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A Hybrid Diagnosis for Gas Starvation Faults in Proton Exchange Membrane Fuel Cells

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***Abstract*—Fuel cell technology is recognized as a green energy alternative for the transport sector and stationary power applications, boasting high current density and zero emissions. Nonetheless, broad adoption and commercial viability of the technology is limited by its low durability and reliability. These limitations can be addressed by developing and implementing a fuel cell management system. In this paper, gas starvation faults in proton exchange membrane fuel cells (PEMFCs) have been studied. The causes, consequences, and the fault indicators (features) are identified. The sensitivities of fault indicators and how they affect the performance have been evaluated. Subsequently, a hybrid fault diagnosis method that combines residual-based fault detection with data-driven fault isolation has been proposed. Fault detection is achieved using a physics-based white-box model while fault isolation is achieved using a data-driven approach. Two supervised machine learning classifiers, namely the k-nearest neighbor (kNN) and the support vector machine (SVM) have been developed. The performances of these methods are compared in terms of their accuracy and computation time. Moreover, the effect of additional indicators has been evaluated. The results show that starvation faults on the PEMFC can be detected and isolated efficiently and correctly, thanks to the fault indicators and the hybrid nature of the diagnostic method. Also, from the presented results, it can be deduced that the kNN classifier has outperformed the SVM classifier.**

***Index Terms*—Fault diagnosis, proton exchange membrane fuel cells, machine learning, model-based fault detection, data-driven fault isolation, reactants starvation, residuals, fuel cell management system.**

I. Introduction

Climate change has emerged as a significant global challenge in the 21st century, necessitating urgent action to adopt cleaner energy sources and mitigate greenhouse gas emissions. In this context, renewable and clean energy production technologies have garnered considerable attention as potential solutions for reducing carbon emissions in transportation and power generation [1]. Among these technologies, fuel cells have stood out due to their impressive attributes, such as high power density, efficiency, and emission-free operation. Particularly, polymer electrolyte membrane (PEM) fuel cells have seen substantial advancements in recent years. However, despite these progressions, the current state of PEM fuel cell technology still falls short of fully replacing conventional stationary and mobile power sources, as concerns regarding performance, stability, reliability, and cost remain [2].

One critical issue affecting the performance, reliability, and durability of PEM fuel cells is gas starvation, often caused by faulty gas supply systems. To ensure the smooth and optimal operation of fuel cells, it is essential to diagnose gas starvation faults accurately. Fault diagnosis can be divided into residual-based methods and non-residual-based methods.

Residual-based fault diagnosis method is splitted into fault detection and fault isolation. During the fault detection stage, a nominal (fault-free) model of the system is developed. The model's outputs are then compared with the actual measurements from the real system to generate residuals. If these residuals exceed a certain threshold, a fault is detected, indicating that the system requires attention. Otherwise, if the residuals are within acceptable bounds, the system is considered to be functioning correctly. The development of the fault detection model can be achieved through various methods, such as white-box, grey-box, or black-box techniques [3]–[8]. After a fault is detected, the generated residuals are further evaluated to identify the type, severity, and location of the fault. This can be accomplished using fault signature matrices or machine learning techniques.

In contrast, non-residual-based fault diagnosis does not require residual generation. Rather, the actual measurements from the system are processed to extract specific features which are then used for fault isolation. Feature extraction can be achieved using dimensionality reduction techniques such as principal component analysis (PCA), univariate analysis of variance (ANOVA), multivariate analysis of variance (MANOVA), or using signal processing techniques [9]–[15]. The extracted features are then further evaluated to identify the type, severity, and location of the fault. This can be accomplished using fault signature matrices or machine learning techniques.

A recent paper that employs non-residual fault diagnosis is presented in [16]. The authors used signal processing techniques to convert measurements from an electrochemical impedance spectroscopy (EIS) into features. Subsequently, an improved k-nearest neighbor (kNN) classifier was proposed to identify air starvation and water management faults. However, it is essential to note that the non-residual-based approach may encounter challenges in dealing with inherent PEMFC voltage variations caused by load fluctuations, potentially leading to false alarms and missed detections. As a result, residual-based methods are generally considered more reliable and efficient in fault diagnosis [17].

In [18], a residual-based fault diagnosis method for PEMFCs is proposed to diagnose five faults (temperature decrease, relative humidity decrease/increase, and pressure decrease/increase) using two indicators (stack voltage and high-frequency resistance). Fault detection is achieved using residuals generated from a white-box model that was previously developed by [19] at CEA. Fault isolation is then achieved using a supervised machine learning classifier (kNN). However, the paper does not consider faults related to reactants' starvations. Secondly, only two indicators (stack voltage and high-frequency resistance) are used as fault indicators instead of adding more to incorporate other fault conditions and improve the performance of the method.

