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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.

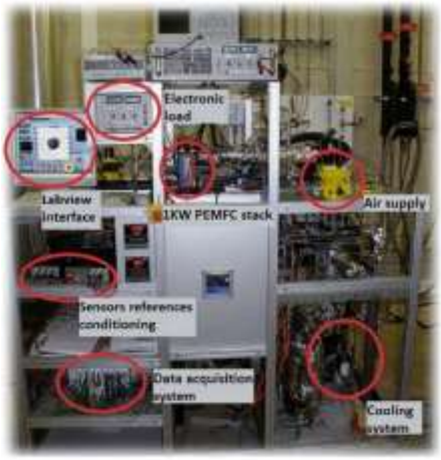
Keywords: Proton Exchange Membrane Fuel cells, Degradation, Health indicator, Predictive maintenance, Voltage.

## 1. Introduction

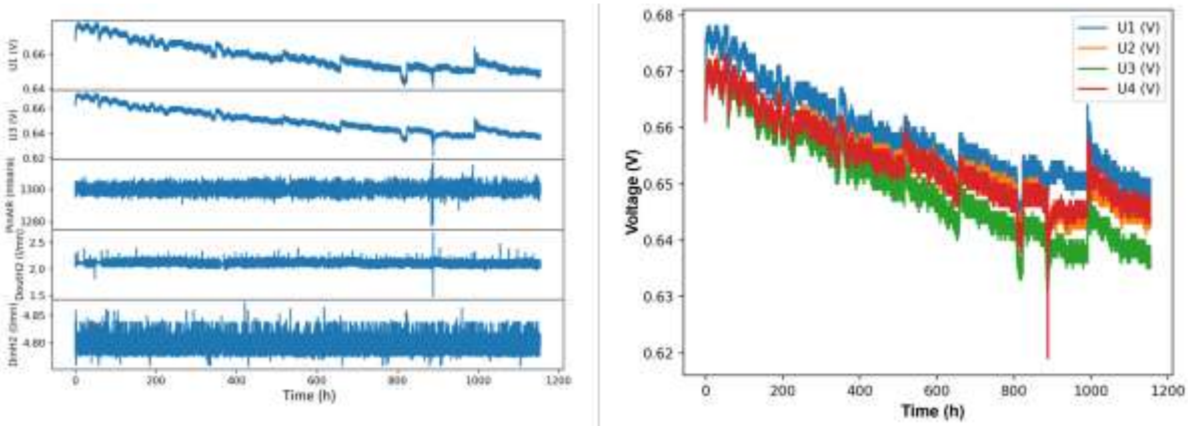
With the world currently going through a pradigm shift in terms of global emissions, one crucial area of interest is the approach that may be adopted in harnesshing energy for diverse applications. Proton exchange membrane (PEM) fuel cells an energy converting device is deemed as one of the viable medium 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 ($^{o}$C) | 20 - 80 |
| Cooling flow (l/min) | 0 to 10 |
| Gas temperature ($^{o}$C) | 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 model being developed is a combination of recurrent neural network and convolutional neural network. This will further be compared with other model from literature to ascertain the accuracy of the model under investigation.

## 2.5 Pre processing of the output voltage

According to a study carried out by Kimotho et al [15], the recorded voltage comes with some abnormalities which have direct implication on the voltage data generated. It therefore becomes imperative that the data is being pre processed before its integration to the developed model. The process often involves samplings of the data, removing all abnormal values as well as ensuring smoothning of the data. Fig. 2 for instance captures the outcome of the pre – processed data. The importance of pre – processing the data is also to reduce computational time and as explained earlier increase the accuracy as well.

