Preprints of the 23rd IFAC World Congress
Busan, Republic of Korea, August 23-28, 2026

Machine Learning Algorithms for Fault Identification in Fuel Cells

Francesco Maione * **Paolo Lino** * **Giuseppe Giannino** **
Erlend M. Coates *** **Ottar L. Osen** *** **Guido Maione** *

* *Dept. of Electrical and Information Engineering, Polytechnic University of Bari, 70125 (e-mail: f.maione@phd.poliba.it; {guido.maione,paolo.lino}@poliba.it).*
** *Isotta Fraschini Motori S.p.A., Bari, 70132, Italy (e-mail:giuseppe.giannino@isottafraschini.it)*
*** *Dept. of ICT and Natural Sciences, Norwegian University of Science and Technology, Alesund, 6009, Norway (e-mail: {erlend.coates,ottar.osen}@ntnu.no)*

Abstract:
The digitalization of the maritime sector, together with related environmental regulations, is reshaping ways to maintain new and innovative marine propulsion systems. This work proposes a data-driven incremental learning strategy for fuel-cell-based systems, where labelled fault data are typically scarce. Starting from normal-operation measurements only, an outlier detector based on one-class SVM identifies deviations from healthy behavior. As new data become available, three incremental one-class SVM schemes are tested and re-trained to select the most accurate. Detected anomalies are then classified using traditional machine learning models, selecting and deploying the best performer. Simulation results confirm the effectiveness and robustness of the proposed approach.

Keywords: Fault detection and diagnosis, power systems, artificial intelligence, AI methods for FDI, condition monitoring.

1. INTRODUCTION

The maritime sector, as well as many other industrial fields, has been deeply influenced by the digitalisation of industrial processes and the development of new technologies to address the environmental goals of the 2030 Agenda and the Paris Agreement for 2050. On the one hand, the introduction of artificial intelligence (AI), through machine learning (ML) and deep learning (DL) algorithms, has totally changed the way to face some common problems: the prediction of the ship's performance and the maintenance concept. For instance, in Radonjic et al. (2015), a single artificial neural network (ANN) and an ensemble neural network are evaluated against each other on how well they predict the power required by towboats and a convoy of barges sailing the Danube river. In Coraddu et al. (2019), the authors applied a data-driven model-based digital twin to accurately predict ship velocity loss due to hull fouling. These examples highlight that AI effectively supports engineers and challenges common and traditional approaches.

As observed by Susto et al. (2015), the ML and DL algorithms allow shipowners to schedule maintenance only when needed and well ahead of the predicted time of failure rather than at a fixed scheduled time. In Maione et al. (2024); Peric et al. (2024), the authors applied ANNs to predict sensor measurements of a marine diesel generator and a pump. ML algorithms like ANNs and decision trees (DT) are trained to estimate the expected sensor measurements, which are then compared to the real measurements. The calculated deviation gives an estimate of the health status of the machinery. Conversely, DL algorithms like Long Short-Term Memory (LSTM) are more suitable for predicting the remaining useful life (RUL) thanks to their ability to recognise time patterns. Good examples can be found in the studies published by Maione et al. (2024) and Han et al. (2021).

Supervised learning, such as described above, learns from labelled data. Alternatives may be semi-supervised and unsupervised learning. In these applications, algorithms such as the autoencoder (AE) are used to extract hidden and valuable information from sensor measurements. Examples are reported by Ellefsen et al. (2019a) and Ellefsen et al. (2019b).

The need to reduce the impact of vessels on the marine environment drives a search for new and less polluting propulsive systems. One of the most promising technologies is the hydrogenated proton exchange membrane fuel cell (PEMFC). In Saponaro et al. (2024), the challenges of electrification in the maritime sector are highlighted and a holistic approach is proposed to analyse the degradation of a PEMFC for vessel propulsion applications. However, fuel cell (FC) vehicles have poor reliability, as highlighted by Chen et al. (2024); Dijoux et al. (2017). Consequently, the development of robust diagnostic algorithms is crucial. In the first of the two aforementioned studies, the authors proposed an LSTM to detect deioniser faults. In Huang et al. (2019), an expert system based on a DT is built

©2026 the authors. Accepted by IFAC for publication under a Creative Commons Licence CC-BY-NC-ND

for the fault diagnosis of an FC engine. In Gebregergis et al. (2008), the authors analysed common FC faults, such as flooding, drying, and CO poisoning, to find the most suitable way to diagnose and mitigate their effects. Finally, in Lu et al. (2022), three binary classifiers are proposed for the diagnosis of drying, flooding, and starvation.