This paper aims to address the limitations of the work presented in [18] by proposing a hybrid method to handle gas starvations in PEMFCs, including fuel starvation, oxidant starvation, and dual-gas starvation. The main contributions of this paper are threefold. Firstly, to develop an accurate fault diagnosis to deal with a single reactant's starvation and a double reactant's starvation in PEMFC. Secondly, improving the diagnostic method by adding more fault indicators. Thirdly, it compares the performance of the proposed method with another method.

II. Gas starvation in PEMFC

PEMFCs operate based on electro-catalytic reactions, involving hydrogen oxidation at the anode and oxygen reduction at the cathode. The presence of a catalyst causes hydrogen atoms to split into protons and electrons. The protons migrate through the membrane to the cathode, while the electrons flow through an external circuit. At the cathode, protons react with oxygen to form water, releasing heat as a by-product. The reactions at the anode and cathode are represented by equations (1) and (2), respectively, while the overall reaction is given by equation (3).

$$H_{2(g)} \longrightarrow 2H^{+} + 2e^{-} \tag{1}$$

$$\tfrac{1}{2}O_{2(g)} + 2H^{+} + 2e^{-} \longrightarrow H_2O_{(g,l)} \tag{2}$$

$$H_{2(g)} + \tfrac{1}{2}O_{2(g)} \longrightarrow H_2O_{(g,l)} + heat + electricity \tag{3}$$

In the PEMFC, precise quantities of hydrogen and air are continuously supplied to the stack through their respective supply systems. However, if a fault arises in the gas supply system, it can lead to gas starvation.

A. Oxygen starvation fault

Oxygen/air starvation refers to a situation where the fuel cell does not receive enough oxygen to sustain its electrochemical reactions. This can happen due to various causes, and it has several consequences that affect the fuel cell's performance and durability. The main causes of Oxygen/Air Starvation in PEMFC are:

1) Insufficient airflow: If the flow of air into the fuel cell is restricted or blocked, it can lead to oxygen starvation. This can be caused by a clogged or damaged air intake system, improper ventilation, or a malfunctioning blower.
2) High current/power demand: When the fuel cell is operating at a high power output, the demand for oxygen increases. If the supply of air is unable to keep up with the demand, the cell experiences oxygen starvation.
3) Membrane drying: The proton exchange membrane in a PEMFC requires a certain level of moisture to function effectively. If the membrane dries out due to inadequate water management, it can hinder oxygen transport and lead to starvation.
4) Contamination: Contaminants in the air, such as particulates or chemical impurities, can block the flow of oxygen to the cathode, causing oxygen starvation.

The following are the main consequences of oxygen/air starvations in PEMFC:

1) Reduced power output: Insufficient oxygen supply limits the electrochemical reactions at the cathode, resulting in a decrease in the fuel cell's power output. This can lead to a drop in the overall efficiency of the system.
2) Voltage decay: Oxygen starvation can cause a decrease in the cell voltage, which affects the fuel cell's ability to deliver a consistent and stable electrical output.
3) Accelerated catalyst degradation: When a PEMFC operates under oxygen-starved conditions, the catalysts at the cathode may undergo accelerated degradation. This reduces the lifespan of the fuel cell and increases maintenance costs.
4) Increased fuel crossover: To compensate for the lack of oxygen, the anode may undergo fuel starvation, leading to increased fuel crossover through the membrane. This crossover can decrease overall efficiency and create safety issues.
5) Membrane damage: Oxygen starvation can lead to the formation of localized hot-spots and a highly acidic environment at the cathode. Prolonged exposure to these conditions can damage the membrane and reduce its effectiveness.

To ensure the efficient and reliable operation of PEMFCs, it is crucial to implement proper system design, effective water and air management, and regular maintenance. Monitoring and control systems can help detect and mitigate oxygen/air starvation to maintain optimal performance and extend the lifespan of the fuel cell.

B. Hydrogen starvation fault

Hydrogen starvation in a PEMFC refers to the condition where the fuel cell does not receive a sufficient supply of hydrogen gas for its electrochemical reactions. This can happen due to various causes, each of which can have significant consequences on the fuel cell's performance and overall efficiency. The main causes of hydrogen starvation in PEMFCs are as follows:

1) Insufficient hydrogen supply: If the fuel cell's hydrogen supply is limited or interrupted, it can lead to hydrogen starvation. This situation may arise due to issues with the hydrogen storage system, inadequate hydrogen pressure, or a restricted hydrogen flow path.
2) Poor hydrogen distribution: In certain instances, the hydrogen gas may not be evenly distributed across the surface of the anode catalyst layer. This non-uniform distribution can result in some regions of the anode receiving less hydrogen, causing localized starvation.
3) Fuel crossover issues: Excessive fuel crossover from the anode to the cathode through the proton exchange membrane can lead to hydrogen starvation. This occurs when hydrogen molecules intended for the anode reaction are inadvertently transferred to the cathode, reducing the available hydrogen for electrochemical reactions at the anode.
4) Catalyst poisoning: The presence of contaminants, such as carbon monoxide (CO), in the hydrogen fuel can poison the anode catalyst. Catalyst poisoning diminishes its activity, resulting in reduced hydrogen availability and contributing to hydrogen starvation.

