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Monitoring of operational conditions of fuel cells by using machine learning

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Abstract

The reliability of fuel cells during testing is crucial for their development on test benches. For the development of fuel cells on test benches, it is essential to maintain their dependability during testing. It is only possible for the alarm module of the control software to identify the most serious failures because of the large operating parameter range of a fuel cell. This study presents a novel approach to monitoring fuel cell stacks during testing that relies on machine learning to ensure precise outcomes. The use of machine learning to track fuel cell operating variables can achieve improvements in performance, economy, and reliability. ML enables intelligent decision-making for efficient fuel cell operation in varied and dynamic environments through the power of data analytics and pattern recognition. Evaluating the performance of fuel cells is the first and most important step in establishing their reliability and durability. This introduces methods that track the fuel cell's performance using digital twins and clustering-based approaches to monitor the test bench's operating circumstances. The only way to detect the rate of accelerated degradation in the test scenarios is by using the digital twin LSTM-NN model that is used to evaluate fuel cell performance. The proposed methods demonstrate their ability to detect discrepancies that the state-of-the-art test bench monitoring system overlooked, using real-world test data. An automated monitoring method can be used at a testing facility to accurately track the operation of fuel cells.

Keywords: Testing data, Fuel cell, Performance, AIML

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1. Introduction

Hydrogen is a zero-emissions fuel source since its combustion produces only water. Therefore, hydrogen energy is a viable means to either a low-carbon or carbon-neutral economy [1, 2]. In addition, hydrogen is a possible future energy carrier [3,20], with 1 kilogramme of hydrogen-containing 33.33 kWh of usable energy compared to only roughly 12 kWh in petrol and diesel [4,19]. The fuel cell is the most widely utilized technology for transforming the chemical energy of hydrogen into electricity for use in mobile and stationary power generation. However, the main obstacles that prevent the commercialization of this clean energy alternative are the fuel cells' limited durability and reliability [5,12]. Fuel cell status monitoring approaches for realistic durability and reliability evaluation are crucial for overcoming these obstacles. The user may keep tabs on the condition of the fuel cell in real-time with the help of these methods by sensing the parameters that reflect the fuel cell's state at a predetermined rate. Using visualization and data-driven methodologies, the user can obtain pertinent information regarding the fuel cell's condition. With this data in hand, one can judge the longevity and dependability of fuel cells [17,18,19].

Although it is difficult to carry out, the alleged over 50% or 51.5% attack is a security concern for Bitcoin. As Bitcoin mining becomes more challenging, miners join pools to coordinate their computational power [20,21]. The network of Bitcoin gets threatened when a collection grows so strong that it can control more than half of the mining power. A gang might alter transactions by mining "invalid" blocks or double-spending if it were to acquire this much power. Because most miners use ASICS mining rigs, they can only operate through pools [22,23]. The energy in some collections is so great that it might get abused. For instance, Bitmain Tech.'s Chinese mining pool Antpool, is controlled by around 27% of the computing power. The combined force would be perilously close to 50% if colluded with another collection. Users of Bitcoin would be worried about reaching that magic number [24,25]. Genuine miners will, however, always recognise the need to exercise caution. Therefore, 51 per cent of attacks are unlikely to occur. Most of Bitcoin's security issues and vulnerabilities are connected to its use, not the blockchain network. Therefore, most of them can be fixed to prevent further cryptocurrency-related problems. These issues and how they may affect investments should be known to all Bitcoin investors [26,27].

