# Remaining Useful Life Prediction for Supercapacitors Using an Optimized End-to-End Deep Learning Approach

Chigozie Uzochukwu Udeogu◆, Angela C. Caliwag*, Wansu Lim°

## ABSTRACT

Remaining useful life (RUL) prediction for supercapacitors is particularly important to ensure the safety of the applied system and reduce the cost of operation. The existing RUL prediction method utilized health indicators (HIs) that are extracted by a conventional method. This method has the risk of dropping useful information in the supercapacitor data which leads to low accuracy because of poor quality features. To resolve this issue, this paper proposes an optimized end-to-end deep learning model for RUL prediction. Specifically, a genetic algorithm (GA) for automatic feature selection and long short-term memory (LSTM) network (GA-LSTM) for RUL prediction. GA is utilized for automatic feature extraction which ensures all important information in the supercapacitor data is considered during HI extraction. The combination of the best-selected features is used as the input to the LSTM model for final RUL prediction. Our proposed model achieved a root mean square error (RMSE) of 0.03 unlike the recurrent neural network, LSTM, and deep convolutional neural network with RMSE of 23.87, 0.51, and 0.38, respectively. When compared with other models, the overall results show that our model exhibits excellent performance for the RUL prediction of supercapacitors.

**Key Words :** Deep Learning, Feature Selection, Genetic Algorithm, Long Short-Term Memory, Remaining Useful Life, Supercapacitor

## Ⅰ. Introduction

Supercapacitors (SCs) are electrical storage devices with high power density, low internal resistance, high charge and discharge efficiency, large charge and discharge current, wide operating temperature range, and extremely long cycle life[1-5]. The basic structure of the supercapacitor is shown in Fig. 1. It consists of positive and negative electrodes, a separator, and the electrolyte (which is an activated carbon in this case). The positive and negative charges are stored on the positive and negative electrodes, respectively, when the electrodes are connected to an external circuit. The separator is a membrane that insulates the electrodes and ensures only the mobility of ions rather than the electric connection between them. The electrolyte generates charges opposite to those on the supercapacitor plates to balance its electric field. Although the cycle life of supercapacitors is affected by operating temperature and electrode materials[6], their cycle life is still longer than that of batteries. Thus, their application is very extensive. For instance, they have been extensively used as energy

※ This research was supported by Kumoh National Institute of Technology(2021)
◆ First Author : Kumoh National Institute of Technology, Department of Aeronautics, Mechanical and Electronic Convergence Engineering, 학생회원
° Corresponding Author : Kumoh National Institute of Technology, Department of Aeronautics, Mechanical and Electronic Convergence Engineering, wansu.lim@kumoh.ac.kr, 정회원
* Kumoh National Institute of Technology, Department of Aeronautics, Mechanical and Electronic Convergence Engineering
논문번호 : 202110-262-C-RE, Received September 30, 2021; Revised December 21, 2021; Accepted December 23, 2021

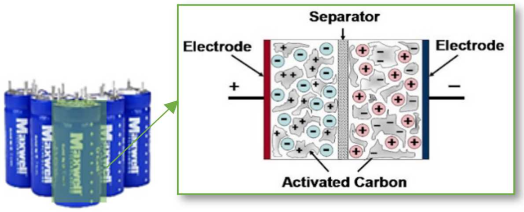


Fig. 1. Structure of the supercapacitor.

storage devices especially in renewable energy applications. They have also been used in communication technology for a) catering for short duration power peaks in cellular phone transmit pulses and high-brightness flashes, b) providing power in pulse applications and telemetry, c) consumer applications such as cellular phones and cameras d) system frequency and stability control devices like the surge protection circuits, and e) Internet of Energy (IOE). Figure 2 is a simple graphical visualization of supercapacitors and their various usage. When a supercapacitor is used as a part of an electronic system, its remaining useful life (RUL) affects the safety and reliability of the system. RUL is the length of time from the current time to the end of its useful life. Hence, an accurate RUL prediction will not only maintain the safe operation of the entire system but will also prevent physical failure.

In recent years, many interesting studies have reported different approaches for supercapacitor RUL prediction. Broadly, these approaches are divided into two methods: model-based and data-driven.