The consequences of hydrogen starvation in a PEMFC are significant and can have a negative impact on the fuel cell's performance and durability. Some of the major consequences are as follows:

1. Reduced power output: Insufficient hydrogen supply limits the number of electrochemical reactions occurring at the anode, leading to a decrease in the fuel cell's power output. This results in reduced electricity generation and a drop in overall system efficiency.

2. Voltage decay: Hydrogen starvation can cause a decrease in the cell voltage, affecting the fuel cell's ability to deliver a stable and consistent electrical output. This can lead to fluctuations in power and performance instability.

3. Increased cathode potential: During hydrogen starvation, the cathode potential may become more positive than the optimal operating range. This can result in potential damage to the cathode catalyst, leading to decreased performance and reduced fuel cell lifespan.

4. Membrane dehydration: The proton exchange membrane in a PEMFC requires adequate hydration to function optimally. Hydrogen starvation can lead to membrane dehydration, affecting its proton conductivity and overall cell performance. Dehydration can also lead to membrane damage and reduced efficiency.

5. Catalyst degradation: Hydrogen starvation can cause an imbalance in the fuel cell's electrochemical reactions. As a result, certain regions of the catalyst may undergo excessive stress, leading to catalyst degradation and a decrease in the fuel cell's lifespan.

6. Reduced efficiency and durability: Prolonged hydrogen starvation can lead to irreversible damage to the fuel cell components, reducing the system's efficiency and overall durability. This can result in costly repairs and a shorter lifespan for the fuel cell.

To avoid hydrogen starvation and ensure the efficient operation of PEMFCs, it is essential to maintain a steady and adequate supply of hydrogen, address fuel crossover issues, and implement effective water and thermal management strategies. Regular monitoring and control of operating parameters can help detect and mitigate hydrogen starvation, thereby maintaining optimal performance and extending the lifespan of the fuel cell.

C. Dual-gas starvation fault

When a PEMFC experiences both hydrogen and oxygen starvations simultaneously, it can lead to a series of adverse effects that significantly affect the fuel cell's performance and can potentially cause damage. Let's explore what happens when a PEMFC suffers from both hydrogen and oxygen starvations:

1. Reduced Power Output: Hydrogen starvation limits the electrochemical reactions at the anode, while oxygen starvation hinders the reactions at the cathode. As a result, the fuel cell's power output decreases significantly. This reduction in power output can make the fuel cell less effective in providing electricity for its intended application.

2. Increased Voltage Decay: With both hydrogen and oxygen starvations, the cell voltage drops further. The decrease in voltage exacerbates the fuel cell's inability to deliver a stable and consistent electrical output.

3. Catalyst Degradation: The simultaneous starvations cause an imbalance in the electrochemical reactions at both the anode and cathode. This imbalance can lead to accelerated degradation of the catalysts, reducing their effectiveness and shortening the fuel cell's lifespan.

4. Membrane Damage: The PEM (Proton Exchange Membrane) requires a specific level of hydration to function efficiently. Both hydrogen and oxygen starvations can lead to membrane dehydration, affecting its proton conductivity and potentially damaging the membrane.

5. System Instability: The dual starvations can cause the fuel cell's operating conditions to become unstable. The cell's performance may oscillate or exhibit erratic behavior, making it challenging to maintain a stable and reliable power output.

6. Safety Risks: In extreme cases, dual starvations can create hazardous conditions within the fuel cell. Hydrogen starvation may lead to the accumulation of hydrogen gas, which can be dangerous if not properly managed. Additionally, oxygen starvation can lead to localized hotspots and potential damage to the fuel cell components.

7. Performance Hysteresis: PEMFCs may experience hysteresis, where performance decreases more significantly dur-

ing dual starvations compared to performance recovery when adequate hydrogen and oxygen supply is restored.

To prevent or mitigate dual-gas starvations in PEMFCs, it is essential to ensure a steady and sufficient supply of hydrogen and oxygen, address any issues related to fuel and air flow, and implement effective water and thermal management strategies. Regular monitoring and control of operating parameters are crucial to detecting and avoiding dual starvations, as they can lead to irreversible damage to the fuel cell components and compromise the overall efficiency and durability of the system.

III. Fault diagnosis in PEMFC - A hybrid methodology

In this study, a hybrid fault diagnosis approach, as illustrated in Fig. 1, was employed to tackle gas starvation faults in PEMFCs. The approach involves combining residual-based fault detection, utilizing a white-box model, with data-driven fault isolation methods based on machine learning techniques.

