is the PDF of feature f of the corresponding OM within the reference pattern and $O_{f,n}$ is the feature value of observation n. The similarity value of an observation is obtained through a linear interpolation between PDF values. The advantage of this approach is using precomputed PDFs to obtain new similarity values interpolating new observations within such precomputed PDFs. This approach allows for an outstanding reduction in the number of operations required to compute similarity values in PDFs of large populations. When comparing two patterns, the observation is substituted by the centroid of the test pattern.

The similarity indicator of feature f for multiple observations is:

$$S_{f,N} = \frac{\sum_{n=1}^{N} p_{ref,f}\left(O_{f,n}\right)}{N} = \frac{\sum_{n=1}^{N} S_{f,n}}{N} \tag{6}$$

where N is the total number of observations under assessment.

In Fig. 10, an example of this method is shown. In this example, the reference features are two normal distributions: $N(\mu = 1, \sigma = 0.5, n = 20)$ and $N(\mu = 3, \sigma = 0.2, n = 20)$. The reference probability distribution is discretized through an equally spaced vector ($\overline{E}$) of 100 samples. The observed features correspond to a normal distribution $N(\mu = 1.3, \sigma = 0.2, n = 20)$. This figure shows how the value of h affects the similarity indicator values obtained for an observed feature distribution. After several values of h were tested, it could be seen that taking a third of the original value of h' (obtained through the rule of thumb of Silverman), allows for a better assessment of the observed distribution, avoiding under-fitted (h') and over-fitted ($h'/10$) configurations. Bandwidth values obtained through the rule of thumb of Silverman usually underperform characterizing bimodal distributions, which is the case shown in Fig. 10. A correction factor is needed in these cases. This factor has to be chosen through visual inspection in most scenarios. Silverman (Silverman, 1986) proposes an assessment range of bandwidth values around 1/4 and 1/2 of its initial value (h'). In this case 1/3 is the correction factor applied.

3.3.2. Deviation indicator

A second indicator quantifies the deviation/distance of each observation n from the feature centroid of its corresponding reference OM.

$$D_{f,n} = \frac{\left|O_{f,n} - C_{OM_{ref},f}\right|}{\sigma_{OM_{ref},f}} \tag{7}$$

where $O_{f,n}$ is the feature value of the observation, $C_{OM_{ref}}$ is the centroid feature value of the reference OM and $\sigma_{OM,f}$ is the standard

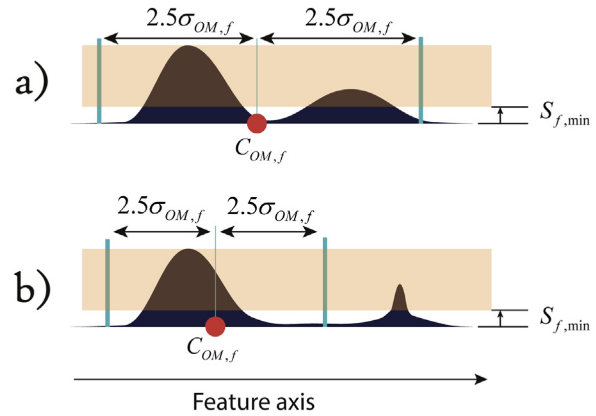


Fig. 11. Particular cases in which the joint use of distance and similarity indicators provide a better assessment of the observation regarding its reference *OM*.

deviation of feature *f* of the *OM*. When comparing two patterns, the observation is substituted by the centroid of the test pattern.

$$D_{f,n} = \frac{\left|C_{OM_{test} f,n} - C_{OM_{ref},f}\right|}{\sigma_{OM_{ref},f}} \tag{8}$$

Distances are normalized with the standard deviation of the corresponding *OM*. As each *OM* has a different standard deviation, this method allows for a comparison of relative distances between *OM*s.

3.3.3. Joint use of both indicators

These two indicators can be used jointly to quantify how much an observation or pattern differs from its reference behavior pattern. An observation is not explained by an *OM* when the feature values of the observation or the centroid of the test *OM* are located outside the probability density distributions of the reference *OM*, i.e. below and above $PDF_{f,min}$ and $PDF_{f,max}$, respectively; (see Fig. 4). One of the advantages of using these two indicators jointly is a more effective detection of deviations in cases where a distance from the centroid is not enough to characterize an observation. Fig. 11 shows two cases in which the joint use of these two indicators allows for a better characterization of the observation regarding its reference *OM*; where a normal behavior condition is defined as:

$$\left[S_{f,n} > S_{f,\min}\right] \wedge \left[D_{f,n} < 2.5\right] \tag{9}$$

Fig. 11 shows two different cases in which only one condition is fulfilled. Case (a) shows an *OM* distribution in which the centroid is located in a region with a low density of samples. In this case, those observations that are located too close to the centroid would be considered as part of a normal behavior when only the distance to the centroid of the *OM* is considered. Taking into account the Similarity indicator, the normal behavior condition is not fulfilled any longer. Case (b) shows an opposite situation in which there is a region located outside of the distance threshold delimited by $\pm 2.5\sigma$, but regarding its Similarity value, it is above the minimum value $S_{f,\min}$.

Both indicators can be combined in a single equation weighing each indicator individually and setting τ as the minimum value to consider the observation or test *OM* (n) within normal behavior conditions:

$$W_s \cdot S_{f,n} + W_D \cdot \min\left(\frac{2.5}{D_{f,n}}, 1\right) \geq \tau \tag{10}$$

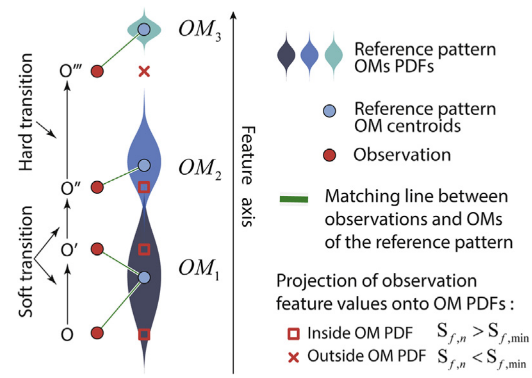


Fig. 12. Examples of soft and hard transitions.

where:

$$S_{f,n} \in [0,1]; \min\left(\frac{2.5}{D_{f,n}}, 1\right) \in [0,1]; \qquad W_s + W_D = 1 \tag{11}$$

Depending on the application, the weight of each indicator can be adjusted (or not) for a better behavior assessment. To avoid an excessive alarming behavior two strategies can be used for fitting better the process of anomaly detection:

- Reduce the minimum similarity value and increase the maximum deviation to relax the conditions used to detect alarming behaviors.
- Include and weight the samples detected as false positive within the training set of reference pattern to consider those samples as part of the normal behavior.