Model-based methods utilize mathematical methods to achieve degradation tracking and prediction while the data-driven methods do not require complex mathematical models to simulate the aging characteristics of supercapacitors. Rather they heavily rely on and tend to learn from huge amounts of data. Although these methods over the years have increasingly yielded good results, they are mostly based on manual feature extraction. Manual feature extraction has the risk of dropping useful information in the data as it is being practiced by previous studies. In RUL estimation, feature selection is essential because the RUL prediction depends on the accuracy of the training model[7], such that poorly extracted characteristic features may limit the performance[8].

To proffer a solution to the aforementioned issue, this study presents an end-to-end deep learning approach using genetic algorithm (GA) and the long short-term memory (LSTM) network. In the proposed GA-LSTM method, GA is used to select features that have the health indicators that best describe the supercapacitor's health condition thereby eliminating the manual feature selection

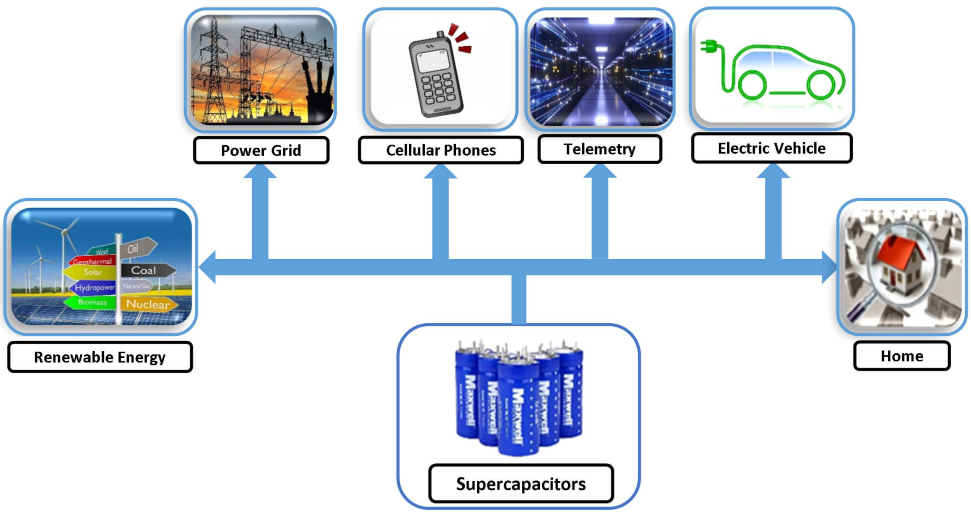


Fig. 2. Application areas of supercapacitors.

approach. Furthermore, the subset of best-selected features by the GA is then used as the input to the LSTM model which is used to predict the final RUL. The main advantages of the proposed method are summarized as follows: 1. By utilizing a deep learning model, this study automates the feature learning process from the large amounts of charge data whereby all measured charge data serve as input to the prediction process. The model by itself learns all features and determines which subset of features best describes the supercapacitor's health condition. This scheme of processes avoids the manual feature extraction which has the risk of dropping useful information in the charge data as it depends heavily on human labor as already being practiced by previous studies.

2. The proposed deep learning method with the aid of its LSTM can learn highly representative features that carry the most useful information of the charge data by tracking and remembering the more important historical degradation information. To the best of our knowledge, this study is one of the first to investigate the use of an end-to-end deep learning method to infer supercapacitor RUL from charge data.

## Ⅱ. Related Works

Various model-based methods have been previously used in predicting RUL. [9] proposed a particle-filter-based RUL estimation model for supercapacitors considering the aging conditions such as temperature and voltage in the developed degradation law and prediction according to capacitance and resistance thresholds both shown to achieve a higher precision. [10] based on the classical Arrhenius model, proposed a life cycle prediction model based on capacity degradation for supercapacitors. To predict RUL, [11] proposed the use of an F-distribution particle filter (FPF) and kernel smoothing (KS) algorithm. Based on the advantages of FPF and KS, the RUL prediction performance of the proposed algorithm was good. The Brownian motion degradation model and particle filter were used by [12] to achieve online short-term State of Health (SOH) estimation and long-term RUL prediction. [13] proposed an RUL prediction method utilizing Kalman filter and an improved particle filter (combination of Kalman filter and particle swarm optimization); which was used to slow down the particle degradation due to particle resampling. However, it is important to note that due to the complex nature of supercapacitors, it is difficult to model all failure modes and implement them using the model-based method.