The first and most crucial stage in determining whether or not fuel cells are reliable and long-lasting is to evaluate their performance. The fuel cell's voltage-current (VeI) curve is often used in these evaluations [6,7]. The VeI curve may be derived by experimentation [8, 9], physical modelling [10, 11], or data analysis [12, 13]. By altering the operational conditions—for example, by switching between loads [7,28,]—the experimental methods can acquire the voltage at various current points. These methods provide the VeI curve immediately, albeit at the expense of expensive testing. Parameters for the fuel cell's electrochemical characteristics a derived from the physical environment, and biological modelling approaches describe these features using tools like the Nernst equation [10,29] and other equations [14,30]. While physical models improve the understanding of the fuel cell's physics, they often simplify the underlying complex processes to streamline model derivation at the expense of accuracy. In contrast to these two methods, data-driven methods, including support vector machines [12,31,32,33] and neural networks [13,34,35,36], train the curve directly from fuel cell operational data. Unmeasured operating points may be estimated and predicted using data-driven methods [15,37,38], but this requires substantial operational data [39,40].

2. Proposed Methodology

The circumstances under which fuel cell stacks operate are controlled by test bench software. A partial rundown of the operating circumstances comprises the following: stack current, intake gas temperatures, pressures, stoichiometry and humidity, for cathode and anode; cooling inlet temperatures and pressures; and either the flowing rate or the temperature of the cooling outflow [14]. Operating conditions and stack history affect the stack voltage, which determines the electrical power output of the fuel cell.

Fuel cell stacks, like other electrochemical systems, experience power loss with time, resulting in a low stack voltage at a constant loading. The fuel cell ageing behaviour is inclined by several degradation processes, which may be classified as either reversible or irreversible [15].

Ghosh et al.'s 2023 study on machine learning for [16] water quality analysis, 'Water Quality Assessment Through Predictive Machine Learning', explores predictive analytics for water parameters. In 2023, Rahat and Ghosh's 'Unraveling the Heterogeneity [17] of Lower-Grade Gliomas' discusses the use of deep learning in brain MR image analysis for medical insights. The 2023 work [18] by Ghosh, Rahat, and their team, 'Potato Leaf Disease Recognition and Prediction using Convolutional Neural Networks', demonstrates the use of neural networks in detecting potato leaf diseases. Mandava, Vinta, Ghosh, and Rahat's 2023 research, 'An All-Inclusive Machine Learning and Deep [19] Learning Method for Forecasting Cardiovascular Disease in Bangladeshi Population', integrates [20] AI for health forecasting. The study 'Identification and Categorization of Yellow Rust Infection in Wheat through Deep Learning Techniques' by Mandava et al. in 2023, applies deep learning to wheat disease detection. Khasim, Rahat, Ghosh, and others' 2023 article, 'Using Deep [`21] Learning and Machine Learning: Real-Time Discernment and Diagnostics of Rice-Leaf Diseases in Bangladesh', explores AI in rice-leaf disease diagnosis. In 2023, Khasim, Ghosh, Rahat [22] and colleagues' 'Deciphering Microorganisms through Intelligent Image Recognition' discusses machine learning for microorganism identification. Mohanty, Ghosh, Rahat, and Reddy's 2023 study, 'Advanced [23] Deep Learning Models for Corn Leaf Disease Classification', focuses on deep learning for classifying corn leaf diseases. Alenezi and team's 2021 research [24]'Block-Greedy and CNN Based Underwater Image Dehazing for Novel Depth Estimation and Optimal Ambient Light' investigates CNN methods for underwater image enhancement.

Special procedures, such as turning off the fuel cells and then turning them back later, may cause voltage loss produced by reversible degradation processes. The severity of the degradation processes is affected by the fuel cell operating strategy besides the quality of the reactant.

The power output of a stack is affected not only by the stack's age but also by the operational dynamics. After a load point change, fuel cells settle into a constant voltage level after a short period. Based on the primary load fact, this nonlinear ramp grows or decreases in steepness.

Oscillations in managing the operating conditions lead to changes in the stack voltage since the stack voltage depends on the operational circumstances specified by the test bench.

Lifetime observing of a power cell load requires 2 prime considerations due to the power cell's operational and degrading procedures.