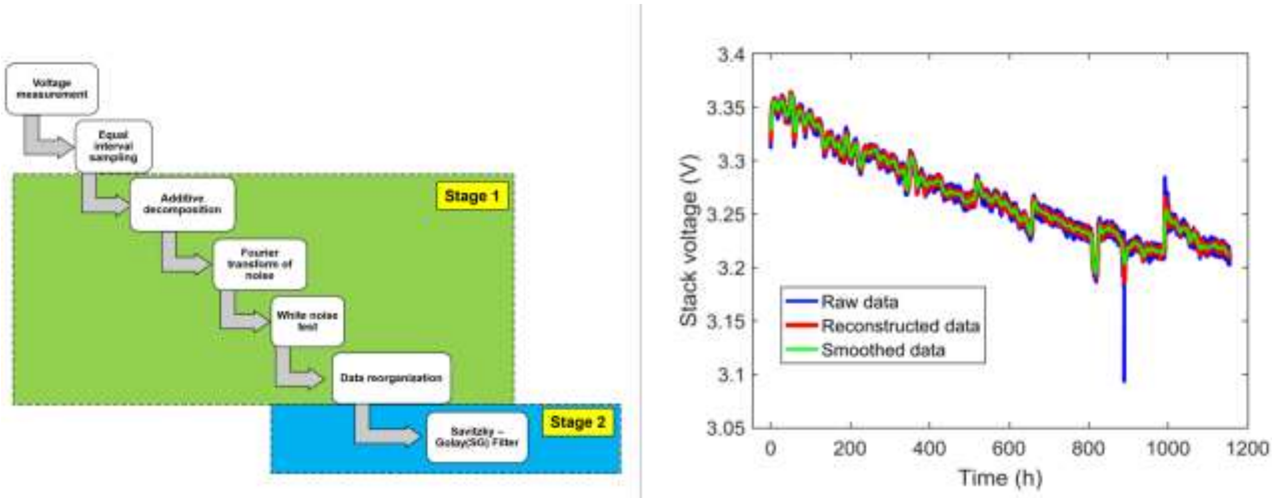



Fig. 2: Pre processing of the data obtained for the voltage

Reconstruction of the actual datum is carried out to reduce the quantum of data as well as derive a realistic data. With constant sampling being carried out within 1 hour interval range, 1155 sets of information datum were derived from the original data. It can be deduced that the original trend in the raw data is maintained even with the smoothed data. The data that was smoothened had 24 dimensional characteristics and this dimensional disparity among the parameters being investigated was more likely to cause the data for the voltage becoming distorted. Normalization of the data is important even after smoothning the data in order to decrease the impact of high variable disparity on the model performance. At the initial stages of the pre processing stage, the voltage signal deduced was decomposed into 3 sections as shown in Eqn. 1

$$Y(t) = T(t) + S(t) + e(t) \quad (1)$$

The time point is denoted as t whiles $Y(t)$ represent the voltage whiles the trend data is captured as $T(t)$. The seasonal data is also $S(t)$ and $e(t)$ is the residual dat with respect to time. In order for the noise passing white noise test, a Fourier transform is used as depicted in Eqn. 2.

$$X(k) = \sum_{i=0}^{t-1} x(i)e^{-j\frac{2\pi}{N}ki}(k = 0,1,2.,t-1) \quad (2)$$

The white noise test is performed to confirm that no key information is omitted during the process. A particle fiter has been recommended in other studies to attain the smoothing effect. This was suggested as being suitable for non linear data due to its ability to ensure the initial and tail data were not lost because they conform to the first order Markov model [33]. In the case of the particle fuilter approach prediction coupled with updating are the 2 key stages that must be solved. Eqn. 3 and 4 are used for capturing the observation and state.

$$x_k = f(x_{k-1}, Q_k) \quad (3)$$

$$y_k = h(x_k, R_k) \quad (4)$$

Assuming the probability density function$(x_{k-1}|y_{1:k-1})$ at $k-1$ is determined, then the process for carrying out the prediction, $f: x_{k-1} \rightarrow x_k$ is computed using eqn. 5.

$$p(x_{k-1}|y_{1:k-1}) = p\ (x_k|x_{k-1})p(x_{k-1}|y_{1:k-1})dx_{k-1} \quad (5)$$

With respect to the updating process $h:\ x_k \rightarrow y_k$ is determined from eqn. 6

$$p(x_k|y_{1:k}) = \frac{p(y_k|x_k)p(x_k|y_{1:k-1})}{p_{(y_k|x_k)p(x_k|y_{1:k-1})dx_k}} \quad (6)$$

The failure threshold is very critical in the determination of the remaining useful life of the cell and this is basically the condition at which the cell is incapable of providing enough power for a specific application. For the purpose of this study the Savitzky – Golay filter was utilised. The green region from Fig. 3 is basically the initial voltage and the threshold was maintained as 96 percent of the initial voltage.