3.4. Transitions among patterns of behavior

This assessment belongs to the fourth step of the methodology proposed. The aim of this assessment is determining whether a set of features have been already registered by the reference model or not. A transition can be defined as a displacement of feature values among *OM*. Two types of transitions are considered: soft transitions and hard transitions. Soft transitions take place when the feature values lie within their reference feature PDFs, otherwise when feature values fall outside from any *OM* feature PDF, a hard transition takes place.

These two types of transitions are depicted in Fig. 12. In this example, an observation evolves over time changing its feature value. The reference pattern is made up of three *OM*s: OM_1, OM_2 and OM_3. Transitions $[O \rightarrow O']$ and $[O' \rightarrow O'']$ are soft transitions as the observation remains within reference *OM* PDFs. Transition $[O'' \rightarrow O''\prime]$ is a hard transition as the observation shifts from being within OM_2 PDF to being outside of any *OM* PDF. Hard transitions give rise to the detection of unknown working conditions that can be used to detect possible anomalies or to discover new *OM*s not covered yet by the reference pattern.

3.5. Deviation assessment

As stated before, in order to assess the behavior of a component, it is necessary to measure how much such behavior differs from a reference behavior pattern. The assessment of deviations is the fourth and last step in the methodology. Deviations can be assessed through several strategies: Applying the indicators proposed in Section 3.3, strategies based on statistical features such as Analysis Of Variance (ANOVA) (Sthle and Wold, 1989), other strategies like Support Vector Machines (SVM) (Scholkopf and Smola, 2001), etc.

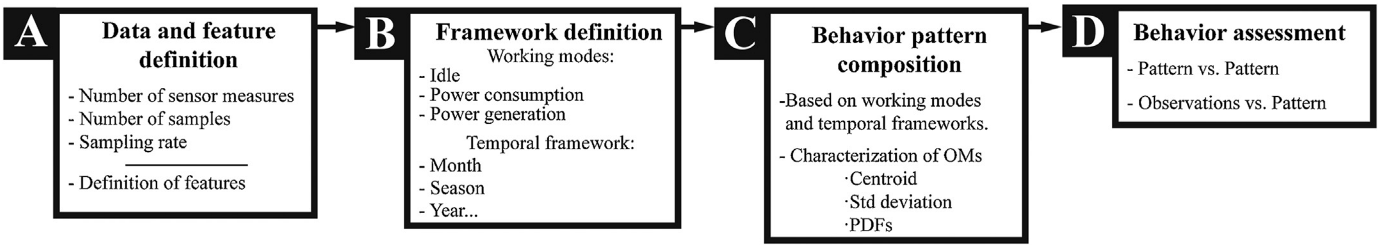
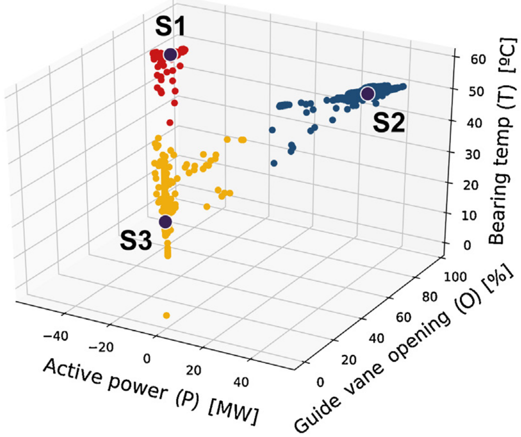


Fig. 13. Workflow chart of the behavior assessment applied to the Nygard hydropower plant.



	P	O	T
S1	-51.3	82.1	50.5
S2	43.8	65.1	56.7
S3	-0.1	0.5	29.7

Fig. 14. Working modes defined automatically through a 3 cluster K-means algorithm.

that could be applied in the study of similarities between features. This paper is focused on an assessment based on similarity and distance indicators, leaving additional strategies as part of a future application and research work. This assessment aims to quantify numerically a deviation from a reference value taking into account the values obtained for the indicators proposed in Section 3.3. The following case-study is an example of an application of the proposed methodology in the behavior assessment of a hydropower plant based on the similarity and distance indicators defined in Section 3.3.

4. Application of the methodology proposed to a hydropower plant

The following case-study focuses on the characterization and diagnostic of the behavior of a hydropower plant. The steps followed in the behavior assessment are depicted in the workflow chart of Fig. 13. The proposed approach is divided into four main steps. The first two steps (A and B) are focused on understanding the characteristics of the data set and the main features of the behavior of the system that can be useful in the composition of the working mode in which the data set can be divided. The last two steps (C and D) are a summary of the four stages of the methodology proposed depicted in Fig. 1. Step C focuses on the composition of behavior patterns according to its working modes. As mentioned before, in the case of the hydropower plant, there are three working modes: idle, pumping water back to the magazine (consuming energy) and producing energy. The last step D, aims to assess the behavior of the hydroelectric power plant through the two strategies described in Section 3.2.

4.1. Step A: Data and feature definition

According to the information available, the behavior of a hydropower plant is characterized using six sensor measures:

- Active power generated/consumed [MW]: This feature makes it possible to know the working mode of the plant: Consuming energy, producing energy or idle.
- Guide vane opening [%]: The opening percentage of the guide vane determines the flow rate of water released/pumped through the turbine. This feature complements the information about the working conditions of the plant.
- Bearing temperatures ($\times 4$) [$^{\circ}$C]: The temperatures collected by the SCADA system correspond to four bearings, two thrust bearings and two upper guide bearings. Bearing temperatures provide information not only about their operating conditions but also about their behavior and status. This feature is the target of this study.

These six sensor measures were registered as the average value of each hour collected from 2011 to 2016. The number of observations is around 8600 samples per year.

4.2. Step B: Framework definition

Three main working modes can be defined by the amount of power consumed or generated by the plant. It is important to take this fact into account when it comes to scheduling maintenance tasks. The time that the hydropower plant operates at each working mode might have different effects regarding behavior deviations of the system. It is necessary to take into consideration the length of those working modes in which the hydropower plant is not consuming nor producing power. These periods, in which the hydropower plant is idle, might lead to a pseudo reduction in temperatures measured in bearings and cooling systems.

