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Data-driven prognostics using a combination of constrained K-means clustering, fuzzy modeling and LOF-based score

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ABSTRACT

Today, failure modes characterization and early detection is a key issue in complex assets. This is due to the negative impact of corrective operations and the conservative strategies usually put in practice, focused on preventive maintenance. In this paper anomaly detection issue is addressed in new monitoring sensor data by characterizing and modeling operational behaviors. The learning framework is performed on the basis of a machine learning approach that combines constrained K-means clustering for outlier detection and fuzzy modeling of distances to normality. A final score is also calculated over time, considering the membership degree to resulting fuzzy sets and a local outlier factor. Proposed solution is deployed in a CBM+ platform for online monitoring of the assets. In order to show the validity of the approach, experiments have been conducted on real operational faults in an auxiliary marine diesel engine. Experimental results show a fully comprehensive yet accurate prognostics approach, improving detection capabilities and knowledge management. The performance achieved is quite high (precision, sensitivity and specificity above 93% and $\kappa = 0.93$), even more so given that a very small percentage of real faults are present in data.

1. Introduction

Unexpected incidental failures imply an important impact in terms of risks, costs, resources and service loss that should be minimized [1]. The growing complexity of industrial equipment, systems and installations results in an ever-increasing amount of health monitoring information, which eventually exceed the capacity of most fault detection systems and makes the design of successful maintenance methodologies more challenging. Moreover, it is important to provide a better understanding of monitored systems and to efficiently characterize the normal behaviors from a huge amount of historical data. The lack of knowledge about the behavior of complex assets makes the problem of maintenance very difficult.

Naval sector, for instance, is traditionally focused on preventive strategies, usually divided by 3–4 maintenance difficulty level groups: vessel crew, vessel base, shipyard, and manufacturer [2]. Crew and base level maintenance tasks are planned and carried out during vessel operating time; however, shipyard and manufacturer tasks are done in programmed dock periods. The whole vessel life cycle is divided by long operating periods separated by short maintenance periods, some of them dry-dock. When an important unexpected breakdown occurs during operation (at both shipyard or manufacturer level), vessel activity stops and planned missions have to be cancelled. Additionally, important repair costs must be envisaged. In such cases it is often necessary to open dismantling routes aiming to remove defective parts. Sometimes a cesarean in the vessel hull or even a dry-dock have to be performed to extract the involved equipment. Therefore, total costs may include: defective parts, reparation manpower, dismantling route procedures and a cesarean or a dry-dock. Indirect tasks are usually more expensive than normal component reparation processes. Moreover, when a failure arises while a mission is in process, objectives could not be fulfilled or the mission might be cancelled and vessel is returned to base. But the worst-case scenario is that in which vessel or crew safety are threaten.

This work is an effort to implement a novel machine learning based approach that aims to minimise the negative effects of unexpected breakdowns, providing a reliable fault detection and

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prediction strategy. This approach has been applied over real operational data acquired from an auxiliary diesel engine during real vessel operation, since it is one of the most critical vessel components: it supplies propulsion and energy to the vessel and its behavior is complex, as it is a reciprocating engine matched with a turbocharger. A study in-depth was carried out into the possibility of improvement through the use of data-driven machine learning techniques to statistically model the normal behavior of the engine, in a fully automated unsupervised fashion. To do so, behavior characterization and fuzzy modeling are applied to monitoring sensor data. Moreover, knowledge models generated are comprehensive, yet accurate methods to anticipate potential critical faults. Resulting models and all available information are integrated in a specific CBM+ (Condition Based Monitoring) system, which combines CBM, RCM (Reliability Centered Maintenance) and AI (Artificial Intelligence) capabilities. Although the study is focused on the exploitation of operational parameters, it must be mentioned that the proposed approach can be also applied to other types of operational parameters that can be used as failure indicators, such as vibrations, fluids analysis, thermography information, in-cylinder pressure or ultrasonic information.

The rest of the article is organized as follows. Section 2 presents a review of related and previous works under the use of condition based maintenance methods and strategies for improving assets reliability, and the position of the present work in the context of previous ones. Sections 3 and 4 explain the machine learning based approaches used to characterize asset behavior and detect anomalies, based on constrained clustering and fuzzy modeling, respectively. In Section 5 the test scenario is presented and the experimental results obtained are discussed. Finally, the conclusions achieved in this study are given in the last section.

2. Related work

Condition based maintenance aims to anticipate a maintenance operation based on evidences of degradation and deviations from normal asset behavior. When observing the condition of a particular system a set of monitoring devices and sensors must be considered. Intelligent monitoring of equipment by means of sensors is essential in order to acquire relevant data, containing the characterization of operational faults in physical signals: acoustic and ultrasonic sensors, accelerometers, current measurements or thermocouples are usually employed [3,4]. In addition to this data, environmental conditions and contextual information, such as temperature, pressure or humidity also provide very useful additional information to enrich the modeling process [5]. From such information, specific Key Performance Indicators (KPIs) are calculated and analysed to discover trends and knowledge of interest that can lead to a potential critical fault.

A traditional preventive strategy may obtain high reliability levels if it is well designed [6]. However, it sometimes implies overmaintaining the assets. This is due to the fact that equipment manufacturers are always conservative in their maintenance policies so that reliability is achieved, but assuming high maintenance costs. It is well known that failure probability of many components is high at the beginning and end of its operational life, following the *bathtub* failure pattern [7]. Therefore, unnecessary maintenance tasks increase failure rate when a defective item is installed or due to a human mistake. Moreover, preventive strategies do not take into account operational context such as load profiles, number of starts or environmental parameters, which strongly affect components lifetime. Finally, preventive maintenance is erroneously based on the idea that the probability of occurrence of operational faults increases exponentially at a certain time. In preventive strategies components are replaced or repaired before that moment occurs. This assumption is not true in many cases, since there are several failure patterns in which failure probability does never increase [8]. In such cases failure probability is constant in time. Thus, a component could fail at any time. Especially relevant examples of this phenomenon are failure patterns of electrical and electronic components, in which reparation and substitution tasks at planned periods of time does not imply an improvement in terms of reliability. For all these reasons there still exists important reliability increase and cost reduction margins.