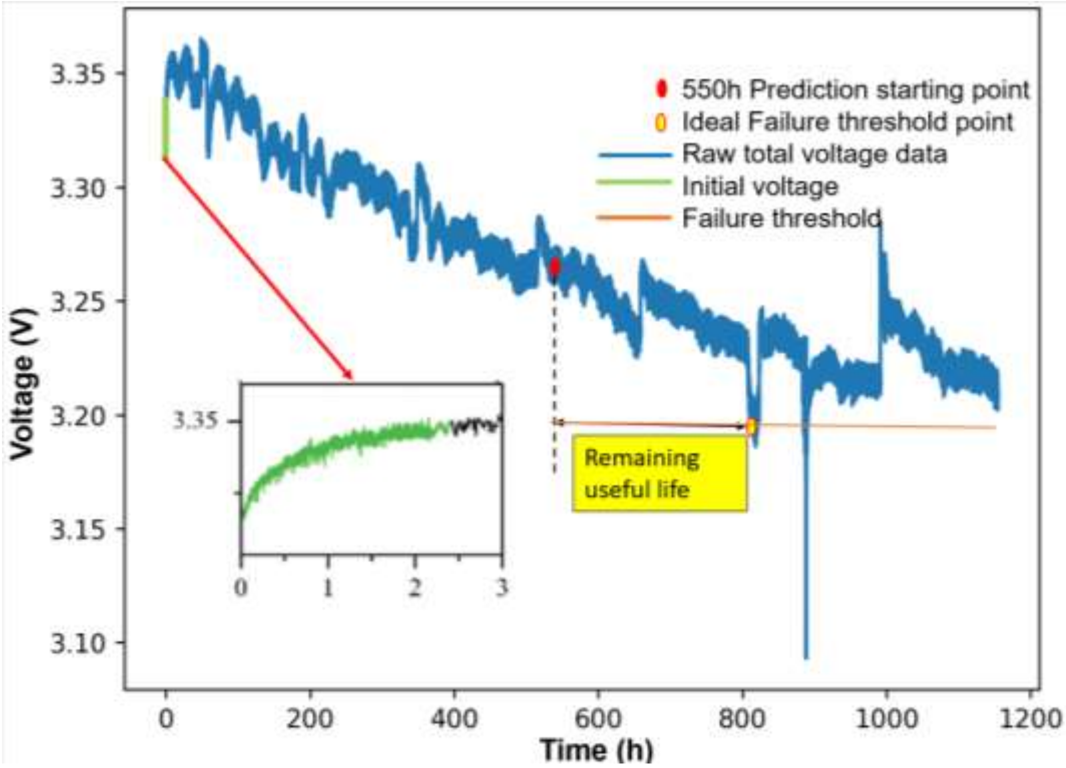



Fig. 3: Remaining useful life determination from initial voltage

2.5.1 Savitzky – Golay filter

Despite the raw data from the experimental setup capable of being fitted to the developed model, the presence of noise in the data is likely to affect the accuracy of the model hence often not ideal to use the raw data in the training of the model. Savitzky – Golay filter has been reported as being an effect filter for the removal of noise from an experimental data [34]. This filter has also been investgated [35] in terms of their application in the estimation of the rate pf degradation for a proton exchange membrane fuel cells. For this current study, the Savitzky – Golay filter aided in the removal of noise from the gathered data from the sensors of the experimental setup. This type of filter is basically a finite impulse response (FIR) where time domain signal is made smooth based on convolution operation. This basically ensures that the shaper coupled with the width for the signal do not change when removing noise from the data. For Savitzky – Golay filter, it’s also been reported that the effect of smoothing is predominant if the order of the polynomial is small. Similarly, this postulate holds true in the event that the window length is large [36]. For the present study, the window length was kept as 51 whiles 1 was selected as the order of the polynomial. From a general perspective, the omittion of normalization during the modeling of data usually lead to the development of models that learns a lot on variables having larger values but performs otherwisr for smally values. It implies that the convergence speed has a direct correlation with normalization of the data hence leading to an improvement in the accuracy of the developed model. Normalization of the data for this study was carried out using the maximum – minimum normalization approach. This method involves the utilization of the maximum and minimum values in the data for standardization. The standardization was kept between 0 and 1. In terms of calculations, the approach involves finding the disparity between the data and minimum values for the column and diving by the range. This is captured in Eqn. 7.

$$\bar{x} = \frac{x - min}{\max - min} \tag{7}$$

The raw data set is captured as $x$ whiles $\bar{x}$ is the normalized value for the individual data set. Min and Max denotes the minmum and maximum values respectively.

## 3. Model investigated

Deep learning is considered as a distributed feature learning technique [37]. The goal in executing deep learning is to ensure enormous amount of information is obtained via multiple progressive training layers. Deep learning equally ensures issues relating to poor training structure hence leading to some deficiency in the accuracy of the results is curbed. There is deepening of all layers trained from the previous layers for all algorithms in the structure of deep learning. Deep learning often utilize multi layer structure hence the initial raw data is capable of being trained coupled of times. This approach ensures important information are captured hence the data characteristics can easily be deduced.

### 3.1 Recurrent Neural Network

Recurrent neural network is best suited for data that is sequential [39]. Recurrent neural networks are designed to record, preserve as well as recorded information for data that is sequential based on historical antecedent via connection of hidden layer nodes periodically [40]. The recurrent neural network comprise of input layer, hidden layer as well as the output layer as depicted in Fig. 4. The weight serves as a point of connection between layers.

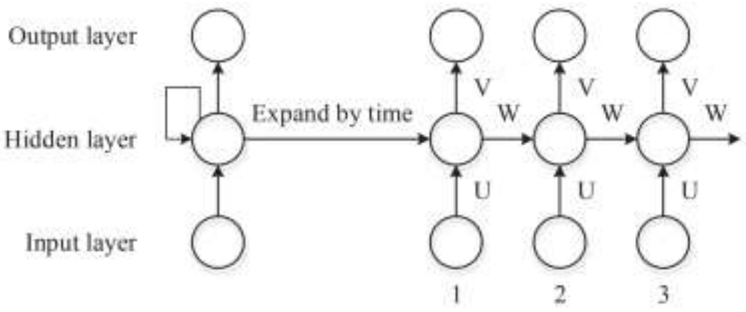



Fig. 4: Recurrent neural network structure

The weight of the input layer are captured as U for the input to hidden layer whiles hidden layer to hidden layer is captured as V and the hidden layer to the output layer is W. The unique features for recurrent neural network compared to conventional neural network is the concept of parameter sharing but U, V as well as W stays same for both types of neural network. For expanded recurrent neural, the data $(\ldots x_{t-1}, x_t, x_{t+1} \ldots)$. is coupled to the next neuron leading to the generation of neural time series $(\ldots h_{t-1}, h_t, h_{t+1} \ldots)$. For a single recurrent neuron, the output us sumarised in eqn. 8.

$$h_t = \sigma(W_x x_t + W_h h_{t-1} + b)$$

$$y_t = softmax(W_y h_t + c) \tag{8}$$

From eqn. 8, the weight vectors are denoted as $W_y$, $W_h$, $W_x$ whiles c coupled with b are the bias terms. On the other hand activation function is $\sigma$. Relu or Tanh is often utilised in recurrent neural network. Output for the recurrent neuron is $y_t$ but this is subject to $h_t$ which is the hidden state.