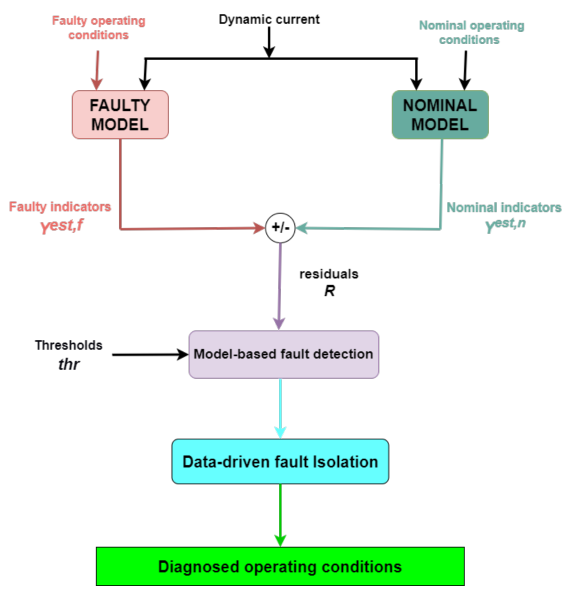


Fig. 1: Hybrid fault detection and isolation method

A. Residual-based Fault Detection

A complex white-box model of the PEMFC, developed at the French Commission for Atomic and Alternative Energies (CEA) is used to simulate the behavior of the PEMFC system under different health conditions, thanks to its capability of simulating faults. The nominal and faulty outputs of the model are then compared to generate residuals. To simulate the system in a healthy condition, nominal operating conditions, tabulated in table I are used. Gas starvation faults in PEMFC can be induced using some parameters such as stoichiometry, molar fraction, or flow rate. In this work, molar fraction which is a function of the flow rate of gases along the channels, has been used to induce various gas starvation at varying levels of severity as presented in table II. The fault conditions considered in this paper are labeled as **F1**, **F2**, and **F3** to represent hydrogen starvation, oxygen starvation, and dual-gas starvation respectively. Three levels of severity of the faults (low, medium, and high) are considered and marked in (blue, red and green) as in table II.

State	**XX**$_a$	**XX**$_c$	**St**$_a$	**St**$_c$	**RH**$_{a,c}$	**P**$_{a,c}(Pa)$	**T**^{0}**C**
N	1	0.21	1.5	2	50%	150000	80

TABLE I: Nominal operating conditions

Fault condition	**Label**	**Severity**	**XX**$_a$	**XX**$_c$
Hydrogen starvation	**F1**	Low	0.75	0.21
		Medium	0.50	0.21
		High	0.25	0.21
Oxygen starvation	**F2**	Low	1	0.15
		Medium	1	0.10
		high	1	0.075
Dual-gas starvation	**F3**	Low	0.75	0.15
		Medium	0.50	0.10
		High	0.25	0.075

TABLE II: Simulation of faults and their severity

The four fault indicators considered as the stack voltage, membrane resistance, pressure drop at the anode, and pressure drop at the cathode. These indicators are measured quantitatively in both nominal and fault scenarios using the model. While stack voltage is a widely used universal fault indicator in PEMFC, combining it with other variables, such as membrane resistance and pressure drops, could provide a more comprehensive understanding of the system's internal dynamics. These variables are used to generate the set of residuals given in equation (4). A varying dynamic load current, ranging from 0 to $200A$ is used for data generation.

$$\begin{cases} R_1 = V_{st}^{est,f} - V_{st}^{est,n} \\ R_2 = R_m^{est,f} - R_m^{est,n} \\ R_3 = dP_a^{est,f} - dP_a^{est,n} \\ R_4 = dP_c^{est,f} - dP_c^{est,n} \end{cases} \tag{4}$$

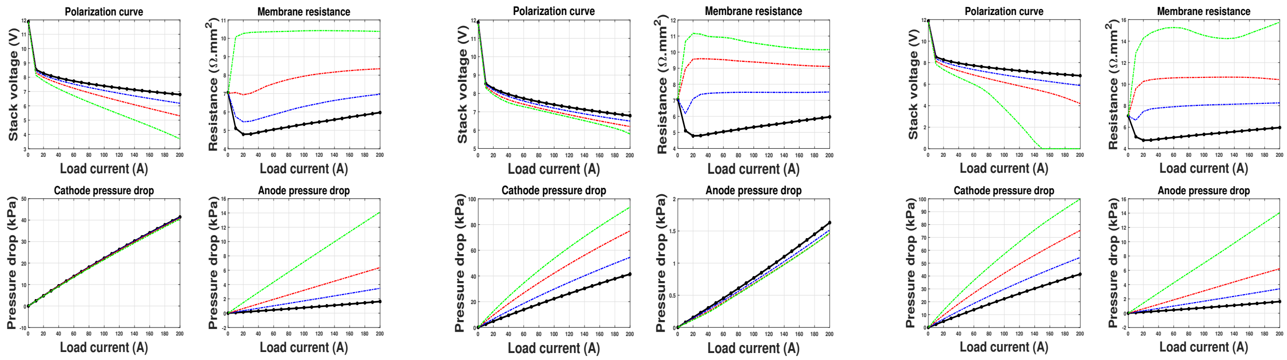
The residuals are then evaluated using some set of thresholds such that a fault is detected when the value of the residuals exceeds the threshold values. Thus, only faulty residuals in equation (5) are applied to the classifier.