Meanwhile, the data-driven methods majorly learn from huge amounts of supercapacitor charge data and have developed rapidly in recent years. Data-driven methods can be further categorized into statistical models e.g., Box-cox transformation[14], and machine learning models e.g., Support vector machine (SVM),etc[15-20]. [15] applied SVM to embed diagnosis and prognostics of system health to estimate the SOH and RUL of lithium-ion batteries. [16] used a grey support vector machine (GSVM) to predict Li-ion battery RUL. [17] utilized a fully connected neural network to predict the life cycle of battery-supercapacitor hybrid electric vehicles achieving the supercapacitor RUL prediction using a short charge-discharge curve. [18] established a recurrent neural network (RNN) based method to predict RUL obtaining good results but RNN has the disadvantage of long-term dependent learning. If information is stored for a long time, the gradient will disappear and it cannot continue learning[19]. [20] used the long short-term memory (LSTM) network, a variant of RNN, to predict the life of supercapacitors by exploiting it to learn the long-term dependency of the degraded capacity of supercapacitors. This singular unique feature of the LSTM makes it a sought-after model by several researchers for predicting RUL seeing that most supercapacitor RUL estimation approaches tend to learn the supercapacitor's degraded capacity. Although this model tends to yield satisfactory results, the approach and accuracy can still be further improved because even though LSTM is used, features are extracted manually.

## Ⅲ. Methodology

In this section, the proposed GA-LSTM model is discussed in detail with highlights on automatic feature extraction with GA and RUL prediction with LSTM.

### 3.1 Automatic feature extraction

Deep learning has broken new grounds that have led to profound successes in a wide range of applications. An example is facial recognition in computer vision. The results produced by deep learning methods in these applications are in some cases comparable or even superior to human experts.

Fig. 3 shows an overall system representation and the main difference between (a) the manual(as used in other existing studies) and (b) the proposed deep learning approaches in handling RUL prediction of supercapacitors. In the manual approach, characteristic features that are indicative of the supercapacitor's health condition (e.g., initial charge voltage, final charge current, charge capacity, the sample entropy, and statistics) are manually identified and extracted from the voltage and current curves and then fed as input to a machine learning model. On the contrary, in the proposed deep learning approach as shown in Fig 3(b), the complete set of raw data obtained during the supercapacitor charge process i.e., voltage, current, time, and energy (as used in this study), is employed as the input to the deep learning model without the extraction and selection of characteristic features. The model by itself learns all features and determines which subset of features best describes the supercapacitor's health condition. This is to ensure that all important information in the supercapacitor data is considered during the extraction. This scheme automates the feature extraction process thereby avoiding the manual process and its limitations. It is also worth mentioning that this is another point where this study is different from previous studies. While previous studies do not use all sets of raw data as they tend to use a subset of raw data based on some already established principles on factors affecting supercapacitor cycle life (e.g., voltage, current), our study uses all sets of raw data allowing the model to make that choice of selecting a subset of the best RUL descriptors based on the given data and use the best-selected features for the final RUL prediction thereby reaffirm the existing already established principles.

GA is an adaptive heuristic search algorithm based on the ideas of natural selection and genetic evolution, widely used to find the approximate optimal solution of optimization problems with large search space, and can be effectively used in the