In the first step ensuring proper functioning is monitoring the test bench's predetermined operating conditions. Simple machine learning approaches, such as clustering, may be utilized since the operational circumstances of every particular load signal do not vary in the lifespan of the heap. Second, it should monitor the fuel cell's output. Because of the fuel cell's ageing behaviour, more advanced ML approaches that account for fuel cell ageing must be applied.

2.1. Fuel cell Monitoring system:

A standard load cycle is used throughout the length of a fuel cell durability test. As a result, several test iterations are performed at each stress point in the load cycle The test bench must maintain consistency in every parameter with their historical value at the same point. This is because the working conditions at every load remain constant. If the variables set by the test benches show a statistically significant difference from their corresponding historical values at any load point, it is considered anomalous and is flagged. A probabilistic approach to cluster and analyse the load spots is necessary for implementing this kind of monitoring.

Data points in a multidimensional space may be grouped using clustering algorithms based on their similarities. Here, the groups picked by the clustering technique stand in for the separate load points in the load set, and the space dimensions are associated with the parameters that define the weight cycle Distributed clustering systems like the Gaussian mixture method [16] not only assign new information points to pre-existing clusters but determines the possibility that these points belong to those clusters. Putting a 3 on this likelihood could help us find data points that don't fit into any current cluster with a 98% certainty level, which are known as outliers.

This may be made easier if the test bench software's data logs included a separate indication for each load point. Separating the data by marker allows us to examine each load point separately. The results at each load point are then used to inform a probabilistic categorization obtained by fixing a multivariate usual distribution. A new data point is considered abnormal if it falls beyond the 3-gap of the multivariate usual spreading of the associated load point.

2.2. Fuel cell performance:

A digital depiction with all the info about the original thing that can replicate its behaviour [17], is used to track how well the stack performs. To estimate the power cell's typical cell voltage under specified circumstances, the DT is used here. As shown in Fig. 1, the average cell voltage may be predicted by feeding the operating circumstances on the test bench which is determined for the actual power cell into the digital twin method. After that, decide whether the power cell's performance was normal by comparison with the expected and measured voltages.

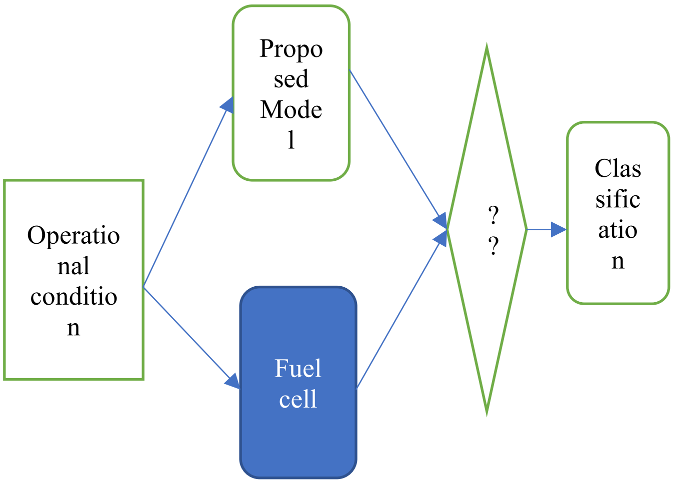

Figure 1: Predicted operational with predicted classification.

The digital twin model may be constructed in many ways, including physically, via data, or as a combination of the two (a "grey box"). Due to the many parameters and age-related impacts that impact fuel cell efficiency, an information-driven model method is used for the DT. The fuel cell's complicated behaviour necessitates using neural networks in the DT model. For the predictions, first use a "vanilla" feed-forward neural net, and then build upon this foundation with a "memory" neural network.

The fuel cell durability test runs for 3,500 hours, yielding 13.1 million information points used to train both models The power cell load series (14) was used to produce the load series utilized for the durable test. This test simulates 4 4-city driving series, followed by a time limit for driving on a motorway. 31 load points are repeated for 3100 hours using FC-DLC, and a polarisation curve is recorded every third cycle. After a workweek of weight cycling, the power cell is turned off for one hour to restore the reversible cell voltage deterioration. 12.9 million information points are used for training after excluding information gathered during the startup and shutdown phases of the load cycle.