$$R_{fault} = f(R_i, thr_i), \qquad i = 1, ..., 4 \tag{5}$$

B. Data-driven fault isolation

Fault isolation can be achieved using different approaches, such as comparing the fault signatures with pre-defined patterns, utilizing statistical analysis, or employing machine learning algorithms to classify faults based on historical data. In this work, a machine learning approach is used for fault isolation, where two supervised classifiers are developed, i.e. the k-nearest neighbor (kNN) and the support vector machine (SVM).

kNN classifier is based on the assumption that data points with similar features are likely to be close to each other in the feature space [18]. The main goal of the kNN algorithm



(a) Hydrogen starvation (b) Oxygen starvation (c) Dual-gas starvation

Fig. 2: Indicator evolution: the **black** dotted-line represents the nominal condition, while the blue, red and green dashes represent different levels of starvations.

is to identify the k-nearest neighbors of a given query point, where k is a user-defined parameter representing the number of neighbors to consider. By finding the nearest neighbors, the algorithm assigns a class label to the query point based on a majority vote among the labels of the neighboring data points. To determine which points are closest to the query point, the algorithm calculates the distance between the data point and the query point. The most commonly used distance measure is the Euclidean distance, which calculates the straight-line distance between two points in the feature space. Other distance measures, such as Manhattan distance, Minkowski distance, and Hamming distance, can also be used depending on the nature of the data and the problem. kNN is considered simple and easy to train because it has only one tuning parameter, k.

Support Vector Machine (SVM) is a powerful machine learning algorithm primarily used for binary classification problems. The goal is to find a hyperplane that can separate the data points of two classes with the maximum margin between them. The margin is defined as the distance between the hyperplane and the closest points of the two classes. In the case of binary classification, the SVM algorithm identifies the hyperplane with the largest margin, and the data points closest to the hyperplane are known as support vectors. These support vectors play a crucial role in defining the decision boundary and classifying new data points. The binary SVM can be extended to a multi-class SVM using the "One-Against-One" approach. This approach constructs multiple binary classifiers, each comparing two classes at a time. In our case for example, three binary classifiers are created for all possible combinations of two classes. During classification, the data point is evaluated by each binary classifier, and the class with the most votes (wins the majority of the binary comparisons) is assigned as the final class label for the data point.

The residuals generated in the detection stage are labeled as **F1**, **F2**, and **F3**, depending on the simulated condition. They are then randomly divided into training and testing in the ratio 70% to 30% respectively. Firstly, the SVM classifier is trained using a specific Matlab function with the same datasets. The residuals in the testing datasets are used as inputs of the trained SVM classifier to predict the fault labels. Secondly, a kNN classifier is trained using a specific Matlab function that takes in the residuals as inputs and the labels as outputs. The tuning parameter, k which is part of the function is then selected. After the trained model is generated, a new dataset (testing data) is applied to the trained model to predict the class label, known as the predicted fault. The predicted fault is then compared with the actual fault from the testing data. The accuracy of the trained model is determined by computing the isolation probability. If the value of the isolation probability is close to 100%, the classifier is good, otherwise, a new model should be trained using a new value of the tuning parameter, k. The accuracy and computation time of these methods are evaluated.

IV. Results and Discussion

A. Evolution of the indicators on fault conditions

1) Hydrogen starvation: The evolution of the four indicators of hydrogen starvation is presented in Fig. 2a. As the anodic molar fraction is reduced in three steps, from the nominal value ($XX_a = 1$) to three lower values, the polarization curves in the top-left figure demonstrate a corresponding decrease in the stack voltage. This decrease occurs because there is a smaller amount of fuel molecules available to complete the electro-catalytic reaction. Moreover, the membrane resistance increases proportionally, as depicted in the top-right figure. While the cathodic pressure drop remains constant, as shown in the bottom-left of the figure, the anodic pressure drop exhibits a proportional increase, as shown in the bottom-right of the figure. These changes in the indicators indicate the presence of hydrogen starvation in the PEMFC.