The main problem of these innovative technologies is the lack of availability of expert knowledge, as highlighted by Chen et al. (2024). Moreover, relevant labelled data that contain faults are not always available from the maritime sector, as remarked by Ellefsen et al. (2019c). Hence, due to its novelty, it is not always possible to apply supervised learning techniques for fault detection. To address these obstacles, we propose to employ incremental learning.

The incremental learning method entails giving little knowledge on the monitoring system and allows it to autonomously extract information from continuously incoming input data. In Zhang et al. (2021) the authors highlighted that collecting labelled data for all possible faults is practically impossible. Consequently, they developed a deep neural network (DNN) to recognise the presence of new faults in the data. In this way, when new data become available, the DNN is retrained. Similarly, in Zhang et al. (2023) it is pointed out that, for an effective fault diagnosis system, faulty data are accumulated by incrementally adding new data. For that reason, they proposed a broad residual network that incrementally learns new fault categories and fault modes.

Building on these results, the contributions of this paper are as follows.

- An incremental learning strategy is proposed and tested by simulation of common PEMFC faults. The simulation analysis examines a hybrid machine (comprised of a fuel cell stack and a battery) affected by a drying and flooding faults severity of 25%. It is remarked that the word severity is used to indicate the percentage of deviation between the expected behavior and the faulty one.
- The incremental learning strategy involves combining both machine and deep learning algorithms in different schemes. Initially, a one-class support vector machine (OC-SVM) is trained only on the normal behaviour. Then, the OC-SVM works as an outlier detector, namely, it classifies a new sample as part of the known distribution or not. If not, a multiclass classifier is trained; in parallel, a new OC-SVM is trained on the new faulty and healthy data. In this way, the new OC-SVM detects new unknown faulty behaviour, and the acquired data is used to add new classes to the multiclass classifier. In order to explore all algorithms and their possible combinations, three OC-SVM schemes and four ML classifiers have been compared.

To illustrate ideas and results, this paper is organized as follows. Section 2 gives an overview of the proposed method; Section 3 presents simulation results; Section 4 draws the conclusions.

2. THE PROPOSED METHOD

The proposed method aims to apply incremental learning to fault identification in an fuel cell ship propulsion system. It combines several machine and deep learning algorithms to find the best suitable solution every time new machine behaviours are identified:

(1) The initial assumption of the proposed method is that no failures of the monitored asset are known at startup. In fact, we assume that if a company is developing a new kind of propulsion system then it is reasonable to assume that they do not have enough real data to develop a multi-classes classifier. On the contrary, it is realistic to assert that the company engineers have a large amount of data from the asset working in normal conditions, namely healthy ones. Therefore, we initially designed an outlier detection model, a machine learning algorithm able to recognise if new sample belong to the ones on which they have been trained or not.

We have tested three different combinations of how to integrate the OC-SVM with an AE and identified the solution that had the best performance. In details, a benchmark is done on the basis of the prediction accuracy between: a simple OC-SVM; an AE and an OC-SVM in series, namely the AE is trained to reconstruct the input data and then the reconstruction error is computed. The reconstruction error is then used as input to the OC-SVM that recognises if the data belong to a normal machine behaviour or not; finally, the third configuration consists on an AE trained to reconstruct the input data and then only the encoder is placed in series with the OC-SVM. In this way, the OC-SVM is trained to recognise the anomaly based on the latent representation of the acquired data.