The information set is at 5 different load point. Therefore, for the last 29s at each load point, the average cell voltage across the stack has been calculated. The ageing behaviour of the fuel cell stack may be better understood after going through this process. As shown in Fig. 2, the mass suffers power loss since the average cell voltage declines with time for a fixed load. Following a reversible ageing process, the plot displays a weekly sawtooth-like profile due to a one-hour regeneration phase.

Although there are over 12.2 million records in the database, each was recorded by cycling through the same 31-point load cycle approximately 450 times. The power cell's irreversible and reversible degrading properties are the primary drivers of variation across these 31 load stages. As a result, there are only 31 unique observations from which to learn how different factors affect fuel cell performance. In addition, all operational variables are related to the current dragged from the power cell according to the manufacturer's operation strategy. Consequently, the model cannot provide insight into the effect of a single operating parameter since all operational parameters of every 31 load points are interrelated.
However, the sum of unique information points increases due to ramps in the load change and fluctuations in the test bench control. The whole data set is utilised without any data aggregation or sampling during the training of the models. As shown in Fig. 2, the entire dataset is broken down into manageable chunks that are then divided 75:25 between training and validation data sets. While data points for both the warranty and training background are drawn from the same distribution, statistical independence is ensured using batching. The last step is to train the networks on the training data set and check their development by making predictions on the validation information set.

Several adjust hyperparameters in the DT neural networks are used to improve accuracy. Some regulate the network structure, such as the total number of layers or neurons in each layer. The optimisation method's learning rate and parameters also impact model training. For the net training junction and forecast precision, hyperparameter selection is critical. As a result, optimising the network's hyperparameters is essential for hyperparameter optimisation, the KI-Lab.EE [18] is employed. The ZSW created this AutoML suite at the Centre for Hydrogen Energy and Solar Research. The PGPE-algorithm [19]-based hyperparameter tuning approach it uses intelligently probes the hyperparameter space of the neural network's hyperparameters.

The whole dataset is used during training, the trained networks are assessed using two test datasets subjected to the exact load measurements. On the same test bench, however, obtain a first information set with 4,200 hrs of operation, and this generation of the better stack shows a distinct cell voltage level and ageing behaviour. The next dataset, consisting of 4,400 operational hours, was acquired on separate test benches using the same generation of fuel cell stack as the training dataset. The dynamic behaviour of the two test benches is distinct because of the varied methods they were constructed. Furthermore, all sensors have slightly different calibrations.
As seen in Fig. 2, employ transmission learning [20] to modify the pre-trained method using the first 2000 hrs of the test information sets. This procedure proves the reliability of the model and its ability to make accurate predictions.

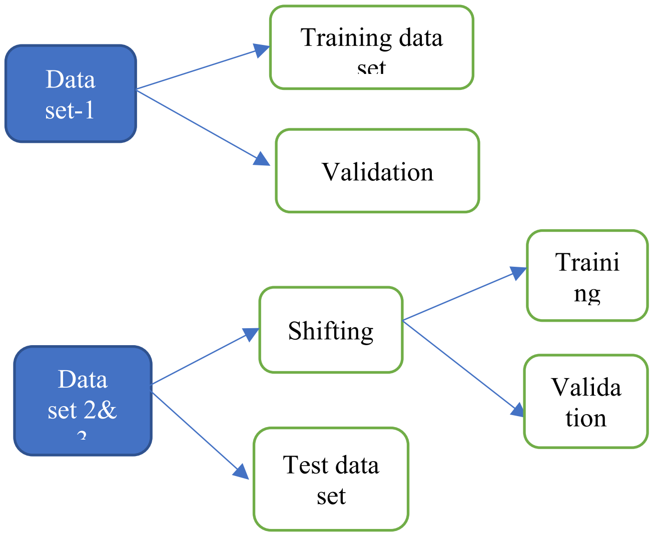

Figure 2: Data sets are shifted in 75:25 into training and validation datasets.