3.2 Bidirectional Recurrent Neural Network

In order to mitigate the challenges pertaining to recurrent neural network as described earlier, bidirectional recurrent neural network is often recommended because they are capable of being trained subject to the availability of input information both historically as well as in future with a specific period. The main concept is to ensure the splitting of state neurons for a regular recurrent neural network. This done to allow positive time direction (forward states) as well as negative time direction (backward states). Forward state outputs are not coupled to backward state inputs, and vice versa [41]. This phenomenon result in the structure captured in Fig. 5. Due to the fact that the delay line would have to be positive and negative in time, it is not feasible to represent the BRNN structure in a form comparable to Fig. 4 with the delay line. A conventional recurrent neural network having a reversed time axis occurs when the forward states are taken out. Because both time directions are handled in the same network, input data from the past and future of the currently evaluated time frame can be used directly to minimise the objective function without the need for delays to account for future data, as in the regular unidirectional RNN discussed above. Because there are no connections between the two kinds of state neurons, the BRNN may be trained using the same techniques as a standard unidirectional RNN. It can then be unfurled into a generic feedforward network. The forward and backward pass procedures become significantly more difficult if, for example, any sort of back-propagation through time (BPTT) is utilised, since the updating of state as well as output neurons cannot be carried out once at a time. When using BPTT, the forward and backward passes over the unfolded BRNN over time are performed very identically to a conventional MLP. Only at the beginning and conclusion of the training data does extra treatment become essential. The forward state as well as backward state inputs at have not been determined. Setting these might be considered a part of the learning process, but they are set to a preset value arbitrarily here. Furthermore, the local state derivatives at for forward states and at for backward states are unknown and are set to zero here, presuming that information beyond that point is unimportant for the current update, which is absolutely the case for the boundary.

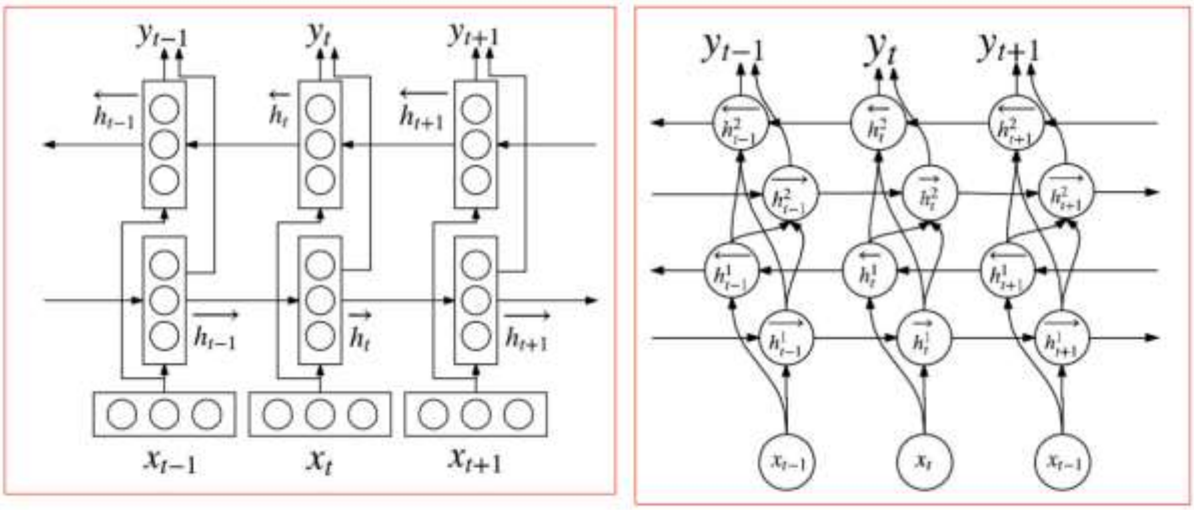



Fig. 5: Bidirectional recurrent neural network

3.3 Combined Convolutional Neural Network and Birecurent nural etwork.

Recording of spatial dependencies in the case of feature domains can be carried out using convolutonal neural network but the recurrent neural network can manage temporal dependencies in sequencial data. Furthermore due to the feedback loop, early information can easily be remembered by the recurrent neural network . Entire accuracy for the RNN model is enhanced due to the convolution neural network being utilised as preprocessing step. The convolution neural network carries out the extraction of high level features in the data and then pass to the recurrent neural network for learning the voltage sequence. In this study, the developed model is made up of 4 layers namely input layer, convolutional neural network layer, Bi – recurrent neural network layer as well as output layer. The structure is depicted in Fig. 6. All required data relating to the PEM fuel cell voltage for prediction goes through layer one Notable features relating to the input data are extracted whiles there is equally lowering of dimensionality in the convolutional neural network layer. Time series prediction is then carried out by the BiRNN layer based on processing conducted in previous layers. The output layer then serves as a passage for the predicted values.