(2) Once the best outlier detector has been trained and chosen, it will be used for online monitoring of the asset. The crucial point of this new phase is to avoid false positives, namely normal behaviour that becomes classified as faulty. Taking into account that the OC-SVM gives $+1$ as output if the sample is normal, and -1 if not, it is reasonable not to give an alarm signal in presence of only one -1 output, but considering a time window in which, if the -1 is continuously observed, the alarm is triggered to signal that maintenance action is needed. This time window has been set equal to 16 minutes. Considering that the data are acquired every second, it means every 1000 sample.

(3) Once the anomaly behaviour is detected, the data acquired are used to train a classifier. Even in this case, in the same way as what was done during the point (1), a benchmark between an ANN, a random forest (RF), a DT, and an Ensemble model obtained combining the arithmetical mean of the three algorithms, is performed. The best one is chosen on the basis of accuracy. Then, as done in the point (1) a new outlier detector is trained on the new data.

(4) Finally, both the new outlier detector and the classifier are used to monitor the asset. Now, the anomaly detection works in the following mode: i) if the OC-SVM trained on the first point detects an anomaly,

the data are sent to the second OC-SVM trained at the previous point. If the data belong to the already known healthy and faulty data, the data are sent to the classifier. Otherwise, a new multi-classifier and anomaly detector are trained and replace the ones of the previous point.

Fig. 1 shows the proposed method. It is worth noting that, as highlighted in the description of the proposed approach, the availability of faulty data is necessary for successfully applying the described strategy.

The following subsections describe the algorithms that are applied in the present study.

2.1 Machine Learning Algorithms

Among the plethora of ML algorithms, ANNs are among the most widely applied for regression and logistic purposes. A single ANN works similarly to biological neurones. It consists of several interconnected hidden layers, each composed of neurones that process data to produce an output. The inputs to the ANN, namely the sensor measurements, are multiplied by the weights in the hidden layers. The weights are first initialised randomly and then, during the training process, optimised for the required task (regression or classification). The outputs of each layer are obtained by combining the results of the neurones. Once the information arrives at the final layer, the ANN outputs are produced. This propagation of information is called forward propagation. The training phase also utilise backward propagation. During this phase, the error propagates from the output to the input to update the weight values (Haykin et al., 1994).

A Decision Tree is a predictive model where the input nodes, which represent the first decision, are called roots; then, the flow of the decision process is represented by the internal decision nodes; the leaves, representing the predicted values, are the final nodes. The entropy is the most important DT property. It has values between 0 and 1, and it is the level of uncertainty in assessing a variable during the decision process. Considering a data sample, the entropy is zero if all the data belong to the same class, otherwise it is near to one. The goal of the decision process is to define the decision nodes that reduce the entropy. It is remarked that unlike ANN, AE, and LSTM the data processed by a DT do not need standardisation or normalisation.

An ensemble of DTs is called RF (Bakdi et al., 2022).

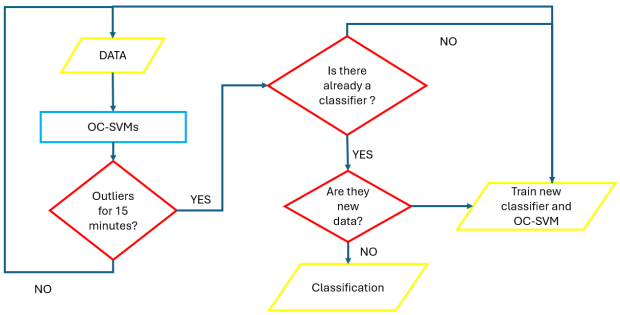


Fig. 1. Proposed method

In case of a regression problem, the output is evaluated by the mean of the results provided by each tree. Similarly, in case of classification problem, the output is the label provided by the highest number of trees.

Finally, OC-SVM is an alternative to traditional SVM that requires labelled data, namely faulty and healthy. In fact, it is trained with only normal data. Consequently, it is suitable for applications that suffer from a lack of labelled data and works as an outlier detector. Specifically, it recognises whether the new sample belongs to the statistical distribution of the data on which it was trained or not. The training data are mapped into a feature space where a boundary is defined. This boundary separates the known data from the unknown.