2) Oxygen starvation: In the case of oxygen starvation, the evolution of the indicators is shown in Fig. 2b. As the cathodic molar fraction is decreased in three steps, from the nominal value ($XX_c = 0.21$) to three lower values, the polarization curves in the top-left figure demonstrate a

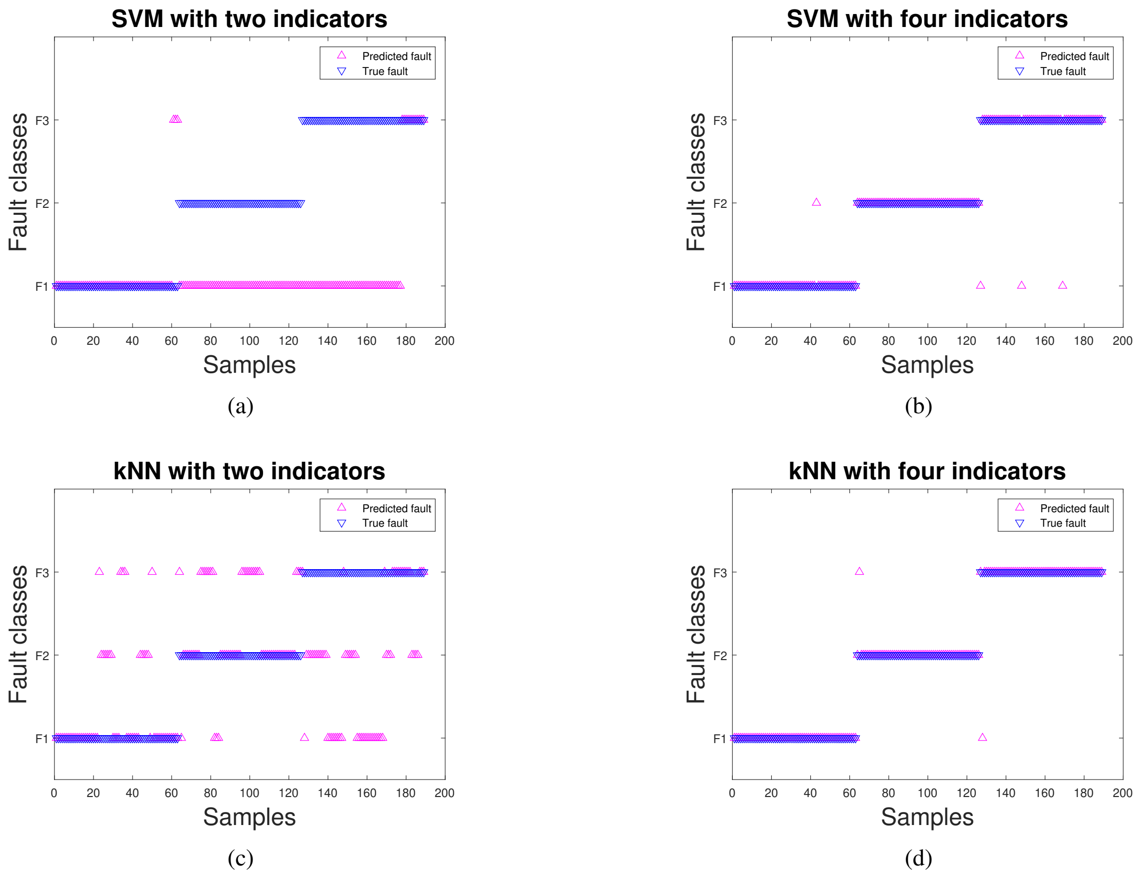


Fig. 3: Performance of the diagnostic results

corresponding decrease in the stack voltage. This decrease occurs due to the smaller amount of oxygen molecules available to complete the electro-catalytic reaction. Moreover, the membrane resistance increases proportionally, as depicted in the top-right figure. The cathodic pressure drop exhibits a proportional increase, while the anodic pressure drop shows slight changes, as shown in the bottom-left and bottom-right figures, respectively. These changes in the indicators indicate the presence of oxygen starvation in the PEMFC.

3) Dual-gas starvation: In the case of dual-gas starvation, where both the anodic and cathodic molar fractions are modified concurrently, the evolution of the indicators is presented in Fig. 2c. It is observed that all four indicators show a positive sensitivity to this fault, unlike hydrogen or oxygen starvation, where only three indicators exhibit positive sensitivity. The changes in all four indicators indicate the presence of dual-gas starvation, which combines the consequences of both hydrogen and oxygen starvation. This makes it essential to diagnose and address this fault to ensure the proper functioning of the PEMFC system.

B. Fault diagnostic results

After training different classifiers, new samples are then tested to determine the accuracy of the algorithm. In each case, a white-box model is used to generate residuals which acts as an input to the classifiers. Depending on the number of indicators used to predict the faults (hydrogen starvation, oxygen starvation, and dual-gas starvation), the predicted results of the classifier are then compared with the true fault class. The comparative performance of the diagnostic algorithms is depicted in Fig. 3 and Fig. 4.