FF-NN:

In a feed-forward neural network, each layer is made up of many individual process elements termed neurons, which together generate a stream of activations with a real-valued output. Activation yk of the kth neuron is defined as:

$$y = \sigma \sum wx + b$$

Each neuron in the first layer, the input layer, is fed a value from the model's input vector. The activations are propagated through the network through weighted connections between the neurons of each successive layer until they reach the output layer, where the system forecasting is displayed [21]. The term "training" is used to describe the process of optimising the weights and biases of a neural network's connections.

To do this, the training prediction fault is propagated back through the net, and the heaviness is adjusted based on the error gradient [22]. Finding the ideal set of weights for a neural network, which might include millions of nodes, is a computationally intensive operation often run on a graphics processing unit (GPU).

KI-Lab.EE automatically selects 20 inputs for this application. The most important operational parameters are stack current, anode and cathode in- and out gas temperature, pressure, humidity and stochiometry, coolant in- and out temperature, coolant flowing rate and running duration. Feature engineering enhances the data set since FF-NNs cannot integrate past occurrences. The network can represent fuel cell history by encoding shutdown, OCV events, and the final load point with artificial characteristics. Network output is stacking average cell voltage.

A cutoff value is needed to categorize the discrepancy between the forecasted and actual normal cell voltage as pathological. Models that produce normally distributed predictions can use the root-mean-squared error (RMSE) on the transfer-learning dataset as a measure of prediction confidence. That is why the model's prediction is the same as the expected value of the normal spreading under Gaussian conditions, and RMSE on the transfer learning dataset is the same as the distribution's standard deviation. Measurements are considered out of the ordinary if they deviate from predictions by more than 3.

The recurrent units of a recurrent neural network (RNN) include internal feedback loops that allow the network to recall past events. During training, the network learns which events are most important to store, making it a highly adaptable model. However, during the exercise, it is necessary to consider the current forecasting error and all previous forecasts. This process, known as back-propagation over time [23], involves repeatedly multiplying the erroneous gradients by the network's weights until the slopes either explode or disappear, rendering the RNN untrainable.

Gates that exclusively affect the BP error in long short-term memory neural nets solve this problem. LSTM cells have 4- gates with trained masses and a unit state C, unlike artificial neurons.

$$= \sigma(w.x + b + wh + b)$$

3. Discussion and Result

3.1. Operational condition:

3.1.1. Cool power shortage:

After approximately 120 operational hours, a secondary testing apparatus linked to the identical cooling conduit was initiated while acquiring the initial dataset.

The circumstance above resulted in a deficit of cooling capacity, which ultimately gave rise to an elevation in temperature within the cooling circuit of the test bench during instances of high load that exceeded the coolant temperature as specified by the load cycle. Despite the observed variation in the operating conditions, which resulted in a three-mV shift in the cell voltage level, the digital twin model remains incapable of detecting this deviation due to its integration of the heightened coolant inlet temperature in its prognostication.

The circumvention of this issue is achieved by excluding the cooling inlet temperature coming from the inputs of the DT. Nonetheless, this approach is limited to the input operating parameters in the decision tree. It necessitates significant computational resources, as a distinct decision tree must be trained for each excluded operating parameter. Furthermore, the alarm module of the test bench software failed to produce an alarm despite the marginal rise in cooling inlet degrees, which persisted within the power cell's operational thresholds.

Assessed utilising the remaining data after being trained using the first 120 hours of operation. Figure 3 shows the three distinct load points, the cooling intake degree, and the associated system parameters. The four data and the second test bench in the process were correctly flagged as unusual by the trained model.