2.2 Autoencoder with LSTM layers

The AE is an ANN widely applied in unsupervised learning. Its output is the copy of the input signal. The encoder is trained to extract "hidden" features from the input data. The features are called "latent representation". The decoder uses the extracted feature to reconstruct the input.

Let Φ be the encoder function and Ψ the decoder function:

$$\Phi : X \rightarrow X_1 \tag{1}$$

$$\Psi : X_1 \rightarrow Y \text{ such that } Y = X \tag{2}$$

where X are the input data, Y the output data of the decoder (equal to X in case of a well trained AE), and X_1 is the encoder output.

The goal of the AE is to minimise the difference between the input and the output, namely the loss function:

$$Loss_{AE} = ||X - Y||^2, \tag{3}$$

which is also called *reconstruction error*.

The AE works as an ANN. specifically, the equations that regulate its behaviour are similar to those of an ANN. For a single hidden layer AE:

$$X_1 = \sigma(WX + B) \tag{4}$$

$$Y = \sigma(W_1 X_1 + B_1) \tag{5}$$

where B and B_1 are the bias vectors, W and W_1 the weights vector. More details on AE can be found in the survey by (Ellefsen et al., 2019a).

To allow the AE extract time-series information from the variables, two LSTM layers have been added. Further details regarding the algorithm can be found in (Hochreiter et al., 1997), while Fig. 2 shows the LSTM-layers integration into the AE. It is remarked that the LSTM is not the only way to address the problem of the time-series dependencies. In fact, other algorithms can be found in literature review, as the GRU or Transformer. These algorithms will be addressed in future applications and the best one will be chosen after a benchmark.

3. SIMULATION RESULTS

A powertrain model was developed by AVL CRUISE M, a software that allows implementation of thermodynamic laws. Fig. 3 shows the scheme of the overall model, which is the traditional composition of a common Fuel Cell Electric Vehicle (FCEV): the flange on the left side represents the mechanical connexion, such as a propeller

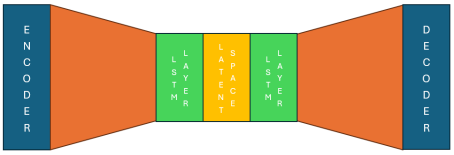


Fig. 2. Integration of the LSTM layers into the AE.

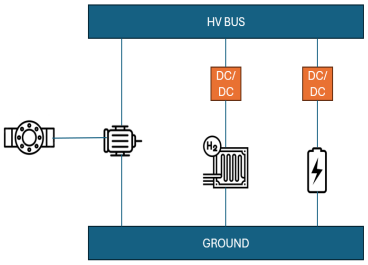


Fig. 3. Modeled powertrain

for maritime applications. The flange is directly connected to the electric machine. The FC and the battery provide the required power. Finally, the DC/DC Converters ensure the voltage conversion. As most of the power is provided by the FC, the battery provides its support during power requests peaks. Technical details on the different voltages are given in Tab. 1.

Table 1. Voltage of the FCEV components

Component	Voltage [V]
FC stack	280-370
Battery pack	270
Electric Machine	650

Based on the literature, drying has been simulated by decreasing the relative humidity of the FC, increasing its temperature, and increasing the Ohmic resistance and the Tafel slope. Similarly, flooding has been simulated by increasing the relative humidity and the Tafel slope. The severity of the simulated failures has been placed equal to the 25%.

The following variables are considered during faulty and healthy simulations: electrical power of the electric machine; battery output or input power; fuel cell output power; battery state of charge; reacted hydrogen mass of the fuel cell; mechanical load; input or output electrical machine current; battery input or output current; fuel cell input current. Figure 4 shows the simulation results for the voltage of the FC.

The variables used as inputs to the ML and DL algorithms are the FC current and voltage. We chose these variables as they are directly correlated with the healthy status of the FC and whose failures we want to estimate.As previously explained, the first step to implement the proposed strategy is to train an outlier detector only on normal data. For that reason, 23 600 samples have been generated and divided into two sets, one for training (75%) and the other for testing (25%); then, through Python language programming, three outlier detectors have been trained:

(1) a simple OC-SVM;
(2) an OC-SVM which has as input the reconstruction error computed through an AE. Namely, an AE is trained to reconstruct the input signal, then the reconstructed signal and the original one are compared by computing the reconstruction error; finally, the OC-SVM is trained on it;
(3) an AE is composed by two elements, an encoder and a decoder; between the encoder and the decoder there is the so-called latent space, namely a compressed representation of data points that preserves only essential features. Once the AE is trained to reconstruct the input signal, the encoder is removed from the trained AE, so that the latent representation provided by it is used as OC-SVM input.