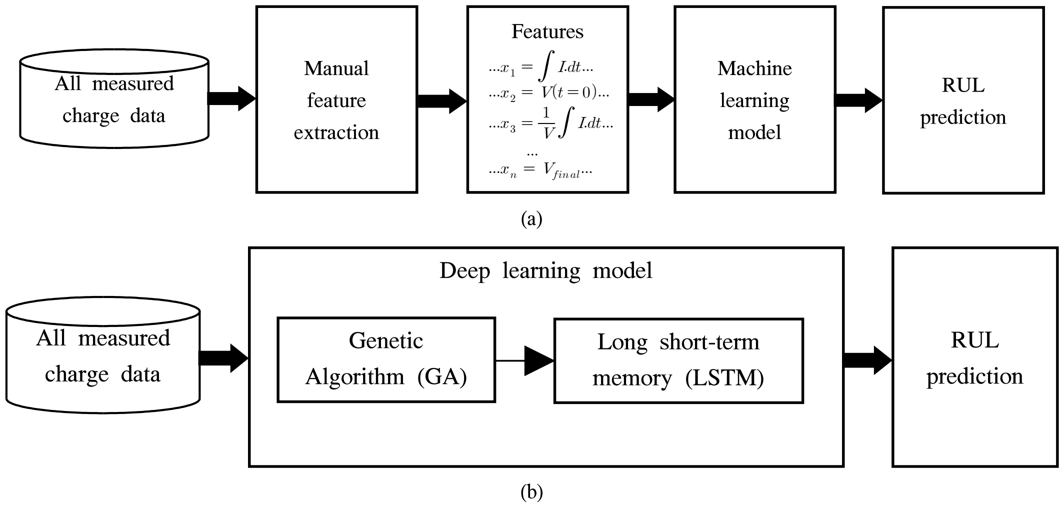


Fig. 3. (a) Manual feature selection approach, (b) Proposed deep learning approach.

selection of optimization features[21]. GA encodes a potential solution of a problem into an individual, and each individual is an entity with characteristics of a collection of multiple genes called chromosomes - the main carrier of genetic material[22]. Thus, the encoding work which is the mapping from the phenotype to genotype needs to be implemented at the beginning. The complexity involved in copying genetic code is usually simplified in the form of binary strings, therefore chromosomes that are closer to the optimal solution will have a better chance of reproducing[23].

The process flow chart of GA shown in Fig. 3(b) is further broken down in Fig. 4. The process is divided into initialization, fitness assessment, termination condition checking, selection, crossover, and mutation stages. $\{\alpha^1, \alpha^2, ..., \alpha^n\}$ represents the original features set. First, it designs a binary encoding for each chromosome $\beta$ that represents a potential solution to the problem. In the initialization stage, the population size is set for the population and a random original population $\{\beta^1, \beta^2, ..., \beta^n\}$ is generated. Then the fitness of each chromosome is evaluated based on the pre-set fitness function. The fitness function is an assessment index used to evaluate chromosome performance. The definition of the fitness function is a key factor affecting performance[24]. The process of calculating the fitness function will be used to retain the excellent solution for further reproduction. High-performing chromosomes are more likely to be selected multiple times, while low-performing ones are more likely to be eliminated. After several rounds of selection, crossover, and mutation operation; the optimal chromosome $\hat{\beta}$ is obtained. Crossing and mutation increase the genetic diversity of the population to exchange the corresponding part of the chromosome chain and change the gene combination to produce new offspring. There are many advantages of GA over traditional optimization algorithms. Two most notable are: the ability to deal with complex problems and parallelism. GA can deal with various types of optimization, whether the fitness function is stationary or non-stationary, linear or nonlinear, continuous or discontinuous, or with random noise. This feature makes it ideal to parallelize the algorithms for implementation such that different parameters and even different groups of encoded strings can be manipulated at the same time[25]. In this paper, $r^2$ determination coefficient was adopted as the fitness function of the GA shown in the overall system diagram - Fig. 3(b). The determination coefficient indicates how much percentage of the fluctuation of Y can be described by the fluctuation of X, ie., the interpretation degree of the characteristic variable X to the target value of Y. The determination coefficient can be described as follows:

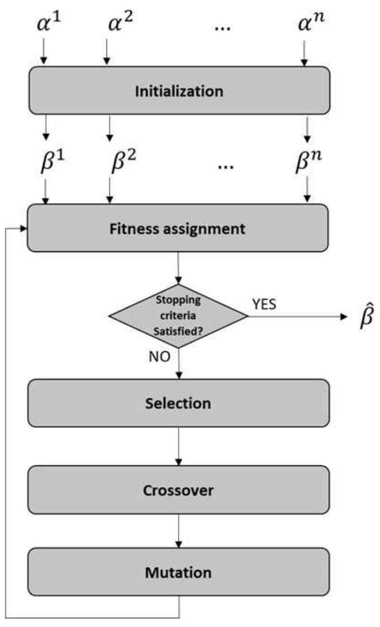


Fig. 4. Flow chart of GA.

$$r^2 = 1 - \frac{\Sigma(y-\hat{y})^2}{\Sigma(y-\overline{y})^2} \tag{1}$$

where $r^2$ represents the determination coefficient, $y$ is the label value, $\hat{y}$ is the predicted value, $\overline{y}$ is the average value, and the value range of $r^2$ is $[0, 1]$. The larger $r^2$ is, the stronger the ability of X to explain Y of this chromosome is, and the more likely is to be passed on to the next generation.