Firstly, the performance of an SVM classifier with two indicators (stack voltage and membrane resistance) is depicted in Fig. 3a. The algorithm correctly predicted the majority of hydrogen starvation fault (the pink triangle and the blue inverted triangle overlapped along **F1**). However, the algorithm wrongly predicted the majority of oxygen and dual-gas starvation as hydrogen starvation, (the pink triangle and the blue inverted triangle do not overlap along **F2** and **F3** respectively). The confusion matrix in Fig. 4a shows the number of faults correctly predicted by the algorithm in the diagonal and the number wrongly predicted in the off-diagonal elements of the matrix. It can be seen that, out of 186 testing samples, only 60 and 12 samples are correctly classified as **F1**, and **F3** respectively. The rest of the samples (63, 51, and 3) are wrongly classified. Thus, this high misclassification rate yields a bad isolation probability of 38.10%.

Secondly, the performance of an SVM classifier with four indicators (stack voltage and membrane resistance, pressure drop at the cathode and pressure drop at the anode) is shown in Fig. 3b. The algorithm correctly predicted the majority of

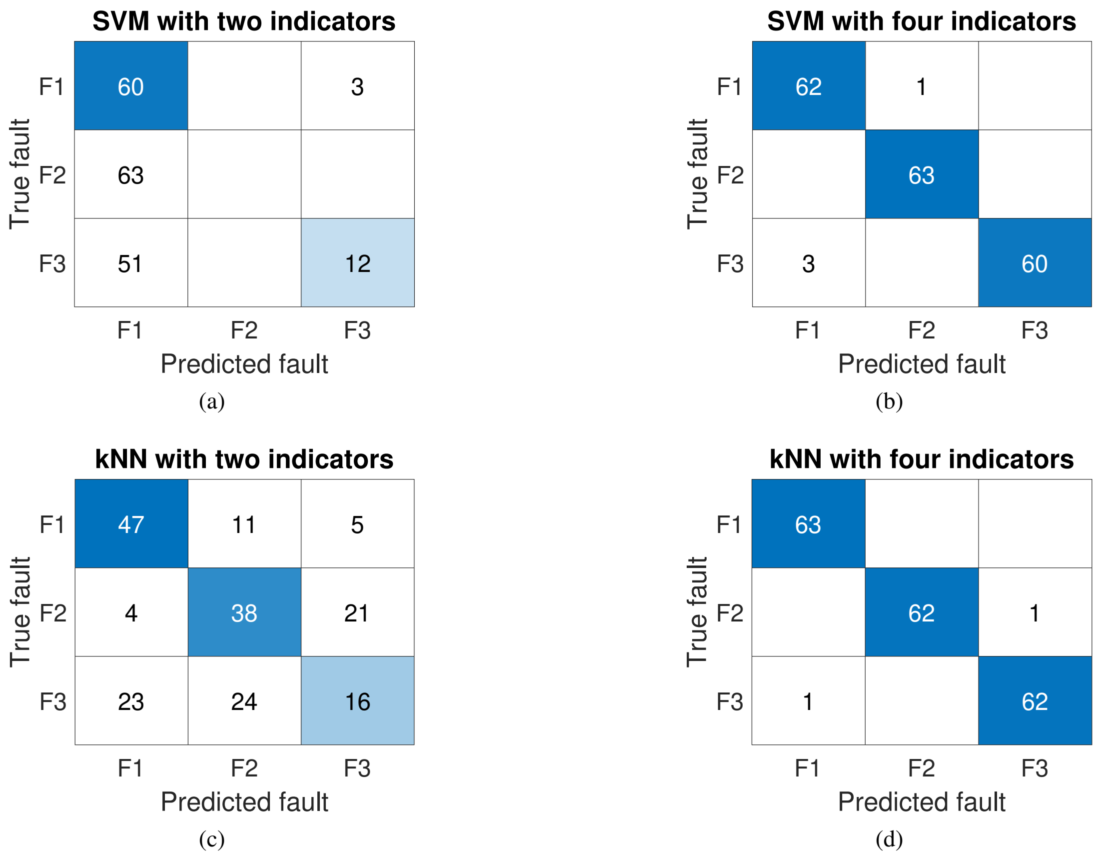


Fig. 4: Confusion matrices of the diagnostic results

the faults (the pink triangle and the blue inverted triangle overlapped along **F1**, **F2** and **F3**). The confusion matrix in Fig. 4b shows the number of faults correctly predicted by the algorithm in the diagonal and the number wrongly predicted in the off-diagonal elements of the matrix. It can be seen that, out of 186 testing samples, 62, 63 and 60 are correctly classified as **F1**, **F2** and **F3** respectively. Only a few samples (1 and 3) are wrongly classified. Thus, the algorithm achieves an improved performance with an isolation probability of 97.88%.

