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Remaining useful life prediction for proton exchange membrane fuel cells using combined convolutional neural network and recurrent neural network

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Abstract

The search for sustainable but environmentally friendly medium of harnessing energy for the automotive industry has led to the evolution of various energy generating as well as converting devices. One of such energy convertig device is fuel cells. Despite the merits associated to the performance of PEM fuel cells, issues relating to the cost and remaining useful life prediction still persist hence impeding their commercialization espcially in the automotive industry. In spite of the progress made by the research community in developing various predictive models in order to mitigate these challenges, the accuracy of these developed models has lately become active research direction. The current study explored the accuracy of recurrent neural network, bi recurrent neural network, combined convolutional neural network and bi recurrent neural network in predicting the remaining useful life of a PEM fuel cell. The presence of the convolutional neural network was mainly to ensure pre – processing of the bi recurrent neural network for the extraction of high level features. To reduce the possibility of overfitting, a dropout approach coupled with callback technique is adopted. Validation of the model was executed based on an experimental data. The outcome of the investigation highlighted the key role of the convolutional neural network in improving the accuracy of the recurrent neural network. Comparing the RMSE and MAPE of the present model with other models, the developed model yielded the least values indicating a higher accuracy compared to other models. Similarly, the relative error used in recording the remaining useful life equally showed a least value when compared with that of other studies.

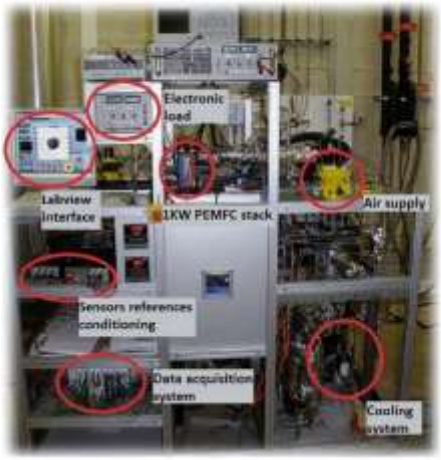
Keywords: Proton Exchange Membrane Fuel cells, Degradation, Health indicator, Predictive maintenance, Voltage.