### 3.2 RUL estimation

LSTM is a special deep RNN designed to learn long-term dependencies. It remembers information for long periods, can discard redundant information and select key information to be stored in the internal state. Through this design, the LSTM model can selectively remember more important historical information. Thus by utilizing LSTM in the RUL prediction, the proposed model can learn highly representative features that carry the most useful information of the charge data by tracking and remembering the more important historical degradation information[26].

The proposed method as shown in Fig. 3(b) involves three major steps summarized as follows:

#### 3.2.1 Supercapacitor data discretization

All measured large volumes of charge data (in this case, voltage, current, time, energy, and capacity) obtained during a supercapacitor partial charge cycle are discretized into n segments (corresponding to n equal time intervals), respectively. The discretized values of the voltage, current, charge time and energy are denoted as the inputs to the deep learning method. As such, the input to the model is a matrix, M, associated with the discretized values of voltage, current, time and energy as defined below:

$$M = \begin{bmatrix} \hat{V}_1 & \hat{I}_1 & \widehat{CT}_1 & \hat{E}_1 \\ \vdots & \vdots & \vdots & \vdots \\ \hat{V}_n & \hat{I}_n & \widehat{CT}_n & \hat{E}_n \end{bmatrix} \tag{2}$$

where $\hat{V}, \hat{I}, \widehat{CT}$, and $\hat{E}$ denote the voltage, current, charge time and energy respectively. Meanwhile their corresponding capacity serves as the true output of the GA-LSTM model.

#### 3.2.2 Feature selection

GA-LSTM is used to select the best features and learn the relationship between the capacity of the supercapacitor and its charge-related variables.

#### 3.2.3 Optimization

The end-to-end deep learning approach is optimized by the optimization effect of GA. Fig. 5 shows the proposed model system flow. Firstly, the raw data is pre-processed to remove out-liners before being fed as input to the GA for the selection of the best features. These selected features form the RUL descriptors that serve as input to the LSTM network because they carry the health indicators for the final RUL prediction. Algorithm 1 gives an overview of the GA-LSTM model algorithm. GA has two parameters: M, and $p_\mu$. M is population size, and $p_\mu$ is the probability of mutation. CHD denotes the offspring chromosomes and has dimensions equal to that of the population (POP). In this paper, M = 200, $p_\mu$= 0.05. In the training process, the LSTM layer had 50 hidden units with a 20% dropout, while the training options had maximum epochs of 250, and Adam optimizer was utilized. To evaluate the proposed model's performance, we used the root mean square error (RMSE) and the mean absolute percentage error (MAPE). The RMSE is obtained as:

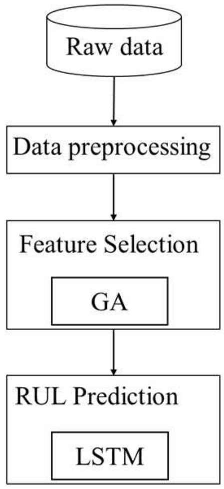


Fig. 5. Overall system flow of proposed model.

$$\mathrm{R_{MSE}} = \sqrt{\frac{1}{\mathrm{K}}\sum_{\mathrm{k}=1}^{\mathrm{k}}(\mathrm{l}(\mathrm{k}) - \hat{\mathrm{l}}(\mathrm{k}))^2} \tag{3}$$

where $l(k)$ represents the actual capacity, $\hat{l}(k)$ is the estimated capacity and $K$ is the total number of cycles, and $k$ represents a specific cycle number.