Different temporal frameworks can be set up depending on the type of assessment intended: months, season of the year, year, etc. The scope of the assessment determines the type of the temporal framework to be set in the study. In this study-case, temperature is one of the variables under assessment. Temperatures are,

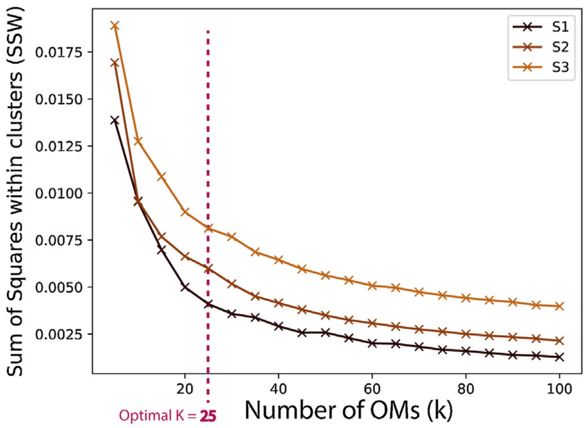


Fig. 15. Assessment of the variance explained depending on the number of *OM*s applied in the characterization of each working mode based on a K-means algorithm.

to a greater or lesser extent, dependant on environmental temperatures. To study how environmental temperatures affect the efficiency of the cooling system, the temporal framework would be the seasons of the year. To study how each working mode affects bearing temperatures, the proper temporal framework would be weeks or months as the working mode of the hydropower plant remains constant for several weeks. When the scope of the study focuses on the assessment of the cooling system behavior, an acceptable temporal framework would be months or even years as the behavior of this type of systems usually shows slow deviations that are only quantifiable in long term assessments.

4.3. Step C: behavior pattern composition

The number of samples of each working mode is not the same in all of them, this means that the hydropower plant is not generating power at the same time that it is pumping water back to the magazine or in an idle state. In order to reduce the bias that an uneven sample distribution might produce in the behavior characterization, three working modes were defined through a 3 cluster K-means algorithm, using the Euclidean distance and 3000 iterations (convergence reached). The centroids of each scenario are shown in Fig. 14, in which: working mode S1, the plant is pumping water back to the water reservoir; working mode S2, the plant is generating power; working mode S3, corresponds to a transition state in which the hydropower plant shifts from an idle state to generating or consuming active power.

The aim of this first clustering is to divide the observations collected during a year into three working modes to be modeled individually through a SOM algorithm. In order to determine the number of *OM*s within each working mode of the behavior pattern, an elbow assessment method (Ketchen and Shook, 1996) was carried out to determine its optimum number according to the variance explained (Kodinariya and Makwana, 2013). The elbow method is based on the percentage of variance explained as a function of the number of *OM*s. The optimum number of *OM*s is defined by the point in which, increasing the number of *OM*s in the pattern, their variance explained (dispersion of the observation regarding their reference *OM*) starts to become stable.

According to the results shown in Fig. 15, the three working conditions have approximately an optimal number of *OM*s equal to 25 according to the results obtained through the elbow criterion. Therefore, each SOM pattern is made up of 25 *OM*. Each *OM* is defined by 6 main features: Active power [MW], Guide vane opening [%] and Bearing temperature [$^\circ$C]$\times$4 (This feature is represented as the mean value of the four temperatures). The number of iterations in the training process of each pattern is defined by the

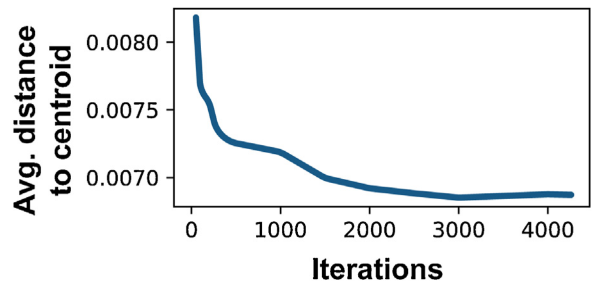


Fig. 16. Assessment of the average distance of the training set to the centroid of their corresponding neuron depending on the number of iterations of the training process.

Table 1
Setup of the SOM used to train the reference behavior pattern.

Reference pattern setup	
Dates	2011-01-01 to 2012-01-01
Number of observations	5290
Dataset normalization	linear normalization [0;1]
KSOM setup	
Feature dimension	6
Neuron layout	25 neurons
Neuron initialization	random [0;1]
Early Stopping condition	$\Delta mse < 2.5 \cdot 10^{-5}$
Maximum epoch	4200
Best Matching Unit	Euclidean distance
Spatial neighborhood function (snf)	Gaussian
Propagation rate [Gradient descent]	$\left[0.5;\left(1-\frac{epoch_{current}}{epoch_{\max}}\right)\cdot 0.5\right]$

early-stopping condition defined in the setup (reached at ~3000 iterations), which is the point at which the average distance to the centroids stabilizes, see Fig. 16. The setup of the SOM used to train the reference behavior pattern is shown in Table 1

Once the location of each *OM* is defined, the information contained in each *OM* is made up of: centroid values of the *OM*, standard deviation and PDF of each feature that defines an *OM*.

4.4. Step D: behavior assessment

This step corresponds to the last stage (D) in the workflow depicted in Fig. 13. The assessment was carried out taking the behavior of the hydropower plant in 2011 as the reference pattern. Fig. 17 shows how the reference pattern of 2011 is compared with the behavior pattern of 2012. First, all the OMs from the pattern under assessment (2012) are matched with their closest OM in the reference pattern (2011). The matching is carried out based on the Euclidean distance between neuron centroids. The type of matching is “many to one”, this means that one reference OM can have assigned none, one, or several OMs from the pattern under assessment.

Similarity and Distance indicators were computed regarding the *OM* centroids of the behavior pattern under assessment. Fig. 17 shows how this process is carried out for a single feature (bearing temperature) in a single reference *OM*; the rest of *OM*s matched are depicted as faded out. This process has to be carried out for each feature of each *OM*. Once *Similarity* and *Distance* indicators are computed for all *OM*s, deviations can be assessed.