1. Introduction

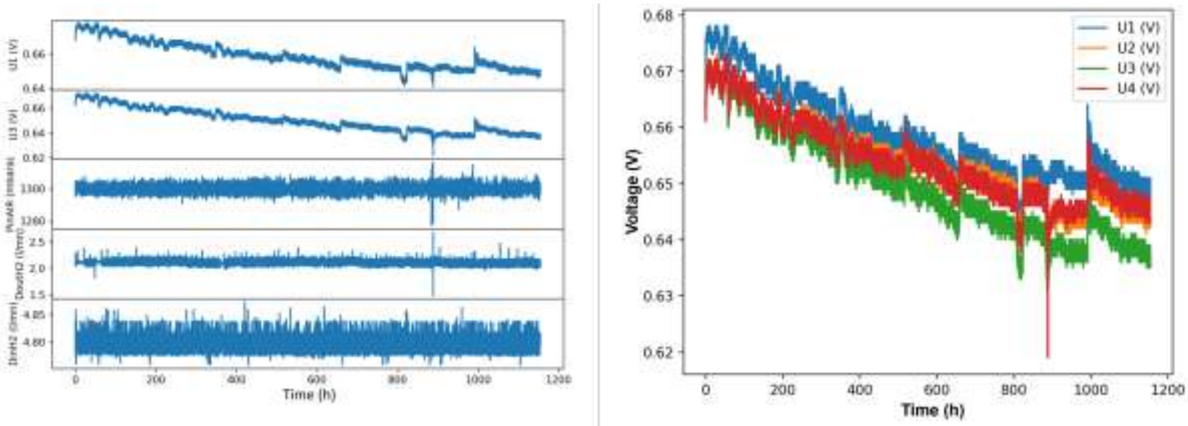
With the world currently going through a pradigm shift in terms of global emissions, one crucial area of interest is the approach that may be adopted in harnesshing energy for diverse applications. Proton exchange membrane (PEM) fuel cells an energy converting device is deemed as one of the viable medium for energy conversion due to it's quick start up as well as higher efficiencies compared to conventional fossil based engines. The reactants required for the energy conversion processes in PEM fuel cells are clean hence the by product of the electrochemical reaction is largely water and heat. Similarly due to the absence of a moving part, fuel cells operate silently and also produce virtually no noise during their operation [1]. PEM fuel cells are however projected as the future in the quest of mitigating the sudden upsurge in the earths temperature due to human activities particularly in the transportation sector [2]. The applications of PEM fuel cells are enormous but predominantly utilised for military as well as automotive purposes [3, 4]. This has lead to recent investigation into fuel economy coupled with the management of energy being harnessed from PEM fuel cells [5]. The main issue impeding the commercialization of PEM fuel cells is related to the cost coupled with the shorter life of the cell [6]. A solution to mitigate this challenge is through an effective management of the rate of cell degradation coupled with an accurate determination of remainining useful life of the cell. It therefore implies that the current challenges impeding the commercialization of PEM fuel cells can easily be addressed provided the cells' durability is improved significantly [7]. It must however be noted that several factors come to play in contributing to the rate of degradation of PEM fuel cell performance [8]. Notable among them include the rate of degration of the catalyst as well as the thermal management issues [9]. This implies that characterizing the rate at which various components in the cell tend to degrade is a bit of a challenge and this hypothesis even holds true in terms of asessing how each components within the cell tends to degrade [10]. It is therefore imperative that an ideal approach in predicting the life of the fuel cell coupled with the precise time for maintaining the cell in order to curb failure of the cell is critically looked into [11 – 13]. Several research activities has been carried out with primary focus on indicators for the degradation of the PEM fuel cell [14]. Voltage as well as the power remain the notable indicators in examining the degradation of the cell as well as predicting the remaining useful life. A study conducted utilized the voltage as an indicator for the cell degrading in order for the prediction of the remaning useful life to be conducted. The margin of error deduced was nearly 5 percent [15]. Another study equally considered the power as the indicator and the results deduced for the remaning useful life was remarkable [6]. Similarly, other researchers suggested using electrochemical surface area degradation for predicting the remaning useful [16]. The main limitation for the study was the fact that it was conducted using only one indicator and this left room for questions regarding the accuracy of the remaning useful life being predicted. To accurately predict the remaning useful life, other authors considered using several indicators simultaneously [17]. A combination of various degradating indicators using voltage coupled with the state of health was executed based on an integration of the 2 models using a model driven approach [18]. The outcome of the investigation highlighted the importance of the integrated approach in hencing the accuracy of the prediucted remaining useful life compared to the single model. A multi scale hybrid degradation indicators using film thickness as well as electrochemical surface area has equally been reported using automatic machine learning technique [19]. The conclusion from the investigation highlighted the effectiveness of the model being capable in predicting the rate of degradation as well as the remanining useful life of the PEM fuel cells. Extended Kalman filter was also adopted in describing the rate of degradation coupled with the state of health for PEM fuel cells [20]. Again a multiparticle filter capable of predicting the change in performacne of PEM fuel cells via the identification of degradation parameters has equally been reported. It was highlighted that the utilization of multiple indicators for the degradation of the fuel cell yielded accurate results compare to single degradation results. Using semi as well as empirical models for predicting the rate of degredation for PEM fuel cells, the rate of degredation for PEM fuel cell was also deduced at a macro scale perspective. This approach in determining the rate of degredation of the fuel cell is largely subject to the expert experience formula [21]. As explained earlier, the complexity in the determination of the rate of degradation of fuel cells is largely due to the nonlinear characteristics of the cell hence a data driven method being suggested as one of the most ideal means of determining the rate of degradation of the cell [22]. The appraoch of using a data drive technique often do not require the development of a metaphysical degradation model [23]. The technique adopts the performance of the cell under study through a learning algorithm in order to ensure the characterization for the non linear changes for the degradating approach is observed [24]. Neural networks remains one of the common data driven approach used in the determination of the fuel cell performance. A wavelet analysis using voltage have also been reported in predicting the degration of a fuel cell [25]. The conclusion of the study highlighted the feasibility in the application of the approach on original data with disturbances. A long G – LSTM model was however equally investigated for the prediction of the degration of PEM fuel cells [26]. Using a model made up of neural network coupled with a swarm intelligence optimiser a prrediction model was equally explored [27]. The study was further advanced using wavelet neural network in combination to cuckoo search algorithm [28]. The outcome for the study clearly showed the accuracy for the model being predicted compared to conventional approach. In terms of time series data, temproal convolutional network has been reported as being ideal in predicting the degradation of the cell compared to conventional methods [29, 30]. Based on the research activities conducted from literature, the present studies will explore the accuracy in combining convolutional neural network and recurrent neural network for predicting the remaining useful like of a fuel cell. This will then be combined with other models from literature like the Eco state Neural Network.

2. Experimental setup for aging test

The experimental setup for the study as depicted in Fig. 1a was obtained from the FCLAB Research Federation [31] and the operating conditions is highlighted in Table 1. The fuel cell considered for the investigation is 1kW and within the stack, there are 5 individual cells having an active area of 100cm^2. Pressure valves coupled with flow valves ensures the oxidant as well as reductance for the anodic and cathodic electrodes are properly regulated. The set up is designed to allow the 2 reactive substances to flow via independent boilers before making their way into the cell. This is more likely to ensure the required relative humidity for the gaseous mixtures are achieved. A water pump aids in adjusting the temperature of the fuel cell. An active load equally ensures the load current is well controlled. For this investigation, the operation of the PEM fuel cell stack occurs within nominal current density of 0.70 A/cm^2. Absolute pressures for the anodic as well as cathodic electrodes are properly controlled around 1.5 bar to maintain steady state conditions for the PEM fuel cells whiles the absolute temperature was kept around 55^{o}C but relative humidity for air is maintained near 50%. Several condition parameters were properly regulated. Characteization for the stack was equally done weekly to guanrantee the reliability of the system.