The algorithm's hyper-parameters, obtained by maximising the accuracy, are shown in table 2-3.

Table 2. OC-SVM specifications

kernel function	Radial Basis Function
kernel function degree	3
ν	0.5

Table 3. AE specifications

Parameter	Value
latent dimension	32
activation function	*tanh*
epochs	850
batch size	220
optimizer	SGD
learning rate	0.01

In table 4 an overview of the training and test performance is shown.

Table 4. Outlier detectors performance

	Performance [%]	
Model	Training	Test
OC-SVM	93.16	73.44
AE+OC-SVM	93.92	74
encoder+OC-SVM	31	54.47

The model that used the reconstruction error as OC-SVM input gave the best performance. Hence, it has been chosen for the application.

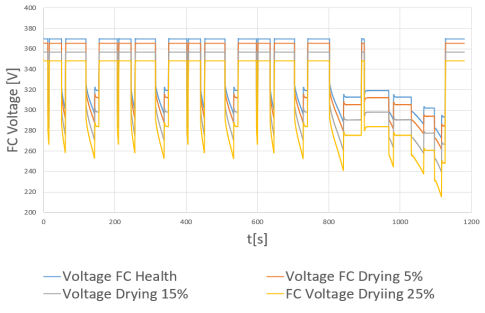


Fig. 4. Healthy and faulty behaviour of FC voltage

Table 5. DT specifications

	Value
Split criterion	Gini
Minimum number of samples to split an internal node	2
Minimum number of samples required to be at a leaf node	1

Further, a profile which goes from healthy behaviour to 25% flooding has been simulated and used as input to the outlier detector. After 1000 samples labelled "no-normal" (-1 as OC-SVM output), the failure was detected. Fig. 5 shows the detection of unknown behaviour by considering the current in the FC. In red there is the beginning of the failure, in green when the outlier detector recognizes anomaly data for 1000 consecutive samples.

After detection of flooding, the acquired data is used to train a classifier. As previously described, the ML algorithms under comparison are ANN, RF, DT, and an Ensemble obtained by averaging the output of each model. The training has been conducted with the objective to maximise the accuracy. The algorithms specifications are shown in table 5-7, while in table 8 the performance is shown.

Table 6. RF specifications

	Value
Number of estimators	100
Split criterion	Gini
Minimum number of samples to split an internal node	2
Minimum number of samples required to be at a leaf node	1

It is worth noting that for each trained classifier the corresponding Confusion Matrix has been created to compactly visualize the False Positive and Negative distribution. For lack of space, herein Fig. 6 shows only the confusion matrix of the RF during the test, as it is the chosen algorithm.

In fact, even if RF and Ensemble would have had the same performance, the RF would be chosen because it consists only of one algorithm, thereby reducing the computational cost of implementation.

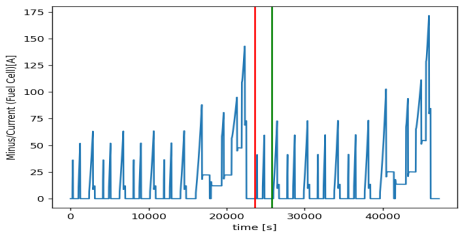


Fig. 5. Detection of the unknown behavior.

Table 7. ANN specifications

	Value
Number of hidden layers	2
Output activation function	softmax
Learning rate	0.01
Optimizer	Adam
Neurons of the first hidden layer	100
Epochs	400

Table 8. ML training performance

	Performance [%]	
Model	Training	Test
ANN	0.99	0.99
DT	1.0	0.97
RF	1.0	1.0
Ensemble	1.0	1.0

Then, a new outlier detector has been trained on the healthy and flooding data. The performance of the compared algorithms is shown in Tab. 9. It is worth noting that since the algorithms recognize new status and train the new outlier detectors and classifiers automatically, the specifications will be the same as previously shown. In future works the possibility to introduce a Genetic Algorithm to optimize them will be discussed.