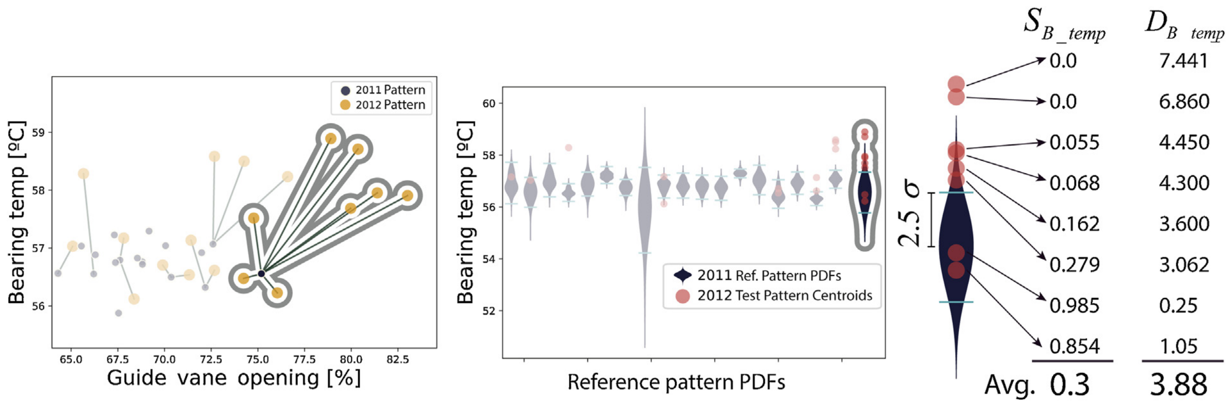


Fig. 17. Pattern comparison. Example of *Similarity* and *Distance* indicators computation.

5. Results

5.1. Behavior assessment

In order to assess the behavior of the hydropower plant, the same pattern of 2011 was used as the reference pattern. The aim is to compare how the behavior of the system evolves over the following years. As explained in previous sections, the variables under assessment were: Active power [MW] (*P*); Guide vane opening [%] (*O*) and Bearing temperature [°C] (*T*). Two different approaches are proposed to assess the behavior of the hydropower plant. The first one, through visual inspection, comparing the PDFs of a reference pattern with other patterns; the second approach, numerically, through the values obtained from the two indicators proposed in this study. As the behavior of the hydropower plant is divided into three main working modes (S1, generating power; S2, consuming power; S3, idle), each working mode has to be studied separately. Therefore, only S1 and S2 were considered in the assessment.

5.2. Behavior assessment through probability density functions

The evolution of test patterns *OM* PDFs is shown in Figs. 18 and 19 . These two figures show a comparison of test patterns obtained from the observations registered throughout the years 2012, 2013 and 2014 with a reference pattern obtained from the observations registered in 2011. This assessment is carried out through the visual comparison of the PDFs of test and reference patterns. The OMs of each test pattern are matched ("many to one") to their closest OM from the reference pattern. Thus, deviations are easily detected via visual comparison of PDFs. The OMs mentioned in the assessment are marked with red arrows in their corresponding figures. OMs 7–25 are magnified for better visualization of deviations in such OMs.

When deviations are detected in variables that are part of the working mode configuration (i.e. variables that can be adjusted through the controller of the system) then, they should be considered as new working modes not covered by the reference pattern. On the other hand, when deviations take place mostly in variables that cannot be manually set by the controller, potential behavior deviations may be occurring. This rule makes it possible to differentiate behavior deviations from new behaviors not included in the reference pattern.

The three features studied are: *P* - Active power [MW]; *O* - guide vane opening [%], *T* - bearing temperature [°C]. PDFs in dark blue correspond to the reference pattern of 2011.

The results obtained for working mode S1 (hydropower plant consuming active power) show that operating conditions defined by *P* and *O*, are very similar to the reference pattern (2011). *T*, on the other side, starts to deviate after 2012. These deviations can be noticed in the test PDFs in *T OMs* 15, 20 and 24 in 2013; and *OMs* 15, 20 and 21 in 2014 in which deviations of +1°C appear.

Working mode S2 (hydropower plant generating active power) shows deviations in all of the three variables. A simultaneous deviation in *P*, *O* and *T* is an evidence of a possible change in the operation conditions of the plant. In 2014, *OMs* 15, 21 and 23 show similar PDFs regarding variables *P* and *O*, but in *T*, a temperature increment close to +2°C can be seen.

When deviations take place only in *T*, it can be classified as a failure, on the other hand when deviations take place in all the features at the same time, it can be considered as a change in the working mode of the hydropower plant.

Taking into account that patterns were obtained for all the samples collected during a year, seasonal variations in temperature can be assumed as not significant.

5.3. Behavior assessment through indicators

In the following, the information shown in previous Figs. 18 and 19 is assessed numerically. The results of the assessment are shown in Fig. 21. The results correspond to the assessment of yearly behavior patterns with regard to the reference pattern 2011. These results include, in addition, years 2015 and 2016. Each assessment shows two different pieces of information:

- Similarity analysis. The scale of the values is located at the left side of the graph and the values are plotted in red. The values are obtained according to the method described in Section 3.3.1. This indicator refers to how "similar" the pattern under assessment is in comparison to a reference pattern. In those cases where similarity values are close to 0 it is recommendable to focus on the obtained values of the deviation indicator in order to have a detailed view of the magnitude of the deviation.
- Deviation analysis. The scale of the values is located at the right side of the graph and the values are plotted in light brown (positive deviations from the reference value) and dark brown (negative deviations from the reference value). Their values correspond to the ones obtained according to the method described in Section 3.3.2. Values shown are already normalized regarding the standard deviation of each reference *OMs*.

In order to understand the results shown in Figs. 21, 22 and 24 ; Fig. 20explains the meaning of each element that appears in the graphs.

The numerical results shown in Fig. 21 confirm the behavior appraisal carried out through visual inspection in Figs. 18 and 19 .