In order to improve reliability and to reduce costs an optimal maintenance strategy should provide a set of predictive, preventive and corrective procedures as a result of a technical and economic analysis of every failure mode, taking into consideration the related consequences [9]. Reliability Centered Maintenance (RCM) strategies include a Failure Mode, Effects and Criticality Analysis (FMECA). Once failure modes are identified and criticality classified, maintenance tasks to be undertaken are established to avoid faults consequences [10]. When predictive maintenance is technically possible and is economically worth it, compared to preventive and corrective ones, it is applied. Maximum reliability is obtained when a robust and trustworthy failure indicator parameter is monitored. When it is not technically possible or it is not affordable, preventive maintenance strategies are adopted. Corrective maintenance is only envisaged in case predictive and preventive maintenance strategies are not feasible. If that is the case, the consequences of a fault are critical and only corrective maintenance is feasible. In those situations, the use of safety devices to apply appropriate troubleshooting tasks or redesigning affected asset (e.g. installing a standby component) is required.

When the aim is to achieve maximum reliability an appropriate CBM+ system with monitoring capabilities must be adopted, gathering and combining all kind of useful sources of information simultaneously and providing the prognostics needed to assure the correct operation of the assets (e.g. the critical components of a paediatric emergency department) [11]. Thus, resulting CBM+ system must include data acquisition and processing, diagnostics and prognostics and decision making functionalities [12]. Generated data-driven models for diagnostics and prognostics must be deployed in a monitoring platform with online data acquisition and inspection capabilities [13]. Several commercial CBM+ systems are already available, most of them using a wide variety of potential failure indicators, separately [14,15].

Data-driven prognostics models are the core of the whole process since they apply the behavioral and statistical methods for fault prediction and classification [16]. Artificial neural networks [17] and support vector machines [18,19] are usually applied to analyze data and infer such models. The use of projection methods (e.g. linear, nonlinear and orthogonal projections to latent structures, kernel methods or PCA) for dimensionality reduction and regression can highly support the prediction process [20–22]. Nevertheless, depending on the application and whenever it is possible, it may be beneficial to instead incorporate specific knowledge directly into whichever algorithm is applied.

In this regard, one of the most challenging objectives is how to explicitly and automatically represent and model expert's knowledge [23], characterizing different behaviors of interest and linking them to critical faults in assets and equipment of the sea vehicle. Nowadays, this kind of methodologies are not yet commonly integrated in maritime sector, due to either companies' agnosticism about their benefits or to integration drawbacks in terms of both time and costs [24]. However, as new research works and even commercial systems under development arise, demonstrating important improvements on reliability when comparing them to traditional strategies and showing appealing Return of Investment (RoI) levels, companies and maintenance suppliers show an increasing level of acceptance of such novel technologies.

3. Behavior characterization

Data-driven behavior characterization consists on grouping similar data into data sets, which physically represent the same operational condition. Within formed groups, there exists data points far from the pattern, which corresponds to the mean point. Such pattern could be very significant in order to classify or to identify behaviors linked to the data, or in order to detect or to infer possible faults or anomalous operational conditions. Big groups, or groups that are close together, usually imply normal behaviors. Whereas small groups or events that are far from the pattern (of the same group or regarding a big group), imply anomalies or outliers (e.g. noise and transient data). It must be noted that the learner is only provided with unlabelled examples. When labels are available, supervised learning and reinforcement learning can be applied to train a classifier. However, it is often very difficult to obtain a large data set containing real faults.

3.1. Constrained K-means clustering

In the proposed constrained K-means approach, k value is automatically provided based on cluster distribution and cluster data variance as established by He et al. and Wu et al. [25,26]. It is computed as a previous step of the clustering process. Variance explained of resulting classification model, or clusters compactness, Cmp, is calculated until $Cmp_k - Cmp_{k-1} \leq 0.5$. As Euclidean distance is applied [27], it becomes coherent to average cluster scattering index [28]. The member of each cluster should be as close to each other as possible. The clusters compactness is computed as it can be seen in Eq. (1).

$$Cmp = \frac{1}{k}\sum_{i=1}^{k}\frac{||\boldsymbol{\sigma}(\boldsymbol{C_i})||}{||\boldsymbol{\sigma}(\boldsymbol{X})||}$$

$$\boldsymbol{\sigma}(\boldsymbol{C_i}) = \begin{bmatrix}\sigma_{C_1}^{1}\\ \vdots \\ \sigma_{C_k}^{m}\end{bmatrix} \qquad \boldsymbol{\sigma}(\boldsymbol{X}) = \begin{bmatrix}\sigma_{X}^{1}\\ \vdots \\ \sigma_{X}^{m}\end{bmatrix} \tag{1}$$

where k is the number of clusters; $\boldsymbol{\sigma(C_i)}$ is the variance of cluster C_i with $\sigma_{C_i}^{p} = \frac{1}{|C_i|}\sum_{j=1}^{n}(x_j^p - C_i^p)^2$ and $\boldsymbol{\sigma(X)}$ is the data variance with $\sigma_X^p = \frac{1}{n}\sum_{i,j=1}^{n}(x_i^p - x_j^p)^2,\ i \neq j$.

When knowledge regarding the system behavior to be modeled is available in addition to the data instances themselves, the algorithm can be modified to make use of this knowledge [29]. A constrained that consists on specifying an asset main input feature, X_f, is thus considered so that instances are grouped on the basis of X_f non-parametric distribution. Given the number of clusters, k, their width in terms of X_f values are estimated as $w = \frac{max(X_f) - \min(X_f)}{k}$. Then, for each cluster C_i, $i = (1, \ldots, k)$, $u_k = min(X_f) + (i+1) * w$ and $l_k = u_{k-1}$, with $u_0 = min(X_f)$, are set as upper and lower limits on X_f values, respectively. Then, a local distance-based outlier detection can be accurately performed considering the asset status, determined by its main input feature values.