Table 9. Outlier detectors performance on healthy and flooding fault

	Accuracy [%]	
Model	Training	Test
OC-SVM	93.33	74.56
AE+OC-SVM	94.54	85.07
encoder+OC-SVM	58.65	58.64

Even in this case the best solution was the combination of AE and OC-SVM.

Finally, a new profile with the presence of drying has been simulated.

Now, the new outlier detector developed is applied in series with the oldest one: if the first one gives -1 as output, the second one receive the data as input. If it is $+1$, it will give the data to the binary-classifier that was previously trained. Otherwise, after 1000 consecutive samples with -1 outputs, the algorithms recognize a new unknown behavior and, once the new data are stored, the binary-classifier is replaced with a new multi-classes classifier. Even this one is chosen among the ML algorithms previously shown comparing their efficiency. The results are shown in Tab. 10.

4. CONCLUSIONS

In this study, we address the problem of fault identification in fuel cell ship propulsive systems. The lack of labelled data and expert knowledge makes it difficult to train a classifier. For that reason, we start with the assumption that only healthy data are available when the machine starts to work. Then, an incremental learning strategy is applied to allow ML and DL algorithms to recognize new

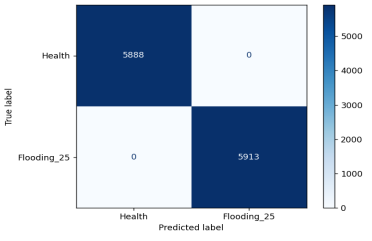


Fig. 6. Confusion Matrix of the test phase of the RF.

Table 10. ML training performance on Health vs Flooding vs Drying.

	Accuracy [%]	
Model	Training	Test
ANN	0.81	0.76
DT	1.0	0.99
RF	1.0	0.99
Ensemble	0.99	0.99

behaviors, namely the faulty ones. In this way, the algorithms self-retrain autonomously, finding the best schemes and combinations based on the new acquired data. In this way, the algorithms with the highest accuracy will be chosen every time. The strategy has been applied by simulating FC faulty data. The results show the validity of the proposed strategy. Future work will explore the possibility of expanding the approach to other FC faults. Moreover, the possibility of using a genetic algorithm to change the algorithm's specifications will be investigated. Finally, the practical software implementation will also be addressed in future research activities. In fact, using a separate one-class classifier for each fault can be computationally heavy, similarly comparing several ML and DL algorithms searching for the best ones. Consequently, a Hardware-in-the-Loop campaign test for analysing the real-time performance of the proposed approach.

ACKNOWLEDGMENT

This research was carried out within the Fincantieri project "Wave 2 the Future" (W2F) funded by the European Union –NextGenerationEU. W2F project is part of IPCEI Hy2Tech.

REFERENCES

A. Radonjic, and K. Vukadinovic (2015). Application of ensemble neural networks to prediction of towboat shaft power. *J Mar Sci Technol 20*, 64–80.

A. Coraddu, L. Oneto, F. Baldi, F. Cipollini, M. Atlar, and S. Savio (2019). Data-driven ship digital twin for estimating the speed loss caused by the maritime fouling, *Ocean Engineering*, vol. 186, 106063.

G. A. Susto, A. Schirru, S. Pampuri, S. McLoone, and A. Beghi (2015), Machine Learning for Predictive Maintenance: A Multiple Classifiers Approach, *IEEE Transaction on Industrial Informatics*.

F. Maione, P. Lino, G. Maione, and G. Giannino (2024), A Machine Learning Framework for Condition-Based Maintenance of Marine Diesel Engines: A Case Study, *Algorithms*, Volume 17, Issue 9, 411

B. Peric, M. Engler, M. Schuler, and P. Woias (2024), Using Neural Networks as Data-Driven Model to Predict the Behavior of External Gear Pump, *Processes*.