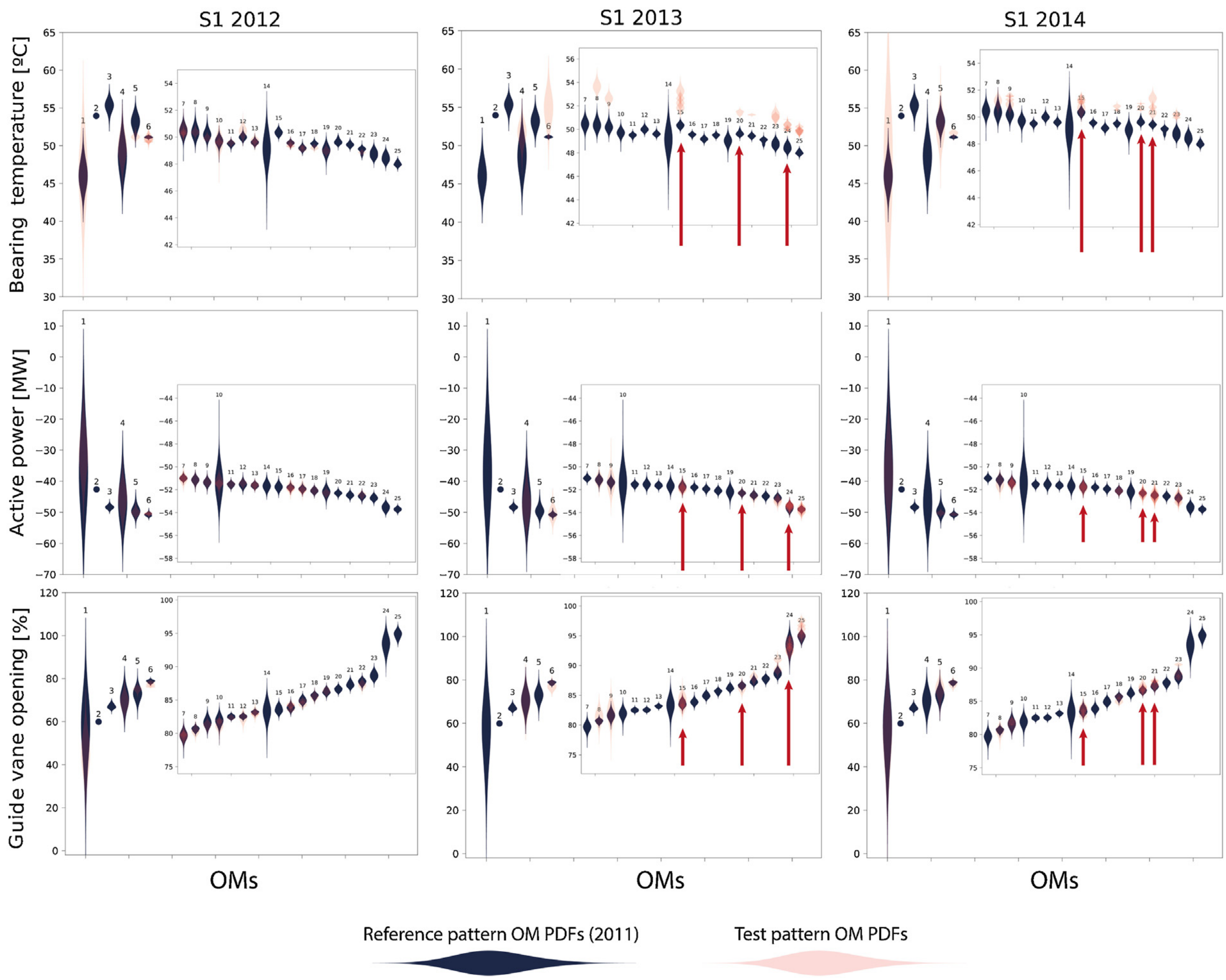


Fig. 18. Pattern comparison and assessment of deviations between 2011 (reference pattern) and 2014 in working mode S1.

In working mode S1, it can be seen that the behavior under assessment is loosing similarity each year with regard to its reference behavior (2011). This loss of similarity is specially remarkable after 2012. It is important to highlight the correlation between *P* and *O*. Although variables *P* and *O* remain above 0.4 and below 2.5σ in their similarity and deviation coefficients respectively, in the case of *T* its similarity indicator drops down to values close to 0.1 and reaches deviations ten times larger than their standard deviation. In particular, in 2014, it can be seen that, approximately only 11% (4%+7%) of the *T OMs* of the test pattern have absolute deviation values lower than 2.5. This explains why the similarity regarding its bearing temperature is around 0.1. Although similarity values in *T* are remarkably low, the correlation between features remains; this is, an increment in *P* implies an increment in *O* and *T* (an apparition of a new working mode is more likely than an anomalous behavior).

Similar relationships between variables appear in working mode S2. In contrast to S1, S2 shows, in 2016, a break in the correlation between *P*, *O* and *T*. It can be observed that although deviations in *P* and *O* become lower during this year than in the previous one, *T* keeps increasing. This behavior evidences the existence of an anomaly in the behavior of the bearing cooling system, due to the fact that the temperature, which keeps increasing despite the opposite trend in the other two features, shows a positive trend.

An additional assessment is carried out through the direct comparison between the observations collected throughout the years tested and the reference pattern (2011). The results obtained are shown in Fig. 22.

Slight variations can be seen comparing the results obtained in the analysis "Observations vs. Pattern" to the previous results obtained with a "Pattern vs. Pattern" analysis. The Similarity indicator value obtained in the reference year (2011), is close to 0.8 (being 1.0 in the previous assessment). This deviation is due to the fact that some observations of the training set are located far away from the distribution centroid. In S2 *T*, there are some years in which the markers of the negative deviation curve have a percentage equal to 0%. This happens because the percentage value is rounded to its nearest integer and these values are lower than 0.5% of the total number of observations during such years.

When assessing periods different from the reference one, both approaches provide equivalent information, although assessing observations directly allows for the detection of deviations caused by outliers and occasional working conditions.

The results and conclusions derived from both approaches are remarkably similar, therefore confirming the coherence of the results obtained through both methods.

5.4. Maintenance assessment

This methodology, not only provides information about the behavior of a component, but also about the effectiveness of a maintenance task quantifying the recovering level of a component behavior from a previous (defective) one. In previous figures, it could be seen that the behavior of the bearing cooling system has changed drastically since 2013. Therefore 2013 was taken as a ref-