**Algorithm 1.** Overview of the GA-LSTM Algorithm

Set parameters $M, p_{\mu}$ ;
Initialize the population POP with $M$ random solutions, and sets CHD, $F^P$, $F^C$ to { } (where $F^P$ and $F^C$ store the fitness values of chromosomes in the POP and CHD sets);
**while** *Stopping criterion not reached* **do**
  **for** $i$ in 1 to $M$ **do**
    Evaluate fitness of $POP_i$ and store it in $F_i^P$
  $\eta = \{\ \}, POP' = \{\ \}, ; i = 1$ ;
  **while** $i \leq M$ **do**
    Apply the tournament selection method to select two chromosomes ($POP_x$ and $POP_y$) from POP, s.t. $x, y \notin \eta$ are non-zero positive integers;
    Apply the single-point crossover operator on $POP_x, POP_y$ to create two off-spring $CHD_i$ and $CHD_{i+1}$;
    Apply mutation operation with probability $p_{\mu}$ on $CHD_i$ and $CHD_{i+1}$;
    Insert $x$ and $y$ into $\eta$;
    $i = i + 2$;
  **for** $i$ in 1 to $M$ **do**
    Evaluate Fitness of $CHD_i$ and store it in $F_i^C$
  Select M chromosomes from POP∪CHD, and store them in POP
**return** POP;
**Input**: POP;
**Output**: Prediction of capacity degradation or RUL;
Split the dataset (POP) into train and test data;
Normalize the data as [0,1] and balance data;
Generate sequence as 3-D array (d, s, f);
∗d = training samples
∗s = sequence length
∗f = number of features
Select a learning rate for training;
Build LSTM network using [2, a, b, 1] dimensions; 2 input layers, a neurons in first layer, b neurons in second layer, 1 output layer
Train the LSTM network;
**for** each $i$ in range(epochs) **do**
    *model.fit(train_inputs, train_outputs);*
**end**
Predict capacity degradation or RUL;
∗RUL - *model.predict(train_inputs)*
Validate trained model on test data;
Evaluate prediction performance

Similarly, the MAPE is obtained as:

$$\text{MAPE}(\%) = \frac{100}{K}\sum_{k=1}^{k}\frac{|l(k) - \hat{l}(k)|}{l(k)} \tag{4}$$

The RMSE represents the average of the errors and therefore reflects the stability of the model. MAPE not only considers the error between the predicted value and the actual value but also considers the proportional relationship between them. Hence, the smaller the above error values, the better the prediction.

## Ⅳ. Results and Discussion

The entire supercapacitor dataset consists of 1500 cycles. After feature selection was concluded, GA selected current and voltage features as the best features that best describe the capacity degradation of the supercapacitor with an accuracy of 81.72%. This further confirms the analysis of aging characteristics of supercapacitors as carried out by previous studies which stipulate that the supercapcitor's RUL is affected by current, voltage and, temperature[6,20,27]. It is important to note at this point that our dataset didn't contain temperature data. Each of the selected features was first fed singly and then combined and fed to the LSTM network for training and final RUL prediction. Also, these selected features were each split into training set and test set three different times by increasing the number of training set from 30% to 60% to 90% respectively. The trained model is used for the RUL prediction of supercapacitors in Fig. 6, and Fig. 7 shows the prediction error. The RUL prediction results are displayed in Table 1. The results in Table 1 show that predicting RUL with any of the best-selected features (voltage or current) singly didn't show much variance with that of the combined best features (voltage and current). At 90% training data, the RUL prediction RMSE and MAPE values were (0.04, 0.0287), (0.03, 0.0263), and (0.04, 0.0298) for the voltage feature, current feature, and the combined best features (voltage and current) respectively. Furthermore, in Table 1 increasing the training dataset from 30% to 60% to 90% saw the RMSE yield the results (0.06 to 0.05 to 0.04), (0.05 to 0.04 to 0.03), and (0.06 to 0.05 to 0.04) for the voltage feature, current feature and the combined best features (V + I) respectively. Also, a

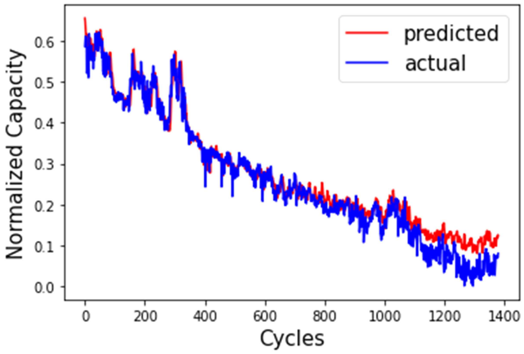


Fig. 6. Supercapacitor RUL prediction result.

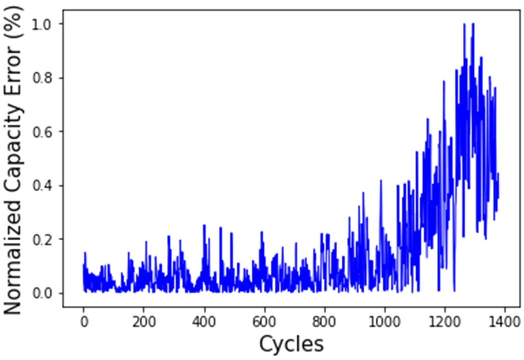


Fig. 7. RUL prediction errors.

similar decreasing trend was observed for the MAPE values of these features as the number of training data increased. This shows that increasing the training dataset didn't have much corresponding significant increase in the prediction accuracy. This is because LSTM is dynamic and able to learn highly representative features even with a little amount of training data.