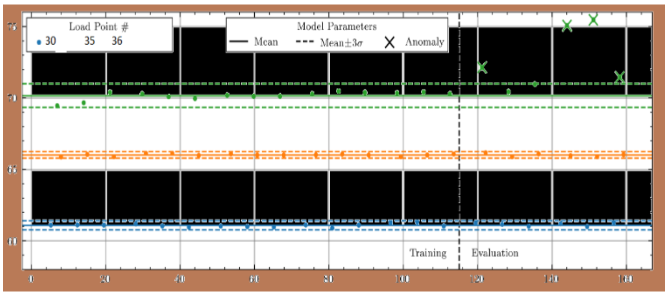

Figure 3: Intake of coolant temperature with different point loads (30,35,36).

The electronic coat is overcoming to solve the overheating issue:

Overheating concerns with the test bench's electronic load, which feeds the fuel cell's power output into the local electrical grid, plagued a durability test on a different test bench. To prevent further heating, the electronic load decreased the power output, reducing the current flowing out of the stack. Once again, this occurrence went undetected by the test bench software.

So trained another model using the first 1200 hours and then checked how it did on the rest of the data. Yo, check out Fig. 4 The model nailed it and found all the data points where the stack acted weird compared to its usual behavior. The current stage received excellent current management of the electronic load, resulting in a hardly perceptible 3 - 3-interval of 0.3 A. This narrow 3-interval enables sensitive anomaly identification but may also incorrectly label nominal data items as abnormal. Figure 4 shows this behaviour at load points 34 and 36, with a maximum deviation of 0.5 A. This deviation may be considered normal by a testing engineer, but it is flagged as unusual by the model.

The problem is fixed by raising the categorization cutoff to 4. However, the problem can be avoided by having a testing engineer manually set a lower acceptable limit for the model's computed 3-interval based on the engineer's prior knowledge.

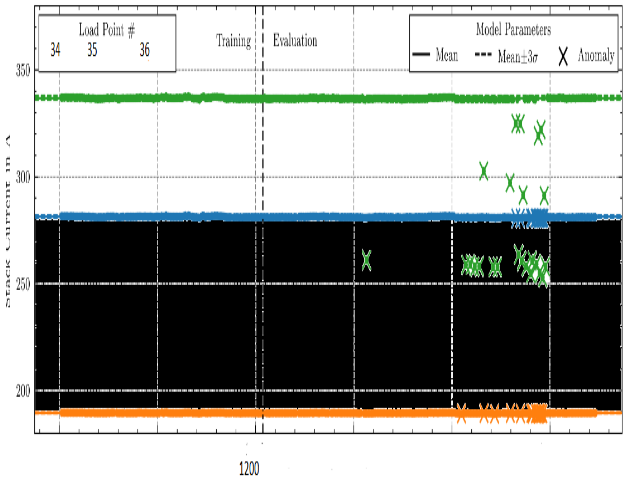

Figure 4: Load behavior at 34 and 36 with the 0.5A deviation correction

4. Conclusion:

Clustering techniques for monitoring operational conditions are stable over extended periods and can detect any abnormalities in the test instances However, the controller for a functioning condition parameter is more accurate than the satisfactory deviation., false positive classifications result from the monitoring concept. This level of control ensures that the threshold for making a classification is lower than the allowable variation. It is possible to artificially raise the classification threshold by providing a more significant value for the permissible deviation of every operation variable. Having each load point independently monitored for its properties increases test reliability, even with the manually given values.

The digital twin LSTM-NN model employed for monitoring fuel cell performance is the only method to identify the accelerated deterioration rate in the test scenarios. The FF-NN's inability to accurately forecast the occurrence of events means that it cannot be used to detect influences of less than a few millivolts. This is because the LSTM-NN can factor in past circumstances while making forecasts. The digital twin can't use raw data to monitor the fuel cell because of how the model's detection threshold is defined. Each load point's measured and anticipated values must be averaged for an accurate categorization free of false positives.

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