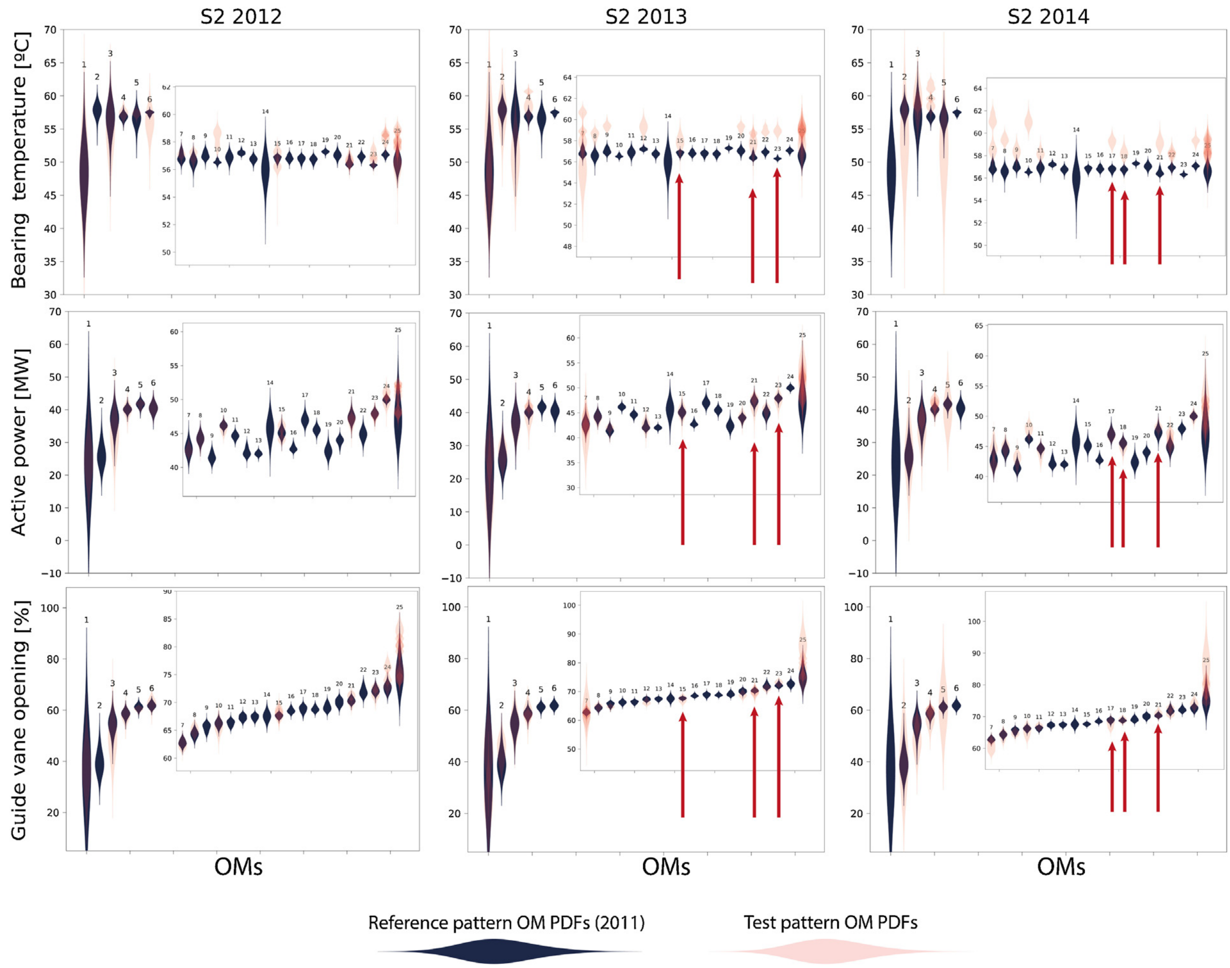


Fig. 19. Pattern comparison and assessment of deviations between 2011 (reference pattern) and 2014 in working mode S2.

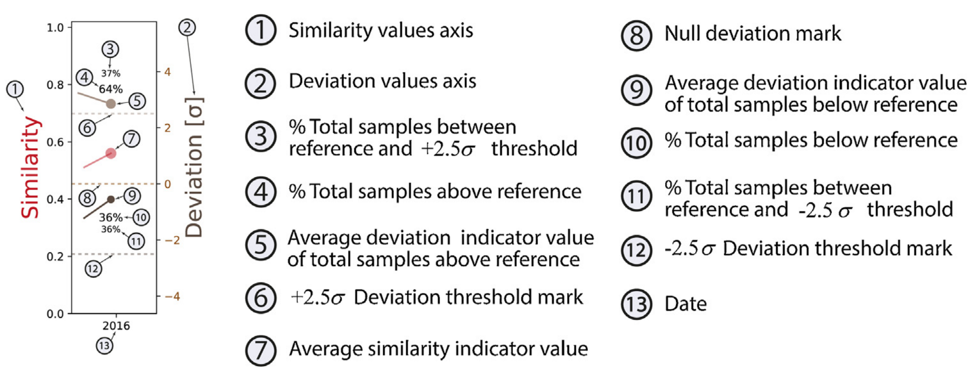


Fig. 20. Meaning of the elements present in the behavior assessment.

erence year due to the fact that comparing two behaviors with big discrepancies between them, can lead to a loss of accuracy in the overall assessment.

The method proposed is a powerful tool as it can be an important source of information about the quality of the maintenance tasks that were carried out, and at the same time it is able to assess the evolution of the behavior of the components. Regarding the maintenance assessment, the method proposed is able to provide information about:

- Efficacy. Fig. 23(A). Improvements in similarity and deviation indicators. After a maintenance task, the behavior of the system reaches back to similarity values above 0.4 and deviation values below 2.5σ.
- Effectiveness. Fig. 23(B). The effects of the maintenance persist over time. The longer of the effects remain, the more effective the maintenance task has been.

Regarding the component behavior, the methodology proposed is able to provide information about:

- behavior deviation trends. Fig. 23(C). Depending on the working conditions of the hydropower plant, some behavior deviations