To compare the accuracy of the proposed model (GA-LSTM), the supercapacitor dataset was trained with the RNN model and LSTM model. The prediction results of these models together with the prediction result of a related deep learning approach - deep convolutional neural network (DCNN) used in [28] though trained with a different dataset are presented in Table 2. The overall RMSE of the RNN, LSTM, and DCNN models stood at 23.87, 0.51, and 0.38 respectively. It can be observed that the accuracy of the LSTM model was improved by the proposed model (GA-LSTM) from 0.51 to 0.03

Table 1. Table showing prediction results of model's different training scenarios.

| Model | No. of training data (%) | RMSE | MAPE |
|---|---|---|---|
| GA-LSTM (V) | 30 | 0.06 | 0.0556 |
| | 60 | 0.05 | 0.0417 |
| | **90** | **0.04** | **0.0287** |
| GA-LSTM (I) | 30 | 0.05 | 0.0523 |
| | 60 | 0.04 | 0.0399 |
| | **90** | **0.03** | **0.0263** |
| GA-LSTM (V+I) | 30 | 0.06 | 0.0596 |
| | 60 | 0.05 | 0.0472 |
| | **90** | **0.04** | **0.0298** |

Table 2. Comparison with state-of-the-art models.

| Model | RMSE |
|---|---|
| RNN[18] | 23.87 |
| LSTM[20] | 0.51 |
| DCNN[28] | 0.38 |
| GA-LSTM | **0.03** |

which is a result of the automated feature selection effect of the GA. In all, the proposed GA-LSTM model outperforms the others as its prediction error did not exceed 1% as shown in Fig. 7.

## V. Conclusion

This paper proposes an end-to-end deep learning approach for predicting the RUL of supercapacitors using GA-LSTM. The proposed method involved automatic feature extraction of the best RUL descriptors by the GA and subsequent RUL prediction by the LSTM. The GA achieved an accuracy of 81.72% while the overall RMSE of the model was 0.03. As a result, the proposed model provides a precise estimation of supercapacitor RUL with a negligible deviation of 1%. Moreover, the proposed model was compared with other state-of-the-art models, which verifies the validity and applicability of the proposed method.

## References

[1] K. Choi, et al., "Implementation of battery

management circuit to improve flight time for unmanned aerial vehicles," *J. KICS*, vol. 44, no. 4, pp. 285-288, Feb. 2020.

[2] K. Choi, et al., "Implementation of RF energy harvesting circuit for wireless charging of iot sensor nodes," *J. KICS*, vol. 44, no. 4, pp. 755-758, Apr. 2019.

[3] P. Zoltowski, "On the electrical capacitance of interfaces exhibiting constant phase element behaviour," *J. Electroanal. Chem.*, vol. 443, no. 1, pp. 149-154, Feb. 1998.

[4] B. L. Guo, et al., "Effect of extraction temperature on hyper-coal structure and electrochemistry of coal-based activated carbon," *Chin, J. Inorg. Chem.*, vol. 34, pp. 1515-1624, 2018.

[5] Y. F. Zeng, et al., "One-step preparation and electrochemical performance 3D reduced graphene oxide/NiO as supercapacitor electrodes material," *J. Inorg. Mater.*, vol. 33, pp. 1070-1076, 2018.

[6] K. Wang, et al., "State of charge estimation of composite energy storage systems with supercapacitors and lithium batteries," *Complexity*, pp. 1-15, 2021.

[7] B. Chinomona, et al., "Long short-term memory approach to estimate battery remaining useful life using partial data," *IEEE Access*, vol. 8, pp. 165419-165431, 2020.

[8] Y. Bengio, et al., "Representation learning: A review and new perspectives," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 35, no. 8, pp. 1798-1828, 2013.

[9] A. El Mejdoubi, et al., "Remaining useful life prognosis of supercapacitors under temperature and voltage aging conditions," *IEEE Trans. Ind. Electron.*, vol. 65, no. 5, pp. 4357-4367, 2018.

[10] X. Xu, et al., "Research on capacity life prediction model of supercapacitors," *Chin. J. Power Sources*, vol. 42, no. 2, pp. 270-82, 2019.