Given a set of m features, $X = \{X_1, \ldots, X_m\}$ where each feature X_i can take a value from its own set of possible values χ_i, and n feature vectors or instances, $\boldsymbol{x_i} = (x_1, \ldots, x_m) \in \chi = (\chi_1, \ldots, \chi_m)$, with $i = 1, \ldots, n$, $L2$ normalization is calculated for each instance $\boldsymbol{x_i}$ in the data set in order to minimise the impact of having different range of values of raw data in the resulting classification model. It is computed as the root of the sum of its squared elements, as it can be seen in Eq. (2).

$$L2(\boldsymbol{x_i}) = \sqrt{\sum_{l=1}^{m}|x_{il}^2|} \tag{2}$$

Once the normalization of data samples is performed using $L2$, and in order to calculate the distance between instances, $\boldsymbol{x_i}$ and $\boldsymbol{x_j}$, Euclidean metric is computed (see Eq. 3).

$$D(\boldsymbol{x'_i}, \boldsymbol{x'_j}) = ||\boldsymbol{x'_i} - \boldsymbol{x'_j}|| = \sqrt{\sum_{l=1}^{m}\left(x'_{il} - x'_{jl}\right)^2} \tag{3}$$

where $\boldsymbol{x'_i} = \frac{\boldsymbol{x_i}}{L2(\boldsymbol{x_i})}$ and $\boldsymbol{x'_j} = \frac{\boldsymbol{x_j}}{L2(\boldsymbol{x_j})}$ are the $L2$-normalized instances $\boldsymbol{x_i}$ and $\boldsymbol{x_j}$, respectively.

The convergence criteria is established as a maximum number of iterations and a stability threshold, which checks the clusters compactness variation of resulting classification model from ith iteration to iteration $i+1$ (see Eq. 1).

An iterative outlier detection loop is then performed, so that from groups of instances formed during the constrained-learning stage, outliers are detected and isolated and behaviors of interest given a certain asset main input feature values are characterized. They are represented by instances that belong to a certain group but differs notoriously from the pattern. For each iteration in the outlier detection process and for each cluster, C_i, an anomaly threshold is calculated based on the distances of instances grouped in C_i to the centroid, as it can be seen in Eq. (4).

$$Th(C_i) = \frac{1}{|C_i|}\sum_{\boldsymbol{x_j}\in C_i} D(\boldsymbol{x'_j}, \boldsymbol{c_i}) + 3\sqrt{\frac{\sum_{\boldsymbol{x_j}\in C_i} D(\boldsymbol{x'_j}, \boldsymbol{c_i})^2}{|C_i| - 1}} \tag{4}$$

where $\boldsymbol{c_i} = \frac{1}{|C_i|}\sum_{\boldsymbol{x_j}\in C_i}\boldsymbol{x'_j}$ is the centroid of cluster C_i and $\boldsymbol{x_j}$, $j = \{1, .., |C_i|\}$, is the jth instance grouped in cluster C_i.

Events whose distance to the centroid are over the anomaly threshold are set as outliers. Consequently, for each iteration during the outlier detection process and for every cluster, centroids are recalculated filtering out detected outliers. The process stops when no more outliers are detected. Outliers detected within a cluster and small clusters could imply abnormal asset behaviors and operational faults.

The overall algorithm can be seen in Algorithm 1.

Algorithm 1 Constrained K-means clustering for outlier detection.

Input: a set of m features, $X = \{X_1, \ldots, X_m\}$

Compute k using Equation 1
Select an asset main input feature $X_f \in X = \{X_1, \ldots, X_m\}$
Compute $w = \frac{max(X_f) - \min(X_f)}{k}$
for all C_i, $i = (1, \ldots, k)$ **do**
  Find $u_k = min(X_f) + (i+1) * w$ and $l_k = u_{k-1}$, with $u_0 = min(X_f)$
  for all $\boldsymbol{x_j} \subset \{l_k, u_k\}$ **do**
    $\boldsymbol{x_j} \rightarrow \{C_i\}$
  end for
end for
$outliers = \{\}$
while *ouliers* found **do**
  for all C_i, $i = (1, \ldots, k)$ **do**
    Compute $Th(C_i)$ using Equation 4
    if $D(\boldsymbol{x'_j}, \boldsymbol{c_i}) > Th(C_i)$ **then**
      $\boldsymbol{x_j} \rightarrow outliers$
      Remove $\boldsymbol{x_j}$ from C_i
    end if
  end for
end while

Although constrained K-means clustering is a known algorithm in the literature [30,31], the main novelty in this work lies in successfully applying the proposed approach in practice, to a complex industrial scenario.

4. Anomaly detection

In this section the anomaly detection process is presented. It is performed on the basis of behaviors characterized from data by applying constrained K-means clustering and on outliers found. The most important behavior to be considered is normality.

4.1. Fuzzy partition

Fuzzy rules generation process and inference engine are based on work proposed by Cingolani et al. [32]. Fuzzy controllers are currently considered to be one of the most important applications of the fuzzy set theory proposed by Zadeh [33]. This theory is based on the notion of the fuzzy set as a generalization of the ordinary set characterized by a membership function μ that takes values from the interval [0, 1] representing degrees of membership in the set. Fuzzy controllers typically define a non-linear mapping from the system's state space to the control space. Thus, it is possible to consider the output of a fuzzy controller as a non-linear control surface reflecting the process of the operator's prior knowledge. A fuzzy controller is a kind of fuzzy rule-based system that is composed by the following parts:

- a knowledge base that comprises the information used by the expert operator in the form of linguistic control rules,
- a fuzzification interface, which transforms the crisp values of the input variables into fuzzy sets that will be used in the fuzzy inference process,
- an inference system, which uses the fuzzy values from the fuzzification interface and the information from the knowledge base to perform the reasoning process, and
- the defuzzification interface, which takes the fuzzy action from the inference process and translates it into crisp values for the control variables.

The knowledge base encodes the expert knowledge by means of a set of fuzzy control rules.

In order to consider each group of similar events, normal and outliers, in a relevant way, a fuzzy partition in two fuzzy sets is defined over the universe U_i of the Euclidean distances to centroid in cluster C_i. Let d_i be the Euclidean distance of event $\boldsymbol{x_i}$ to centroid of cluster C_i, computed as it can be seen in Eq. (3). The membership function of these fuzzy sets, respectively denoted as μ_n and μ_o are defined in Eq. (5) and Eq. (6).

$$\mu_n(d_i) = \begin{cases} \frac{Th(C_i)-d_i}{Th(C_i)-min_n} & \text{if } d_i \in [min_n, max_n] \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

$$\mu_o(d_i) = \begin{cases} \frac{d_i-Th(C_i)}{max_o-Th(C_i)} & \text{if } d_i \in [min_o, max_o] \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

where min_n and max_n and min_o and max_o are the minimum and maximum values in fuzzy sets *normal* and *outlier*, respectively, $\mu_n(d_i)$: $d_i \to [0, 1]$ quantifies the degree of membership of d_i to *normal* and $\mu_o(d_i)$: $d_i \to [0, 1]$ quantifies the degree of membership of d_i to *outlier*. Obtained fuzzy partition is described in Fig. 1. Note that considering a membership degree allows to provide experts with more interpretable information about the real status of the asset.