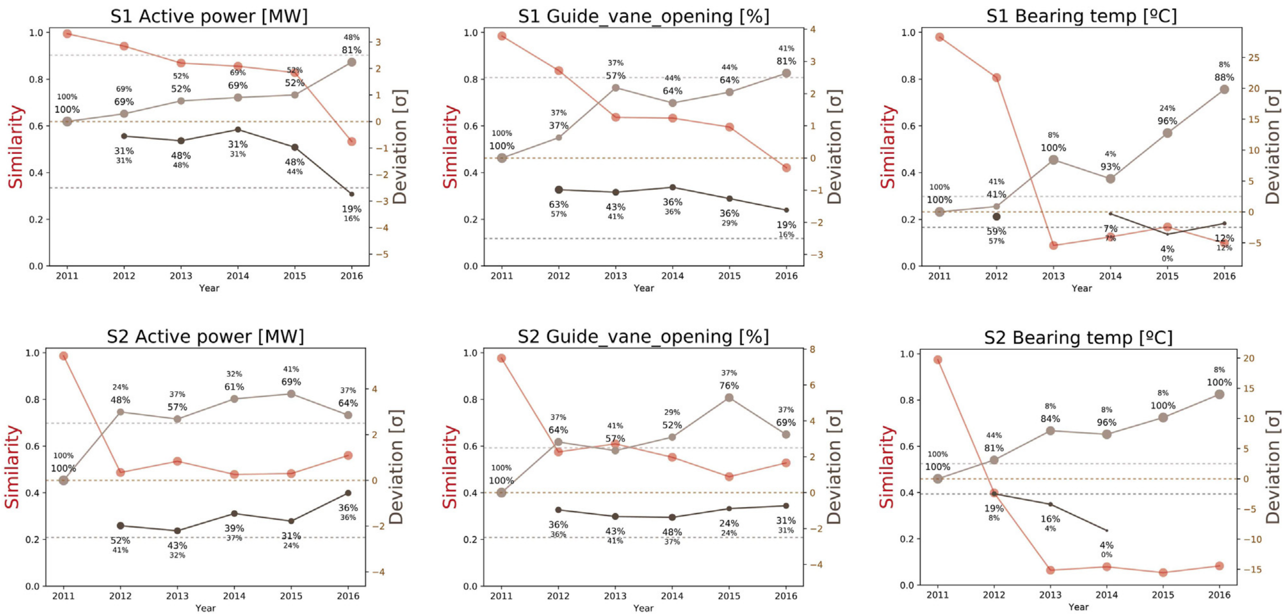


Fig. 21. Pattern comparison and assessment of deviations. Reference pattern obtained in 2011 compared with test patterns obtained from 2011 to 2016.

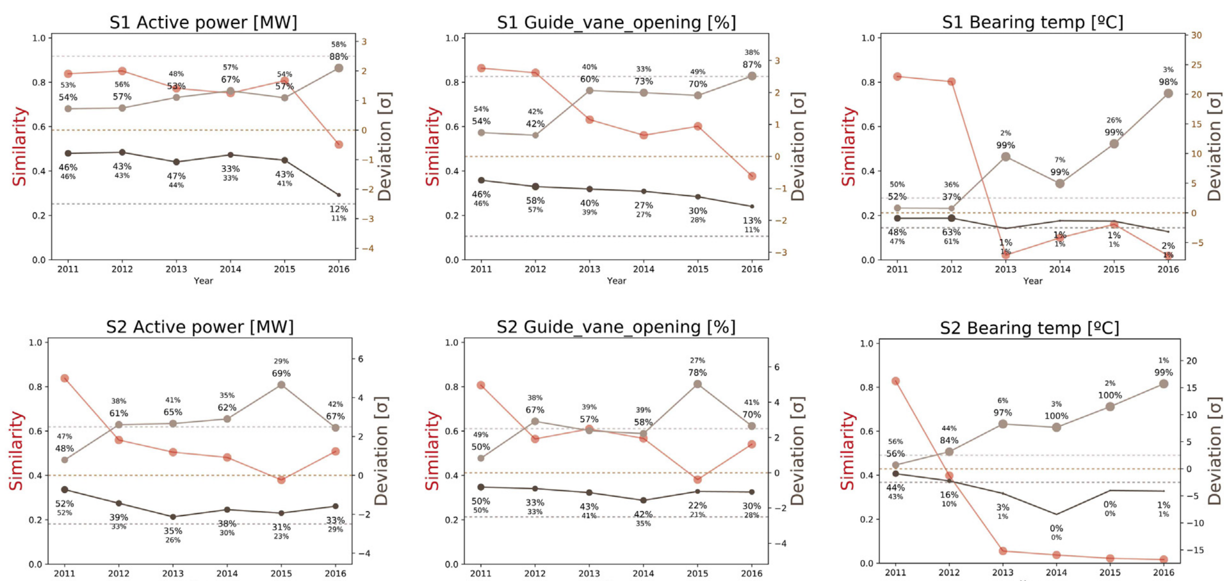


Fig. 22. Comparison and assessment of deviations between reference pattern (2011) and observations registered between 2011 and 2016.

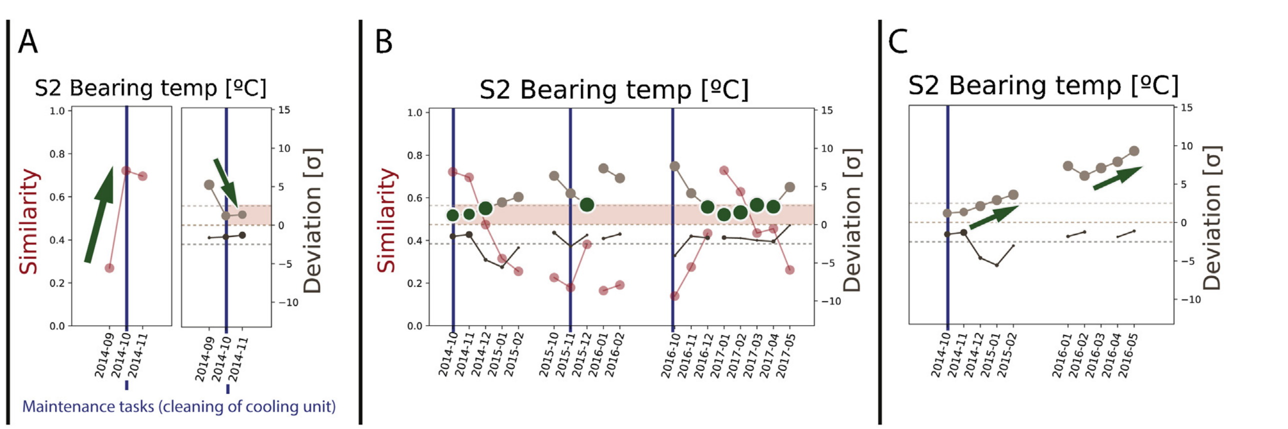


Fig. 23. (A) Maintenance task efficacy. (B) Maintenance task effectiveness. (C) Component behavior deviation trend.