Thirdly, the performance of a kNN classifier with two indicators (stack voltage and membrane resistance) is depicted in Fig. 3c. The algorithm performs averagely as it correctly predicted nearly half of the faults and misclassified a lot (the pink triangle and the blue inverted triangle partially overlapped along **F1**, **F2** and **F3**). The confusion matrix in Fig. 4c shows the number of faults correctly predicted by the algorithm in the diagonal and the number wrongly predicted in the off-diagonal elements of the matrix. It can be seen that, out of 186 testing samples, 47, 38 and 16 samples are correctly classified as **F1**, **F2** and **F3** respectively. The rest of the samples are wrongly classified. An isolation probability of 53.44% is obtained with a tuning parameter $k = 9$.

Finally, the performance of a kNN classifier with four indicators (stack voltage and membrane resistance, pressure drop at the cathode and pressure drop at the anode) is shown in Fig. 3d. The algorithm correctly predicted nearly all the faults (the pink triangle and the blue inverted triangle overlapped along **F1**, **F2** and **F3**). The confusion matrix in Fig. 4d shows the number of faults correctly predicted by the algorithm in the diagonal and the number wrongly predicted in the off-diagonal elements of the matrix. It can be seen that, out of 186 testing samples, 63, 62 and 62 are correctly classified as **F1**, **F2** and **F3** respectively. Only a few samples (1 and 1) are wrongly classified. Thus, the algorithm achieves an improved performance with an isolation probability of 98.94% at $k = 2$. It should be observed that the addition of more indicators does not only improve the isolation probability but also reduces the number of neighbors to be computed. This is significant as it affects the computation time of the algorithm.

Overall, the results indicate that the kNN classifier generally outperforms the SVM in fault classification for PEMFC systems, especially when additional indicators are included. The comparison provides valuable insights into the strengths and weaknesses of both classifiers in the context of fault diagnosis in PEMFCs. A summary of the diagnostic performance of the algorithms developed is presented in III.

V. Conclusion and perspectives

In this paper, a hybrid fault diagnosis method for PEMFCs was proposed, combining residual-based fault detection and data-driven fault isolation. Four model outputs were selected as fault indicators, and residuals were generated by com-

Approaches	Isolation probability	Computation time
SVM with 2 indicators	38.10 %	0.0675 secs
SVM with 4 indicators	97.88 %	0.0465 secs
kNN with 2 indicators	53.44 %	0.0365 secs
kNN with 4 indicators	98.94 %	0.0165 secs

TABLE III: Comparative summary of the accuracy and the computation time of the proposed diagnostic algorithms

paring the faulty and nominal states of the system. The sensitivity of each indicator to different fault conditions was investigated. It is is observed that hydrogen starvation fault, it sensitive stack voltage, membrane resistance, and anodic pressure drop while oxygen starvation fault is sensitive to stack voltage, membrane resistance, and cathodic pressure drop. Whereas dual-gas starvation fault is sensitive to all the four indicators (stack voltage, membrane resistance, anodic pressure drop, and cathodic pressure drop).

Moreover, the proposed fault diagnosis method, combining residual-based detection and data-driven isolation could perform well when implemented of the real system, deducing from the performance indicators obtained. Thus, contributing to improved system reliability and performance.

The future perspectives and steps outlined in the paper are essential for further enhancing the fault diagnosis approach and its applicability in real-world scenarios. Here are the key points summarized:

1. Experimental Validation: As the current results are obtained from simulations, the next step would be to validate the fault diagnosis method using experimental data from a real fuel cell stack. This validation is crucial to assess the method's performance and reliability under real operating conditions.

2. Integration of Water Management Faults: Expanding the fault diagnosis method to include water management faults is vital since water management is a critical aspect affecting PEMFC performance. Including these faults will improve the overall diagnostic capability of the system.

3. Consideration of Dynamic Operating Conditions: Incorporating dynamic operating conditions in the fault diagnosis approach will make it more robust and relevant for real-world scenarios where fuel cell systems experience varying load and operating conditions.

4. Addressing Aging Phenomena: PEMFCs are subject to aging phenomena over time, which can affect their performance and reliability. Integrating aging effects into the fault diagnosis approach will help in predicting and diagnosing age-related faults.

5. Implementation in FCMS: Ultimately, the developed fault diagnosis algorithm should be integrated into a Fuel Cell Management System (FCMS) project at CEA. Implementing the method in a real-world application will provide valuable insights into its practicality, efficiency, and potential for industrial adoption.

By addressing these future perspectives, the fault diagnosis approach can be further refined, making it a valuable tool for ensuring the reliable and efficient operation of PEMFC systems, thereby contributing to the advancement of fuel cell technology for clean and sustainable energy applications.

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