4.2. Event score

In order to distinguish between outliers and real faults, a local outlier factor is computed for each event distance, as it can be seen in Eq. (7). It is based on the work proposed by Breunig et al. [34] and it measures the degree of isolation of a point with respect to its neighbors. Thus, the local density is also considered

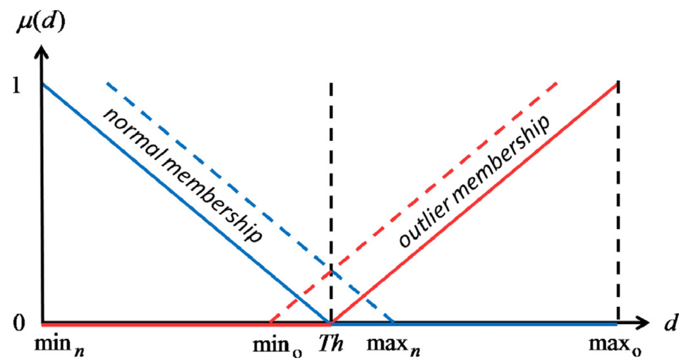

Fig. 1. Proposed fuzzy partition.

when determining if an outlier is an actual anomaly.

$$LOF(d_i) = \frac{\sum_{d_j \in N(d_i)} \frac{LRD(d_j)}{LRD(d_i)}}{|N(d_i)|} \tag{7}$$

where $LRD(d_i)$ is the local reachability distances of d_i, computed for the closest subset of distances $N(d_i)$ of size $max\left\{\frac{|C_i|}{10}, 1\right\}$, as it is shown in Eq. (8). $LRD(d_j)$ is calculated likewise.

$$LRD(d_i) = \left(\frac{\sum_{d_j \in N(d_i)} reachDist(d_i, d_j)}{|N(d_i)|} \right)^{-1} \tag{8}$$

where $reachDist(d_i, d_j) = \max\{K - dist(d_i), d_j\}$ and $K - dist(d_i)$ is the K–distance neighborhood of d_i, with $K = |\{outliers\}|$ for each cluster, being $K = max\left\{\frac{|C_i|}{100}, 1\right\}$ in the case that no outliers are found in cluster C_i.

The *score* of event $\boldsymbol{x_i}$ is then defined as a combination of the membership function to fuzzy sets *normal* and *outlier* and the local density of distances to the normal behavior.

$$score(\boldsymbol{x_i}) = \begin{cases} \frac{\mu_n(d_i) * LOF(d_i)}{max\{\boldsymbol{LOF}\}} & \text{if } d_i \in [min_n, max_n] \\ -\frac{\mu_o(d_i) * LOF(d_i)}{max\{\boldsymbol{LOF}\}} & \text{if } d_i \in [min_o, max_o] \end{cases} \tag{9}$$

where $\boldsymbol{LOF} = (LOF_1, \ldots, LOF_n)$, calculated for the whole set of distances $\boldsymbol{d} = (d_1, \ldots, d_n)$.

An event will be considered as anomaly if its *score* falls below −0.5. Fig. 2 shows an example of the evolution of the resulting event score calculated over time. The proposed event score is an optimal method for reducing false positives in anomaly detection process. It also allows users to access results quickly and efficiently.

5. Test scenario

The main goal of the present work is to improve anomaly detection and prediction capabilities of existing condition monitoring strategies. In this sense, proposed approach should be able to improve current mathematical models and preventive strategies put in practice. Once the knowledge models are learned and validated, they are deployed in the CBM+ system to automatically anticipate real-time faults in an online fashion.

5.1. Experimental setup

In order to evaluate proposed approach, several experiments were conducted on a real scenario, processing operational data acquired from an auxiliary marine diesel engine for onshore/offshore genset application. Its main specifications can be seen in Table 1.

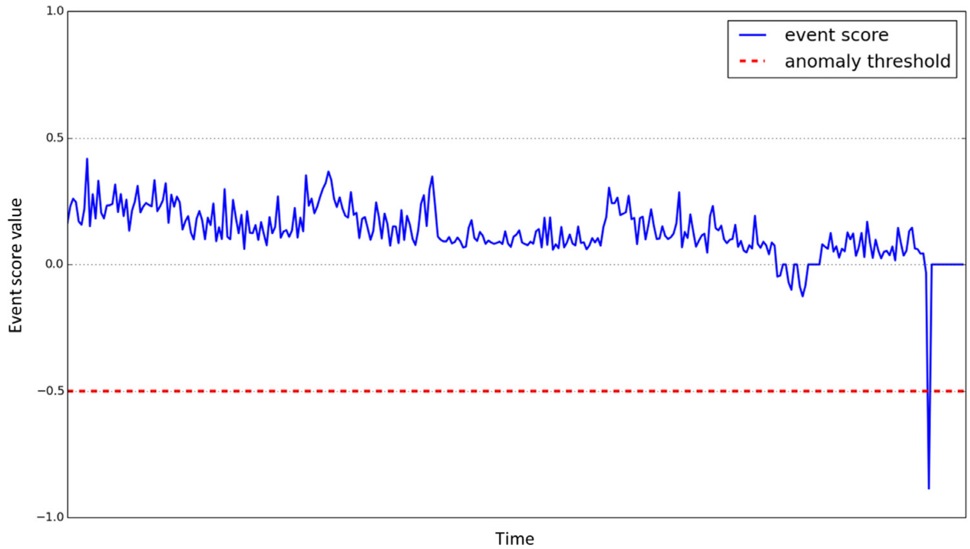

Fig. 2. Event score example.