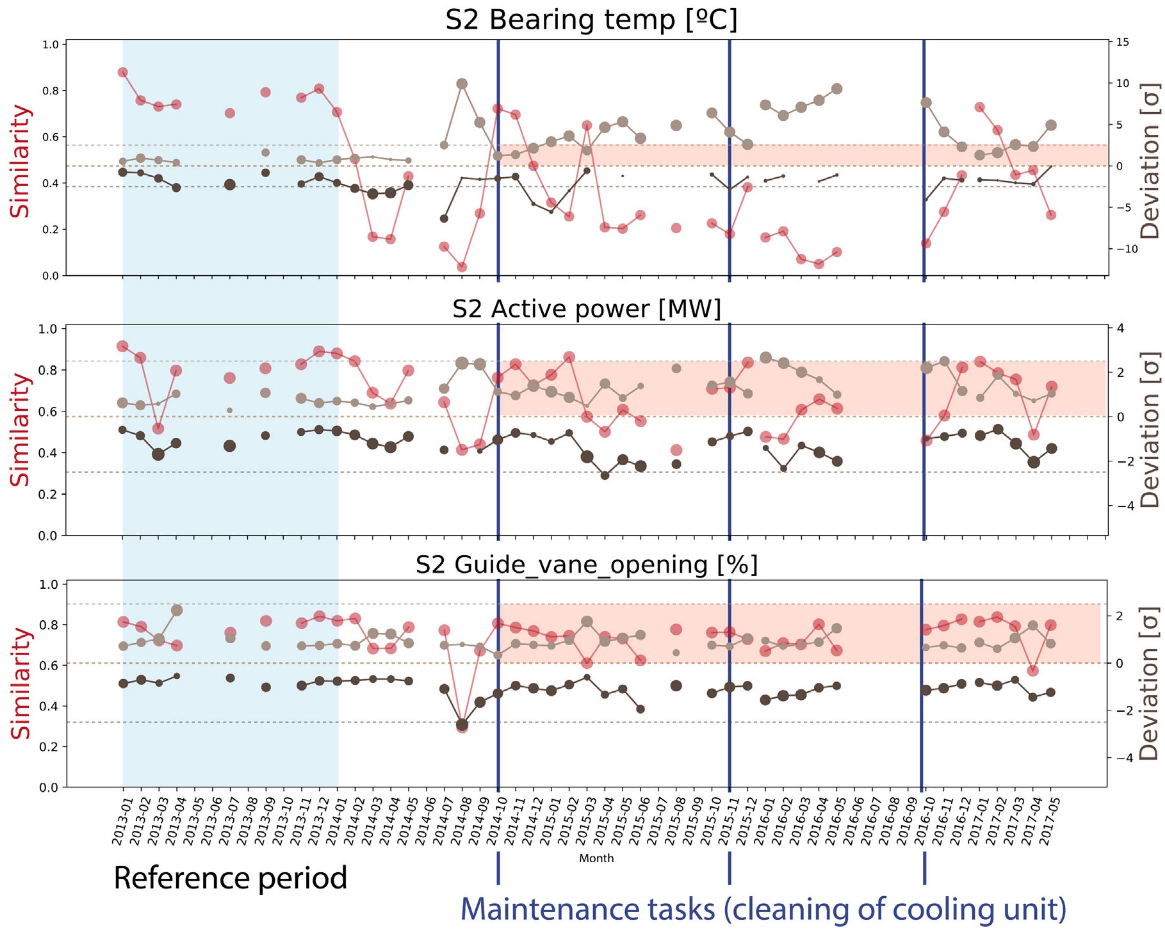


Fig. 24. Comparison and assessment of deviations between reference pattern (2013) and observations (2013 and 2017).

display trends that can be studied and applied to a PHM strategy program.

Fig. 24 shows how this methodology can be applied in the assessment of maintenance tasks. The maintenance activities registered are focused on the bearing cooling system. This study aims to provide different approaches to assess the effectiveness of such maintenance activities. As the maintenance tasks registered were applied to the bearing cooling system, the attribute under assessment is the bearing temperature. Three cleaning activities in the cooling unit were registered on 29/09/2014, 21/10/2015 and 21/09/2016.

The behavior under assessment corresponds to the working mode S2 (hydropower plant producing energy) from 2013 until 2017. The results of this assessment show that working conditions regarding P and O from 2013 until 2017 remain within deviation limits $\pm 2.5\sigma$ according to the reference pattern (2013). In contrast, T shows greater deviations from their confident limits. The results obtained in 09/2014, show an improvement in similarity and deviation indicators before the maintenance task took place. In order to explain this behavior, it is necessary to know that during this month the hydropower plant experienced several stops during which bearing temperatures cooled down, leading to slight improvements in both indicators. It can be seen that the first and third maintenance tasks achieved a more effective recovery in T than in the second one which did not achieve a significant improvement. A good maintenance should produce a reduction in the deviation value, an increment in the similarity value and should extend a normal behavior as much as possible.

6. Conclusion

This paper describes a novel methodology based on behavior patterns obtained from the application of unsupervised machine learning algorithms for anomaly detection of industrial component behaviors. Behavior patterns are obtained through clustering algorithms such as K-means and Self-Organizing maps (SOMs) as a starting point, to be used in later diagnosis. The novelty introduced by this method is the procedure to carry out a deep analysis of the information initially clusterized in reference behavior patterns and their later adaptation to the new behaviors observed. As core of this analysis, an algorithm based on local Probability Density Distributions (PDD) of the clusters obtained is used to enhance the characterization capability of the patterns. Another important contribution was the description of two different strategies for the assessment of behaviors based on patterns and two indicators: *similarity*, which measures how similar an observation is regarding the PDF of its reference pattern; and *distance*, which measures deviations regarding the standard deviations of the reference pattern. The methodology proposed emphasizes the joint use of both indicators to improve the accuracy of the assessments of the behaviors registered. These indicators are useful inputs for detecting degradations or changes in the behavior of a component that also can give support to an approach based on data-driven maintenance strategies.

This paper has presented the application of the methodology to a real case in the field of hydropower plants. In this case study, the behavior of the hydropower plant was characterized through three variables: active power [kW/h], guide vane opening [%] and bearing temperature [°C]. The results of the assessment showed a deviation trend in the temperature of the bearings while the other two variables, active power and guide vane opening, remain within normal behavior conditions defined by the chosen reference pattern. Three maintenance tasks are also included and assessed in this study. Applying the same methodology proposed for the behavior analysis, maintenance efficacy and effectiveness were also assessed. This part of the study shows how the quality of maintenance tasks can be studied from a behavioral point of view. The results obtained are a successful demonstration of the capability of the new method proposed in the diagnosis and maintenance assessment for real-life industrial applications.

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