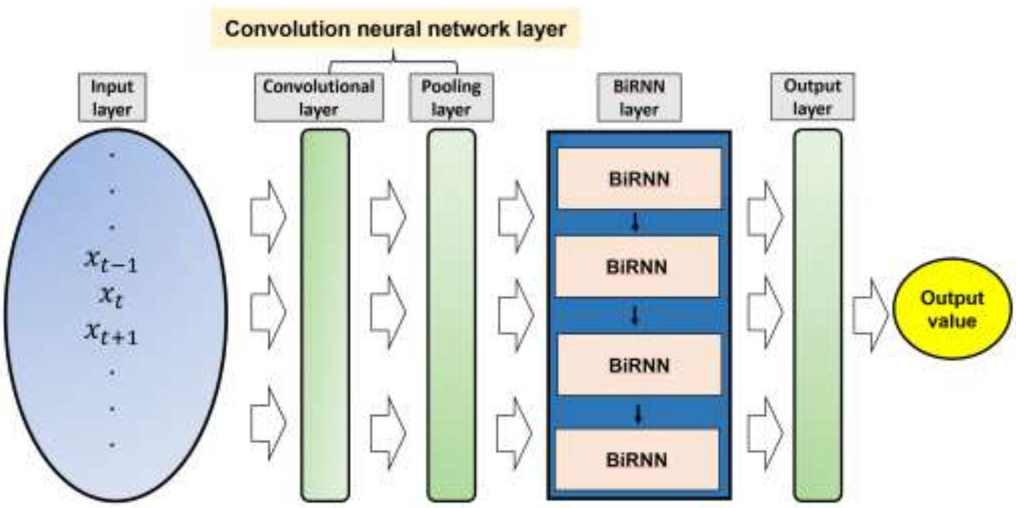



Fig. 6: Combined convolutional neural network and Bi – recurrent neural network model

3.4 Convolutional Neural Network(CNN)

This model was first developed in 1998 [42] for pattern recognition coupled with the extraction of features as feedforward neural network. The input data’s characteristics are captured using a convolutional neural network and coupled into a high level features for regressional coupled with classification prediction. For the present investigation, a one dimensional convolutional was utilised as pre – processing step for the recurrent neural networks. The convolutional neural network parameters are depicted in Table 2. From table 2, the highest pooling layer window is represented as the Pooling layer Pool_size whiles the output space dimension is the convolution layer filter.

Table 2: Constrainst for the convolutional neural network

| Parameters | Value |
|---|---|
| Convolutional Layer Filters | 128 |
| Convolution Layer Kernel_size | 7 |
| Convolutional Layer Activation function | Relu |
| Pooling Layer Pool_size | 4 |
| Dropout | 0.2 |

4. Model optimization and selecting parameters

For the present investigation, 2 primary evaluation standards were utilised namely root mean square error (RMSE) as well as mean absolute percentage error. These two parameters were selected to ascertain the prediction performance for the model. A lower RMSE as well as MAPE were considered as an ideal performance of the model hence the model with the best accuracy in terms of prediction. Eqn 7 and 8 highlights the 2 parameters investigated. The original voltage is denoted as $x_i$ whiles the predicted PEM fuel cell voltage is noted as $\overline{x_\iota}$ as highlighted below.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x_\iota})^2} \tag{7}$$

$$MAPE = (\frac{1}{n}\sum_{t=1}^{n}\left|\frac{x_i - \overline{x_\iota}}{\overline{x_{(n)}}}\right|) * 100 \tag{8}$$

4.1 Learning rate selection

The current study adopted the adaptive moment optimization algorithm in ensuring the weight were properly adjusted in order to reduce loss value. To obtain learning rates at high precision, varying learning rates for the adaptive moment optimization algorithm were explored. For the combined convolutional neural network and the bi – recurrent neural network, the batch sive was kept at 50 whiles the epochs were mained at 250 whiles the units were maintained at 35.

Tanh was equally maintained as the activation function whiles a callback techniques was adopted to curb overfitting. The callback was necessary to ensure overfitting was prevented by stopping the training process whenever the loss values attained a specific value. The mean absolute error is basically the loss function. The varying learning rate is depicted in Table 3. It can be deduced from table 3, that the least error is recorded at 0.01 learning rate but highest at 0.1 learning rate. Fig. 7 equally highlights the predictive model at varying learning rates hence 0.01 was selected as the most suitable learning rate for the adaptive moment optimization algorithm.

Table 3: RMSE and MAPE of RNN at different learning rates

| Learning Rate | 0.1 | 0.01 | 0.001 |
|---|---|---|---|
| RMSE | 0.013703272 | 0.003595755 | 0.003982157 |
| MAPE | 0.235627770 | 0.08383161 | 0.09178552 |