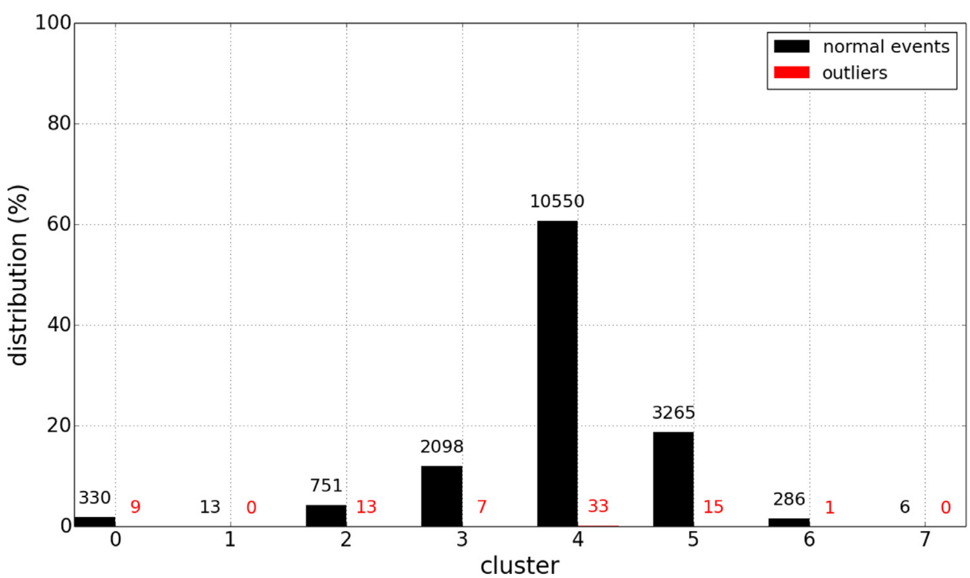

Fig. 3. Bar chart of resulting clusters distribution.

A set of operational features were monitored, collected and analysed. From these parameters the engine behavior and its health status can be established. They are shown in Table 2. Then, the data processing techniques proposed are employed to learn statistical models from historical data, which will allow identifying and modeling normal behaviors, isolating outliers and detecting operational faults.

An event is collected every minute and it is composed by values of all monitored parameters at a specific time instant. The CBM+ system automatically transfers asset sensors' readings in buffer mode to an on-board database. These data are daily sent in streaming mode to a ground control database for further analysis. Prognostics models learnt from historical data are then applied in real-time for the intelligent monitoring of the asset, checking new events on-board.

Main input parameter is the inlet fuel flow, which is the primary engine source of energy. Alternatively, main output parameters are torque and speed, which can be considered as the mechanical energy produced by the engine. In addition, there are secondary input parameters that may affect engine efficiency, which are: ambient air pressure, humidity, input air temperature, sea water temperature and fuel temperature. The engine load is set by the alternator active power, which is selected to build up the constrained clustering-based model, but alternatively it can be also set by the cylinders and turbo temperatures. Exhaust temperatures are proportional to heat generated by the fuel combustion in cylinders. Additionally, auxiliary systems are in charge of keeping appropriate lubrication and refrigeration conditions. They can be used to detect a more critical problem before it really occurs. Raw data is filtered

Table 1
Auxiliary marine diesel engine main specifications.

Parameter	Value
Number of cylinders	12V
Rated maximum power	1200 kW
Rated operating speed	1800 rpm (constant)
Bore	165 mm
Stroke	185 mm
Compression ratio	15.5

Table 2
Monitored auxiliary diesel engine parameters.

Type of variable	Parameters
Contextual variables	Environmental pressure and temperature
	Relative humidity
	Circulation seawater temperature and pressure
Engine input variables	Inlet and return fuel flow
	Fuel pressure
	Engine speed
	Cooling water pressure and temperature
	Oil pressure and temperature
	Cooling water temperature
	Intake manifold charge air pressure and temperature A
	Starting air pressure
Engine output variables	Exhaust temperature of cylinders 1A to 6A and 1B to 6B
	Inlet exhaust temperature of turbochargers A and B
	Outlet exhaust temperature of turbochargers A and B
	A and B turbo temperature drop
Generator input variables	Alternator cooling air temperature
Generator output variables	Alternator frequency
	Alternator reactive and active power
	Alternator voltage and intensity
	Alternator winding temperature in phases R, S and T
	Alternator bearing temperatures

Table 3
Percentage of variance explained for each number of clusters.

Number of clusters	% of explained variance
2	76.03
3	88.23
4	93.46
5	95.32
6	95.91
7	96.52
8	96.96

so that time regions where the engine is not working are not considered, since they have no significance regarding operational failure modes.

Domain experts' contribution takes place when identifying the asset input feature in the constrained K-means clustering step. Then, the proposed approach is automatically applied and anomalies found at the end of the process are checked and validated by the same experts. To do so, meetings and interviews with experts must be held.

The software platform used is Java Platform Enterprise Edition from Oracle. It is based on the Java programming language. Experiments were conducted in the Java-based Eclipse RCP (Rich Client Platform, Kepler version) environment on Ubuntu-Linux 14.04 (64bits), on a CORE i5 desktop PC with 4 GB of RAM memory.

In the following subsection the analysis process followed by the proposed methodology is shown over a real dataset. Moreover, a cylinders leaking problem characterised by low exhaust gas temperature in cylinders, and an alternator problem characterised by high intensity and reactive power are detected and discussed.

5.2. Experimental results

The proposed methodology has been tested on two months' time operational data, from January to February 2015, of an auxiliary diesel engine. A total of 17,377 events are analyzed. The number of clusters, k, is set to 8 given the percentage of explained variance, as it can be seen in Table 3. Although other complementary tests were performed with different k values (e.g. $k = 6$ and $k = 10$), results obtained were less accurate in terms of the number of false negatives and false positives.

As a result of the constrained K-means clustering-based outlier detection process, a total of 78 events are isolated from normal patterns. The resulting cluster distribution can be seen in Table 4 and in Fig. 3.

More in detail, events grouped in each cluster can be seen in Fig. 4. The dashed line represents the cluster centroid and operational parameters values are represented by dots, being each event a set of dots (one value per operational parameter) at a specific time instant. Operational parameters values are normalized between 0 and 1. It can be seen as a simplified Kohonen map or network with a small number of nodes, from lower to higher engine load, and no neighborhood function when updating the BMU (best matching unit) at each iteration [35].

As it can be expected, clusters containing stable engine load conditions grouped the majority of events. That is the case, for instance, of Cluster 3, 4 and 5. Outliers detected in such clusters are more likely to imply real system faults. However, and depending on nature and type of system fault, a problem can also occur when the engine is not in stable operating conditions. That behavior can be observed in relation to Cluster 0, when the engine is starting up. In Fig. 5 a typical normal engine behavior under stable operation is shown. It corresponds to normal events grouped within Cluster 3.