[11] K. Zhang, et al., "Remaining useful life prediction of aircraft lithium-ion batteries based on F-distribution particle filter and kernel smoothing algorithm," *Chin,. J. Aeronaut.*, vol. 33, no. 5, pp. 1517-1531, May 2020.

[12] G. Z. Dong, et al., "Battery health prognosis using Brownian motion modelling and particle filtering," *IEEE Trans. Ind. Electron.*, vol. 65, pp. 8646-8655, 2018.

[13] B. Mo, et al., "A remaining useful life prediction approach for lithium-ion batteries using Kalman filter and an improved particle filter," in *Proc. IEEE Int. Conf. Progn. Hea. Manage.*, pp. 1-5, Jun. 2016.

[14] Q. Xue, et al., "Remaining useful life prediction for lithium-ion batteries based on capacity estimation and box-cox transformation," *IEEE Trans. Veh. Technol.*, vol. 69 no. 12, pp. 14765-14779, 2020.

[15] A. Nuhic, et al., "Health diagnosis and remaining life prognostics of lithium-ion batteries using data-driven methods," *J. Pow. Sou.*, vol. 239, pp. 680-688, Oct. 2013.

[16] X. Li, et al., "Lithium-ion battery remaining useful life prediction based on grey support vector machines," *Int. J. Adv. Mech. Eng.*, vol. 7, no. 12, pp. 1-8, Dec. 2015.

[17] T. Weigert, et al., "Cycle life prediction of battery-supercapacitor hybrids using artificial neural network," *Batt. for Renew. Ener. Stor.*, vol. 28, no. 22, pp. 35-42, 2010.

[18] L. Guo, et al., "A recurrent neural network based health indicator for remaining useful life prediction of bearings," *Neurocomp.*, vol. 240, pp. 98-109, 2017.

[19] H. Chaoui, et al., "State of charge and state of health estimation for lithium batteries using recurrent neural networks," *IEEE Trans. Veh. Technol.*, vol. 66, pp. 8773-8783, 2017.

[20] Y. Zhou, et al., "Remaining useful life prediction for supercapacitor based on long short-term memory neural network," *J. Pow. Sources*, vol. 440, pp. 227149, 2019.

[21] Y. C. Li, et al., "Review of genetic algorithm," *Adv. Mater. Res.*, vol. 179, no. 180, pp. 365-367, Aug. 2011.

[22] S. Chen and C. Zhou, "Stock prediction based

on genetic algorithm feature selection and long short-term memory neural network," *IEEE Access*, vol. 9, pp. 9066-9072, 2021.
[23] G. Armano, et al., "A hybrid genetic-neural architecture for stock indexes forecasting," *Inf. Sci.*, vol. 170, no. 1, pp. 3-33, Feb. 2005.
[24] K. Deb, "Multi-objective genetic algorithms: Problem difficulties and construction of test problems," *Evol. Comp.*, vol. 7, no. 3, pp. 205-230, Sep. 1999.
[25] X.-S. Yang, "*Nature-inspired optimization algorithms*," Academic Press, 2021.
[26] T. A. Shifat, et al., "Remaining useful life estimation of bldc motor considering voltage degradation and attention-based neural network," *IEEE Access*, vol. 8, pp. 168414-168428, 2020.
[27] C. Liu, et al., "State-of-charge estimation and remaining useful life prediction of supercapacitors," *Renew. and Sus. Ener. Rev.*, vol. 150, pp. 111408, 2021.
[28] S. Shen, et al., "A deep learning method for online capacity estimation of lithium-ion batteries," *J. Ener. Stor.*, vol. 25, p. 100817, Oct. 2019.

**치 고 지** (Chigozie Uzochukwu Udeogu)
2021년 3월~현재 : 금오공대, 항공기계융합전공
<관심분야> 임베디드 시스템, 지능형 제어
[ORCID: 0000-0002-3199-9107]

**안 젤 라** (Angela C. Caliwag)
2019년 10월~현재 : 금오공대, 항공기계융합전공
<관심분야> 임베디드 시스템, 지능형 제어
[ORCID: 0000-0002-0279-935X]

**임 완 수** (Wansu Lim)
2014년 9월~현재 : 금오공대 전자공학부 부교수
<관심분야> 임베디드 시스템, 지능형 제어
[ORCID: 0000-0003-2533-3496]