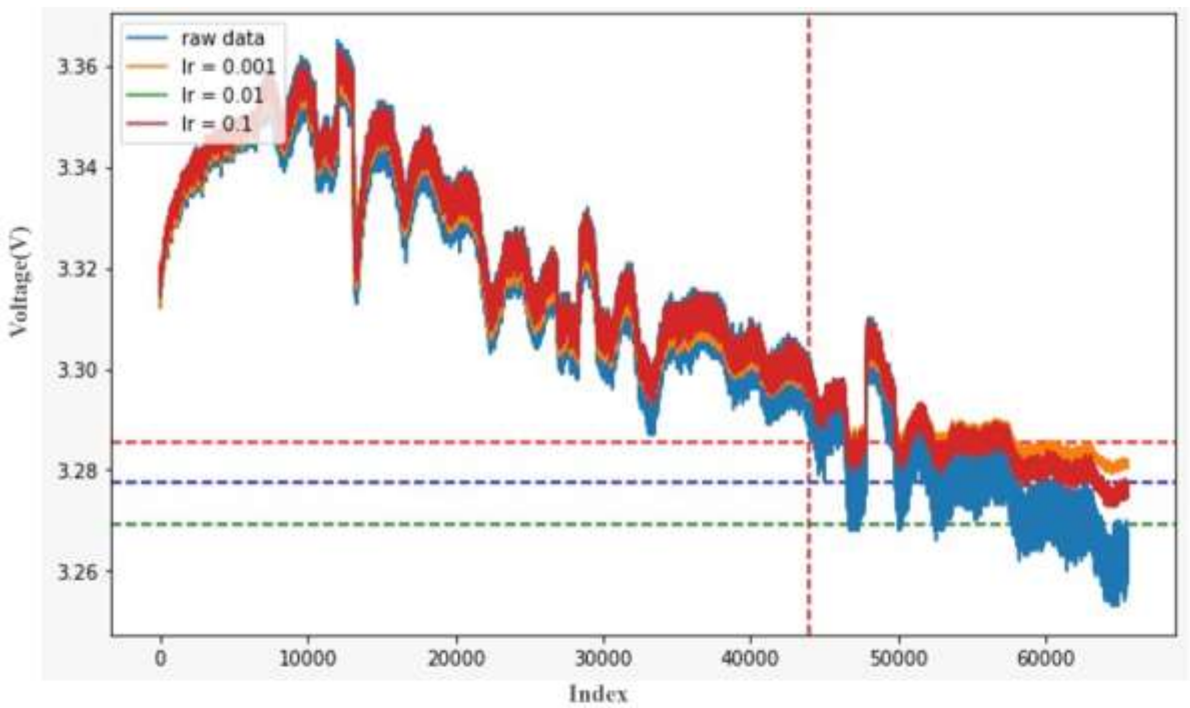



Fig. 7: Model prediction under varying learning rates.

4. 2 Selection of dropout

One of the key down side of deep learning is the occurrence of overfitting. Overfitting is a condition where the developed model aligns perfectly well with the trained data set but does not fit properly on the test set. A mitigation appraoch that be be adopted to curb this challenge is the dropout technique. Deliberately freezing neurons temporarily at random conditions over some probability during the training  procedure often results in good robustness of deep learning. This phenomenon occurs via the elimination of random neurons concurrently. For the present studies, varying drop outs are utilised in training the degradation model whiles the rest of the data was used in testing the predictive model after the training process. The results are highlighted in table 4.  A drop out of 0.2 was selected in terms of accuracy as it was able to help curb the issue of overfitting.

Table 4: Root mean square error coupled with MAPE for recurrent neural network at varying dropouts

| Dropout | 0.1 | 0.2 | 0.5 |
|---|---|---|---|
| RMSE | 0.048446664 | 0.03595755 | 0.05234955 |
| MAPE | 0.105870515 | 0.08383161 | 0.11062717 |

5. Discussion of results

Python language was used in  the development of the predictive model and the operation enviornment included a central processing unit AMD® A8-4500 M™ CPU®1.90 GHz. memory: 8.00 GB; operating system (OS): Ubuntu 16.04. The learning data used in the model varied between 0 -550 hours whiles the testing data was between 551 – 1154 hours. This is highlighted in the Fig. 8 below.

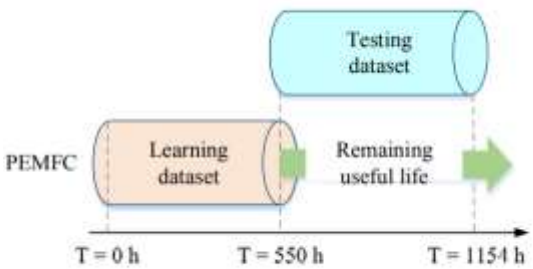



Fig. 8: Representation of the training as well as testing datasets

5.1 Evaluation of all models under investigation

The study further explored varying batch size  from 32, 64 and 128. The number of hidden neurons utilised in the training of the degradation predictive model was kept constant. Table 5 captures the results from combining the 4 neural network models. Fig. 9 also captures the prediction results  for the 4 optimised recurrent neural network.

Table 5: The optimal parameters of the 4 recurrent neural network.

| | Unit | Batch_size | Dropout | RMSE | MAPE |
|---|---|---|---|---|---|
| RNN | 25 | 32 | 0.2 | 0.005310813 | 0.17665497 |
| Bi-RNN | 25 | 32 | 0.2 | 0.007433851 | 0.23586397 |
| CNN-RNN | 25 | 32 | 0.2 | 0.0036010389 | 0.08983413 |
| CNN-BiRNN | 25 | 32 | 0.2 | 0.002581254 | 0.035485635 |