Among outliers found, some events correspond to abnormally low exhaust temperatures in cylinders, probably due to a scavenge fire and/or a defective fuel valve, both of which are caused by a fuel system fault. This fault was present in a total of 13 events distributed in different clusters. In Fig. 6 an example of such behavior in three events of one of the clusters formed can be appreciated. An alternator system symptom was also detected in 2 events in two different clusters. It is characterized by extremely high alternator intensity and reactive power at a normal engine load, as it can be seen in Fig. 7. It is usually produced during docking manoeuvres and could lead to critical system failure or compromised security.

The obtained confusion matrices are presented in Table 5. As it can be seen, only very few events correspond to the real fault under study: 15 in total, distributed throughout different engine load groups. This is one of the main difficulties in the anomaly detection process: how to distinguish between outliers and real faults.

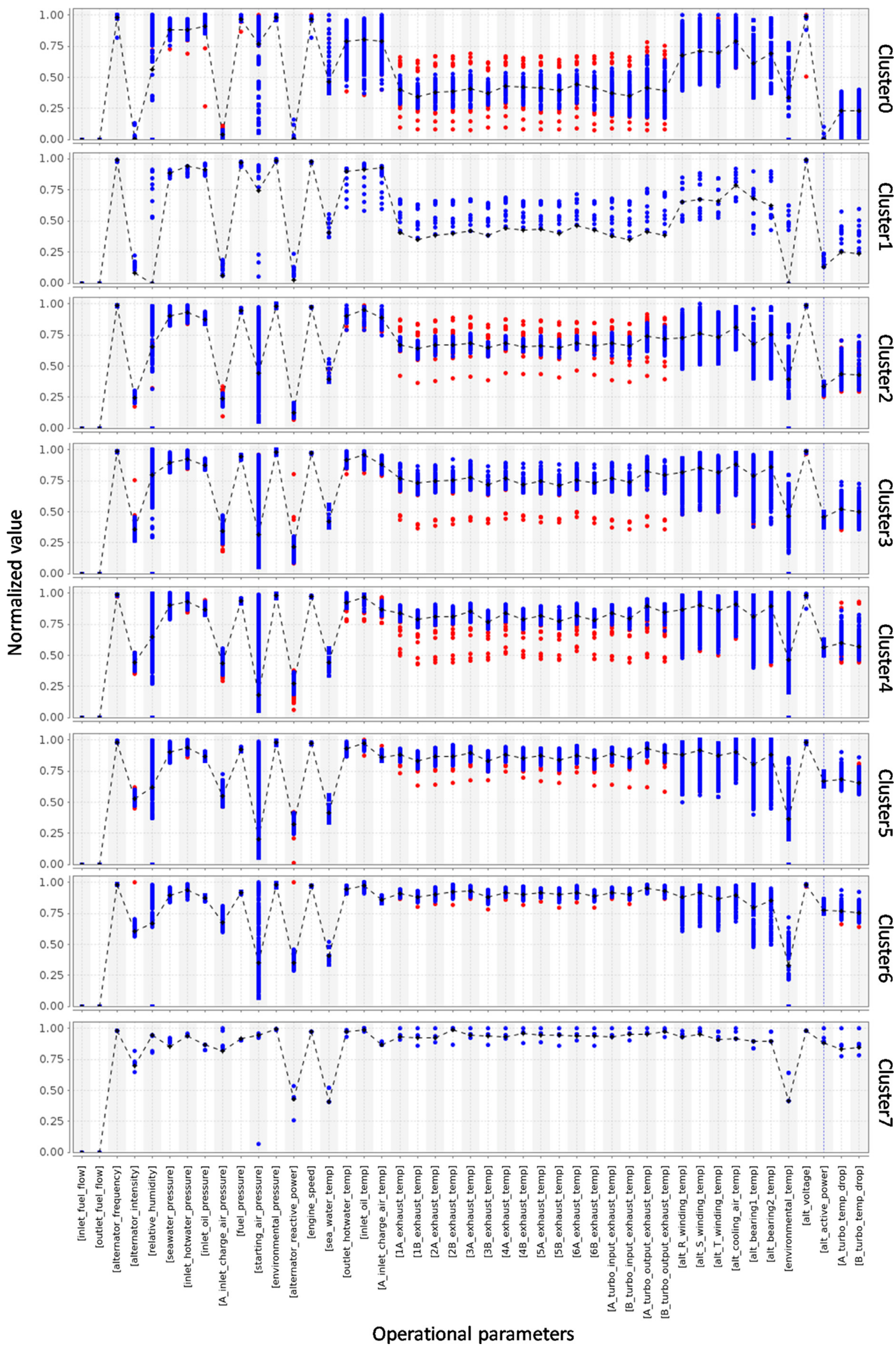

Fig. 4. Events grouped in each cluster.

Table 4
Clusters distribution.

Cluster	0	1	2	3	4	5	6	7
Total number of events	330	13	751	2098	10,550	3265	286	6
Outliers Found	9	0	13	7	33	15	1	0