(a)



(b)

Fig. 1: a) Experimental setup for the investigation b) output data deduced from the experimental process

Table 1: Fuel cell conditions of operation

Constraint	Control range
Temperature range for cooling (^oC)	20 - 80
Cooling flow (l/min)	0 to 10
Gas temperature (^oC)	20 – 80
Gas humidification% RH	0 – 100
Air flow(l/min)	0 – 100 l/min
Flow of Fuel (l/min)	0 – 30
Gas pressure (bars)	0 – 2 bars
Fuel cell current (A)	0 - 300

2.1 Rate of degradation for the PEM fuel cell – Characteristic analysis

Several parameters were monitored during the investigation process to check the degradation of the PEM fuel cell. Notable among these parameters include stack voltage, current, temperature etc as depicted in Fig. 1b. Due to the fuel cell being operational in a more precise as well as conducive environment the trends of the signals being harnessed from the cell is often stationary. It must be stated that the signals from the cell stack comes with noise as well as peaks. With respect to time, compared to the other parameters investigated, the rate of degradation of the fuel cell using voltage as a primary indicator was more predominant. This may be largely due to a decrement in the overall material characteristics of other components within the cell as well as the rate of degradation internally. It therefore explains why several research works usually uses voltage as the health indicator to capture the rate of degradation of the cell. The gathering of voltage signals is equally simple compared to using other parameters. The present study will therefore focus on the voltage signals as health indicator for a PEM fuel cell. In a nut shell, the present study intends to explore the remaining useful life for a PEM fuel cell from voltage historical data. From Fig. 1 it is obvious that there are several spikes and noise indicating that there are some voltage regeneration characteristics the comes to play during the data collection. It further explains that the voltage rose reversibly during the PEM fuel cell aging test. A justification for the observable reversible changes can be attributed to the operation of the stack being halted for characterization of the cell during the experiment. Again, due to the fact that the characterization of the cell was done at least once a week, voltage regeneration was seen as being periodic. After the characterization, the cell continues it operation but the voltage tend to drop over a period of time. From a technical point of view, the interruption of the stack for the weekly characterization of the cell impedes the diffusion of reactants as well as by product within the cell. It must however be stated that the voltage data from the PEM fuel cells are non linear with some element of uncertainty.

2.2 Remaining useful life prediction – Problem description

The primary focus of the present study is to evaluate a more proactive means of tracking the health status of the fuel cell in order to plan a maintenance routine especially for the automotive industry. The method discussed in the determination of the prediction period for estimating the remaining useful life is time consuming hence real – time characteristics as well as the cost for determining the prediction was not considered as evaluation indicators. The method adopted primarily focused on accuracy as well as anti interference coupled with generation. First and foremost, the predictive model developed was expected to be able to extract good degradation characteristics from the voltage data that is non linear. The model was further anticipated to be able to build a correlation between the input characteristics as well as the output characteristics. The model is also further anticipated to be able to deal with any form of spikes due to the weekly characterization of the experimental set up as well as any form of noise that comes with the experimental procedure. The model is further expected to be robust in terms of training the data.

2.3 Challenges of approaches used in remaining useful life determination

There are current 4 types of data driven prediction approach being used in estimating the rate of degradation of proton exchange membrane fuel cells. Each of these approaches comes with their own merit and demerit. In spite of the usefulness of each approach, there are still challenges that needs to be addressed in terms of the prediction of the accuracy of the model, anti – interference characteristics as well as generalization. One of the come technique used is the non – parametric regression approach which is quite simple to implement as well as recommended due to their excellent portability. The main limitation here is the fact that more historical data is needed and there are issues in terms of non – linear data during the data processing stage hence the accuracy of the prediction made using this approach cannot be guaranteed. Similarly, others have argued that the machine learning approach is quite flexible and easy to implement compared to the other models. This model is suitable for nonlinear data but an increase in complexity of the data can make its application quite challenging. It also heavily relies on the quality as well as quantity of the trained data. The accuracy of the prediction using this model is significantly low as well as exhibit some challenges in terms of generalization. The probability statistics approach is the third option but the Gaussian methods exhibit poorer learning ability hence the accuracy in terms of prediction is significantly low as well. Others like the grey models are equally dependent on the quality as well as the quantity of the trained data hence leads to poor generalization characteristics. The application of deep neural network is considered as being ideal for non linear data because of their strong extraction features as well as their learning process.

2.4 Rational behind the study

2.4.1 Motivation

Several research activities has been conducted to ascertain the rate of degradation as well as estimate the remaining useful life for PEM fuel cell hence this study will evaluate the accuracy of predicting the remaining useful life using deep learning based lifetime predictive model. The

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