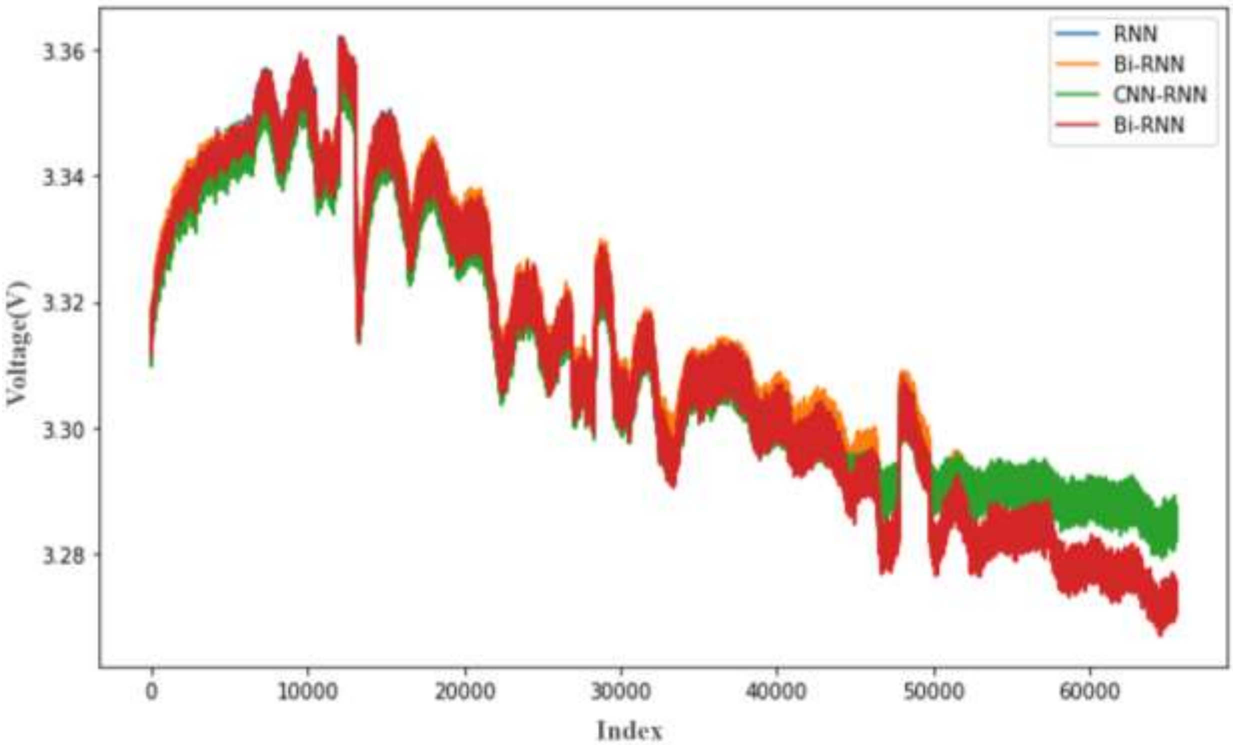



Fig. 9: The prediction results for the four predictive model under investigation

From table 5, it is observed that the RMSE for CNN-BiRNN was 0.002581254 and the MAPE was 0.035485635 and this was the least value indicating the most accurate model among the 4 other models being studied. It can be deduced that the presence of the convolutional neural network enhanced the accuracy of the predictive model. For instance the root mean squared error for the recurrent neural network was deduced as 0.005310813 but the incorporation of the convolutional neural network improved the accuracy to  0.0036010389. In terms of MAPE, the recurrent neural network yielded a result of 0.17665497 whiles that of the CNN – RNN was 0.08983413 buttressing the point regarding the improvement of the entire model due to the presence of the CNN.

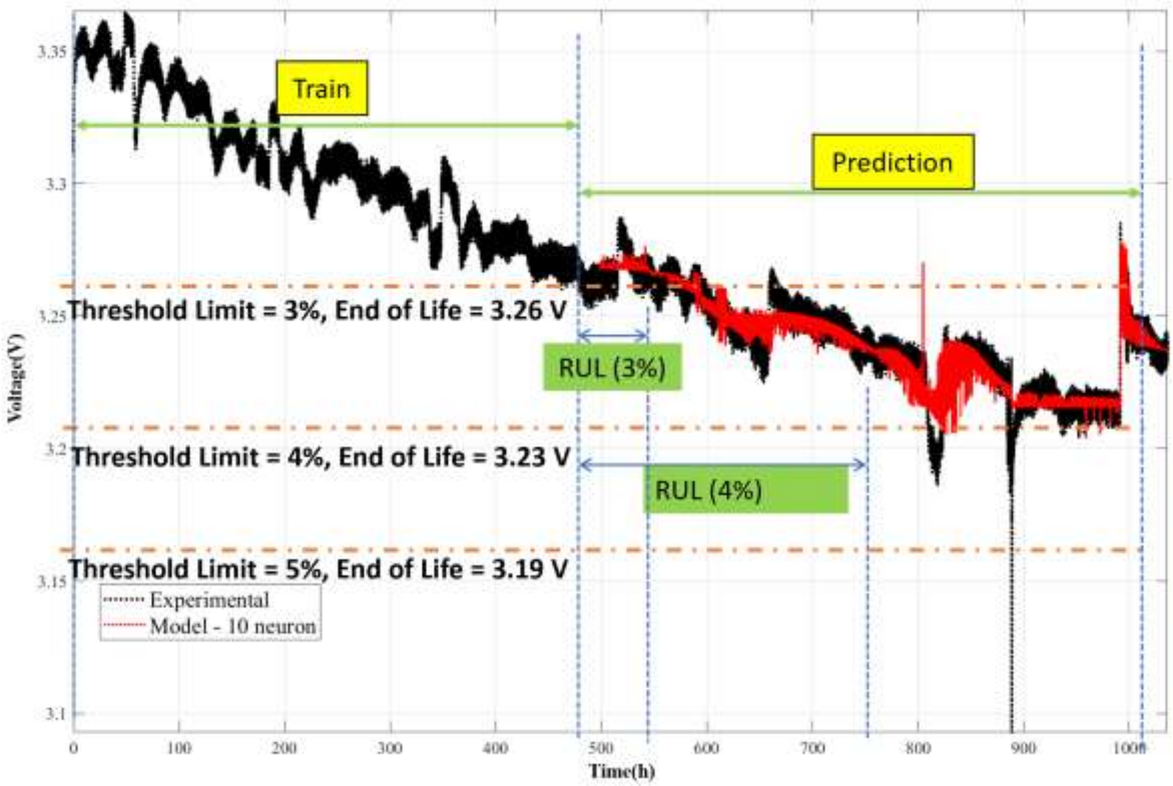



Fig. 10: 80%of data training for predicting the remaining useful life.