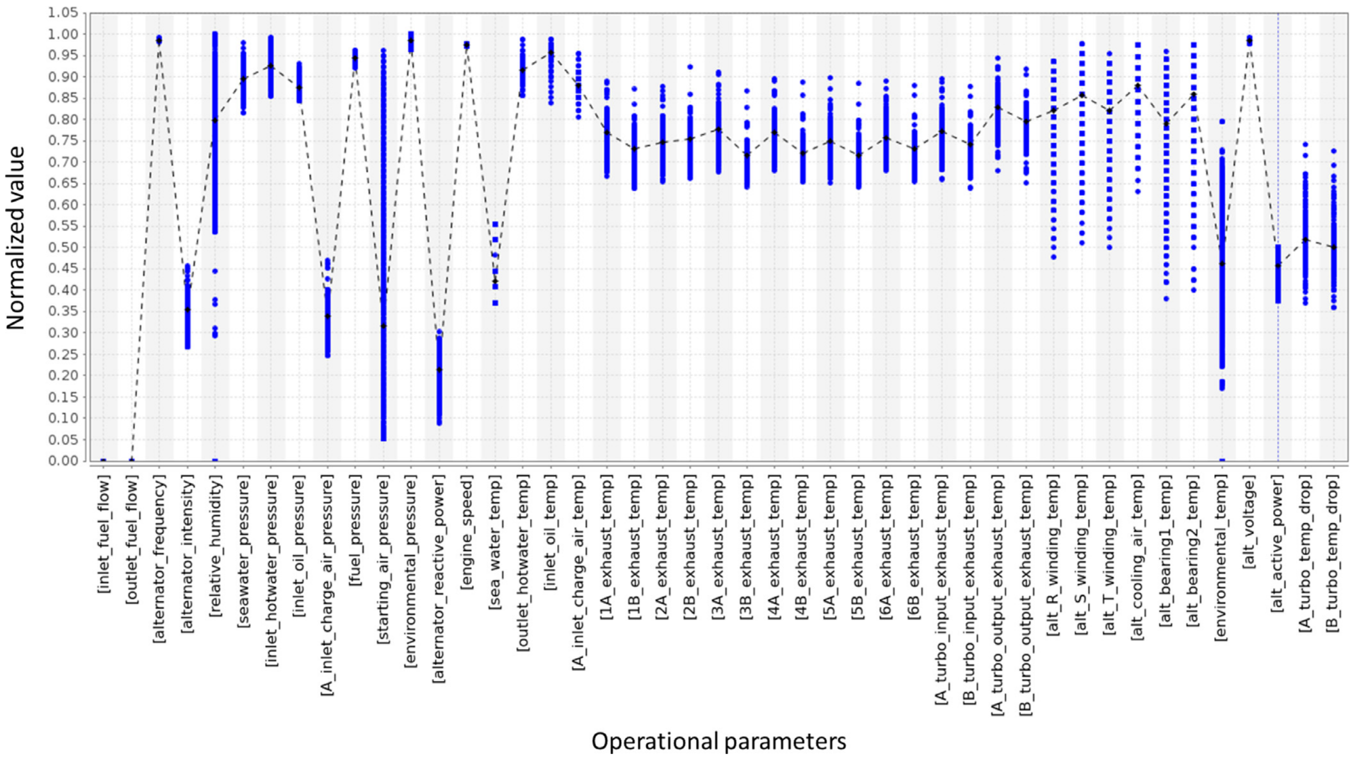

Fig. 5. Normal engine behavior.

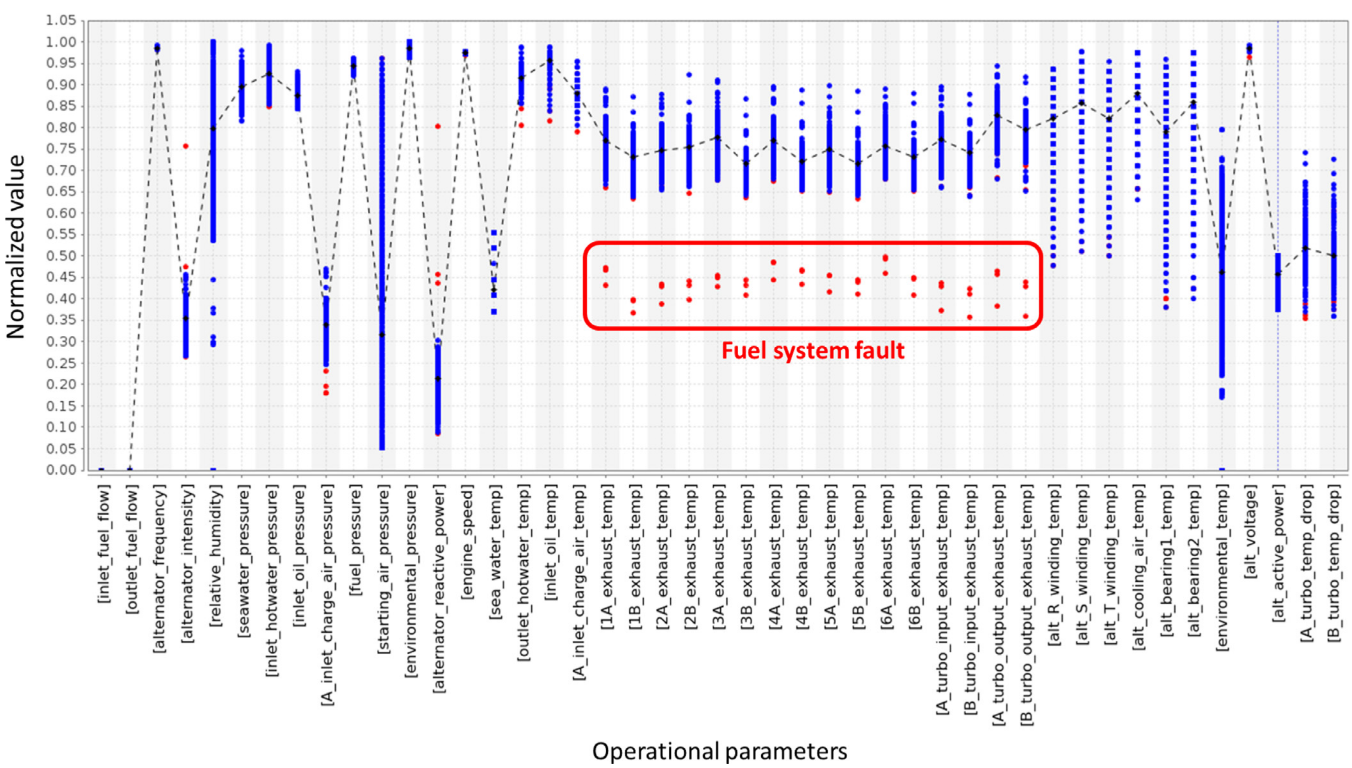

Fig. 6. Fuel System fault detected at a normal engine load.