F. Maione, P. Lino, G. Maione, and G. Giannino (2024), Predictive Maintenance of Marine Engines using Long Short-Term Memory Algorithm, *8th Research and Technologies for Society and Industry*, Lecco, Italy, pp. 578–583, 18–20 Sep. 2024.

P. Han, A. L. Ellefsen, G. Li, V. Æsøy, and H. Zhang, (2021) Fault Prognostics Using LSTM Networks: Application to Marine Diesel Engine, *IEEE Sensors Journal*, vol. 21, no. 22, pp. 25986–25994.

A. L. Ellefsen, V. Æsøy, S. Ushakov and H. Zhang (2019a), A Comprehensive Survey of Prognostics and Health Management Based on Deep Learning for Autonomous Ships, *IEEE Trans. on Reliability*, vol. 68, no. 2, pp. 720-740.

A. L. Ellefsen, S. Ushakov, V. Æsøy and H. Zhang (2019b), Validation of Data-Driven Labeling Approaches Using a Novel Deep Network Structure for Remaining Useful Life Predictions, *IEEE Access*, vol. 7, pp. 71563-71575.

G. Saponaro, M. Stefanizzi, M. Torresi, and S.M. Camporeale (2024), Analysis of the degradation of a Proton Exchange Membrane Fuel Cell for propulsion of a coastal vessel, *International Journal of Hydrogen Energy*, Volume 61, pp. 803-819.

Y. Chen, J. Zhang, S. Zhai, and Z. Hu (2024), Data-driven modeling and fault diagnosis for fuel cell vehicles using deep learning, *Energy and AI*, Volume 16, 100345.

E. Dijoux, N. Y. Steiner, M. Benne, M.-C. Péra, and B. G. Pérez (2017), A review of fault tolerant control strategies applied to proton exchange membrane fuel cell systems, *Journal of Power Sources*, Volume 359, pp. 119-133.

L. Huang, Q. Zeng and R. Zhang (2019), Fuel Cell Engine Fault Diagnosis Expert System based on Decision Tree, *2019 IEEE 3rd Information Technology, Networking, Electronic and Automation Control Conference (ITNEC)*, Chengdu, China, pp. 282-286.

A. Gebregergis, P. Pillay, and R. Rengaswemy (2008), PEMFC Fault Diagnosis, Modeling, and Mitigation, *2008 IEEE Industry Applications Society Annual Meeting*, Edmonton, AB, Canada, pp. 1-8.

Y. Lu, S. Zhou, D. Yin, L. Fan, G. Zhang, and J. Gao (2022), Simultaneous fault diagnosis of proton exchange membrane fuel cell systems based on an Incremental Multi-label Classification Network, *International Journal of Hydrogen Energy*, Volume 47, Issue 59,

A. L. Ellefsen, E. Bjørlykhaug, V. Æsøy, and H. Zhang (2019c), An Unsupervised Reconstruction-Based Fault Detection Algorithm for Maritime Components, *IEEE Access*, vol. 7, pp. 16101-16109, 2019.

D. Zhang, and Z. Gao (2021), An Ensemble Approach for Fault Diagnosis via Continuous Learning, *2021 IEEE 19th International Conference on Industrial Informatics (INDIN)*, Palma de Mallorca, Spain, 2021, pp. 1-5.

S. Zhang, R. Wang, L. Wang, Y. Si, A. Lin and Y. Wang (2023), Fault Diagnosis for Power Converters Based on Incremental Learning, *IEEE Transactions on Instrumentation and Measurement*, vol. 72, pp. 1-13, Art no. 3512813.

S. Haykin (1994), Neural Networks: A Comprehensive Foundation, *Macmillan: New York*, NY, USA.

S. Hochreiter, and J. Schmidhuber (1997), Long short-term memory, *Neural Computation*, 9(8), pp. 1735–1780.

Bakdi, A., Kristensen, B. N., and Stakkeland," M. Multiple instance learning with random forest for event logs analysis and predictive maintenance in ship electric propulsion system", *IEEE Transactions on Industrial Informatics* **2022**, *18 (11)*, 7718–7728.