The next stage of the study is to compare the outcome of the CNN – BiRNN and three other models using the FC1 data set. The models being compared with the present study are back propagation neural network having 2 hidden layers, long short – term neural network and stacked long short – term memory neural network. Further information regarding the models being compared is obtainable from Fu et al [43]. The combined convolutional neural network and the Bi recurrent neural network exhibited the least RMSE as well as MAPE results hence the most accurate compared to other results gathered in literature. This implies that the model being investigated presented the most accurate results.

Table 6: Prediction result of different models using data set for FC1

| | LSTM [43] | S – LSTM [43] | Random Forest [44] | 2 - hidden layer BPNN [45] | CNN-RNN | CNN-BiRNN |
|---|---|---|---|---|---|---|
| Case 1 : 651h | | | | | | |
| RMSE | 0.0058 | 0.0047 | 0.0157 | 0.0049 | 0.00349 | 0.00319 |
| MAPE | 0.1421 | 0.0944 | 0.3644 | 0.1128 | 0.05708 | 0.05408 |
| Case 2 : 751h | | | | | | |
| RMSE | 0.0045 | 0.0039 | 0.0140 | 0.0119 | 0.00329 | 0.00309 |
| MAPE | 0.0947 | 0.0836 | 0.3290 | 0.3007 | 0.04978 | 0.04678 |

Similarly, from FC2 data set, an investigation to assess the performance of the model in predicting the remaining useful life was equally explored. The remaining useful life is simply the period prior to the attainment of a specific voltage loss. Failure of the cell is meant to be reported once the voltage goes below a certain threshold which is defined as it's end of life. In all, 3 voltage losses were considered and this were 3, 4 and 5 % of the entire voltage. The relative error was utilized in the determination of the remaining useful life prediction performacne for the model using eqn. 9. 70, 80 and 90% for the overall data set are used for training and the most ideal model prediction is attained at relative error of 0.012 and 0.039 at a voltage threshold of 5%. Using 80% of the data set for the training relative error of 0.06 was attained at voltage threshold of 4%.

$$Relative\ Error = \frac{|RUL - \overline{RUL}|}{RUL} x\ 100 \quad (9)$$

Again the smaller the relative error value, the more accurate predictive results obtained. The data being tained were varied between 70 , 80 and 90% in order to carry out the prediction. The reamining data were used for testing the data. The droupout used were equally mained as 0.2 as explained previously.  Table 7 captures the gathered predictive results obtained from the study.

Table 7: Model RUL prediction results

| Threshold(%) | EOL | 70% Actual RUL | 70% Predicted RUL | 70% RE | 80% Actual RUL | 80% Predicted RUL | 80% RE | 90% Actual RUL | 90% Predicted RUL | 90% RE |
|---|---|---|---|---|---|---|---|---|---|---|
| 3 | 3.26 | 332.39 | 337.05 | 1.40 | 387.17 | 387.01 | 0.31 | 432.14 | 432.06 | 0.87 |
| 4 | 3.23 | 337.59 | 338.67 | 0.32 | 387.18 | 387.40 | 0.06 | 442.14 | 442.05 | 0.0179 |
| 5 | 3.19 | 339.24 | 337.35 | 0.12 | 387.69 | 386.93 | 0.11 | 486.16 | 486.06 | 0.039 |

As explained earlier even from Fig. 8, the data set before 550 hours were utilised for trainign the model and the threshold for the voltage was maintained at 5% and this is compared with other results from literature. From the results gathered in literature the relative error values for the LSTM was noted as 2.61 whilrs that of the S – LSTM was 0.31. on the other hand, for the CNN – BiRNN the relative error was 0.12. In summary the CNN – Bi RNN yileded the least RE compared to other models in literature hence suitable for predicting the remaining useful life of the the fuel cell.

## 6. Conclusion

As the demand for sustainable source of energy keeps surgining up globally particularly for the automotive industry, fuel cells are projected as the future to ensure the realization of the hydrogen economy. However, for fuel cells to become viable for various applications, issues pertaining to the cost as well as degradation of the cells must critically be investigated. The present study explored the evolution for bi - recurrent neural network and its combination with convolutional neural network. As discussed earlier, Savitzky – Golay filter was utilised to ensure the data was smooth and free from noise. Curbing of overfitting was equally executed using a dropout approach. The model was then optimised. From the study, a combination of the convolutional neural network and the recurrent neural network ensured the performacne of the fuel cell was significantly improved. Again the accuracy for the convolutional nueural network bi recurrent neural network was noted to be higher based on the results generated from the relative error. It therefore justify the suitability of the convolutional nueural network bi recurrent neural network in accurately predicting the remianing useful life for fuel cells compared to other models investigated.

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