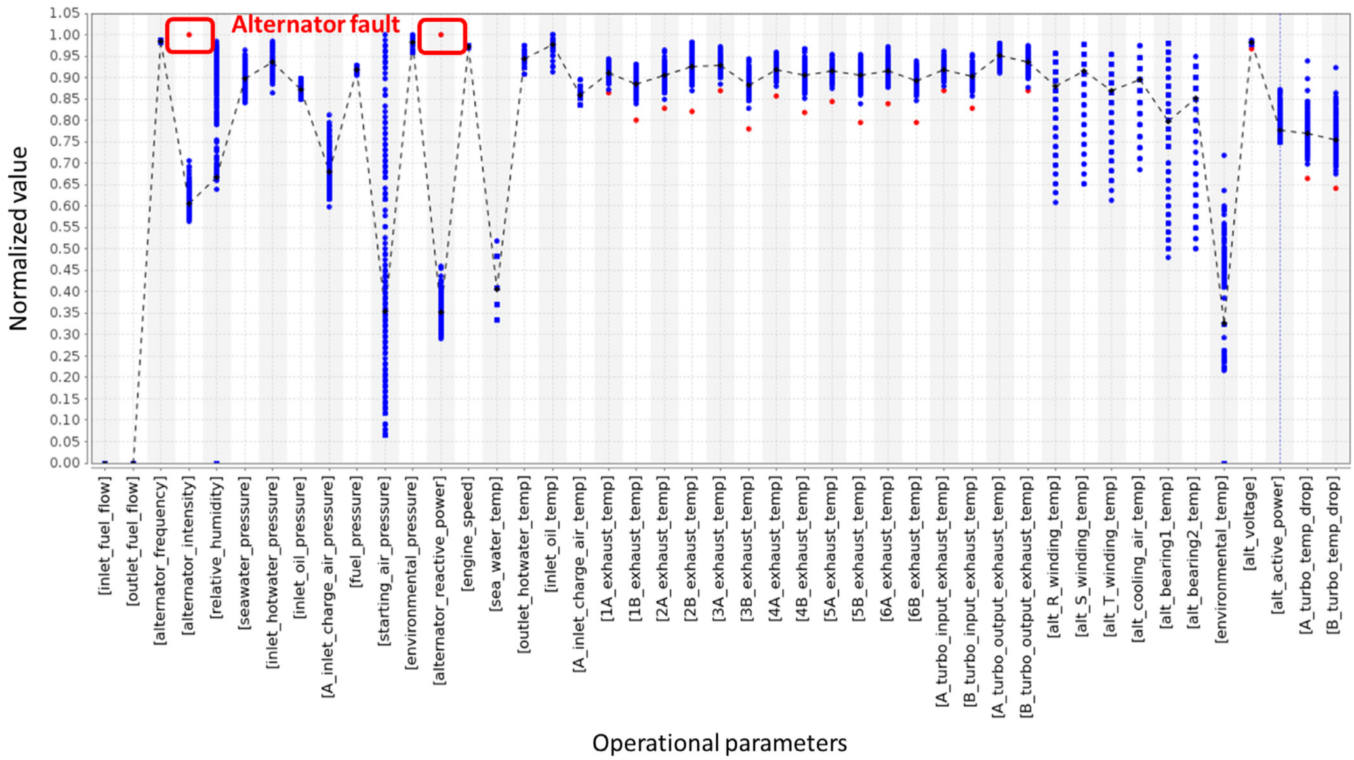

Fig. 7. Alternator System fault detected at a normal engine load.

Table 5
Results obtained per cluster.

Cluster	0	1	2	3	4	5	6	7
Real normal	326	13	750	2094	10,547	3263	285	6
Predicted normal	328	13	750	2094	10,547	3263	285	6
Real fault								
Fuel system	4	0	1	3	3	2	0	0
Alternator system	0	0	0	1	0	0	1	0
Predicted fault	2	0	1	4	3	2	1	0

Table 6
Global confusion matrix.

78 outliers found	Predicted normal	Predicted fault
Real Normal	TN=17,362	FP=0
Real Fault	FN=2	TP=13

Table 7
Global precision, sensitivity, specificity and κ coefficient.

	Real normal	Real fault	Global results
Precision	99.99%	100%	**99.98%**
Sensitivity	100%	86.67%	**93.34%**
	Specificity		**100%**
	$\boldsymbol{\kappa}$		**0.93**

To quantify the number of anomalous events in each cluster, an event is considered as a real fault if its score is below −0.5. Given that the test case scenarios showing the fuel system and alternator faults were deliberately chosen to be difficult to detect, it is still encouraging that the classification of faulty events rises above the false positive rate, accurately distinguishing real faults among outliers found.

Then the approach for anomaly detection was tested on a 10-fold cross-validation basis for each cluster, by segmenting the total set of cluster events into 10 equal parts. Thus, the confusion matrix presented in Table 6 is obtained, containing the average results of the 10 folds. Note that the constrained K-means clustering step is performed on the whole data set only once, in order to establish the different engine load operational ranges that will be used to isolate the outliers and predict the real faults.

In order to evaluate the results, the precision, sensitivity and specificity of the detection process are calculated. They are three widely used quality measures in this kind of processes. As it is shown in Table 7, precision, sensitivity and specificity are globally above 93%, so the approach accurately limits false anomalies and undetected faults. The inter-rater agreement statistic coefficient (Cohen's kappa, κ) is also computed aiming to evaluate the agreement between normal and fault events [36]. The resulting κ coefficient is 0.93, therefore a high strength of agreement is achieved.

By taking into account estimations made by this approach and next asset maintenance periods, usage planning, spare parts availability and manpower resources, optimal maintenance strategies can be suggested.

6. Conclusions

This work presents a data-driven prognostics approach to predict and identify anomalies and operational faults. Experimental results show the potential of the proposed approach to successfully address fault modes characterization problem, providing a finer and easier to interpret technique for experts to anticipate potential failures on the basis of the health status of the asset from monitoring sensor data. The complexity of such assets (e.g. marine engines and industrial machinery) makes their behavior difficult to understand and interpret. Under such circumstances it is particularly challenging to anticipate abnormal behaviors that often foresee significant and costly faults.

It was found that machine learning methods can highly support the traditional diagnostics and prognostics condition-based maintenance strategies. The combination of constrained K-means clustering for outlier detection and behavior characterization, the fuzzy modeling of distances to patterns found and the final LOF-based event score provide a fully comprehensive yet accurate prognostics approach. Discussed test scenario shown an accurate detection of critical faults in an auxiliary diesel engine, characterized by abnormal exhaust temperatures in cylinders regarding fuel system and by extremely high alternator intensity and reactive power in alternator system. The performance achieved is quite high (global precision, sensitivity and specificity above 93% and $\kappa = 0.93$), even more so given that a very small percentage of real faults are present in data.

The deployment of discussed data-driven models in a CBM+ system results in important benefits in terms of fault detection and prediction. The monitoring and analysis of additional operational parameters (e.g. in-cylinder pressure, torque, turbocharger speed, cylinder heads vibration, main bearings vibration and fluids analysis), and environmental conditions (e.g. weather variability from Arctic Sea to Red Sea waters), will allow increasing prediction accuracy and system capabilities as more failure modes are considered. This will allow maximizing reliability and minimising risks and unnecessary costs derived from unexpected breakdowns. Moreover, predictions and diagnosis obtained by adopting this approach can serve as input for an optimal decision making support and planning of maintenance operations, which will lead to important benefits in the reliability, safety and performance of the assets.

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