Advanced Mechanical and Mechatronic Systems

Research Article
Volume 1(1), 2025, 11–28
https://doi.org/10.53623/amms.v1i1.676

A Classification and Prediction Method of Electric Battery Condition during Discharging Process Utilizing Adaptive Neuro-Fuzzy Inference System and Support Vector Machine

Mukhidin[1], Yogi Reza Ramadhan[2], Januar Panca Adi[2], João Bosco Belo[3], Nur Arifin Akbar[4]*

[1]Faculty of Integrated Technologies, Universiti Brunei Darussalam, Brunei Darussalam
[2]CV. Rekayasa Desain Manufaktur (REDESMA), Jalan Bulusan VI No 37, Tembalang, Semarang 50277, Indonesia
[3]Mechanical Engineering Department, Dili Institute of Technology, Rua de Aimeti Laran, Aimutin Dili, Timor Leste
[4]Department of Mathematic and Computational Sciences, University of Messina, Italy

*Correspondence: nur.akbar@studenti.unime.it

SUBMITTED: 3 May 2025; REVISED: 10 June 2025; ACCEPTED: 12 June 2025

ABSTRACT: This paper presents a data-driven prediction method for electric battery condition monitoring with different loads. The prediction is subject to the usage time of the electric battery during the discharge condition. Two variables are selected as the prediction input i.e. load (Watt) and discharge voltage (Volt) to predict how much time (hour) has left during the discharge period. Adaptive Neuro-Fuzzy Inference System (ANFIS) serves dual purposes of classification and prediction of battery discharge conditions, while Support Vector Machine (SVM) is implemented for classification comparison. While SVM demonstrates superior classification performance with 95% accuracy compared to ANFIS's 88%, ANFIS provides the added value of precise time prediction. The time-series data was collected from the discharge battery experiment for a few hours that uses the electric rechargeable battery from a fully charged capacity to an empty capacity. The experiments were conducted on four different load conditions i.e. 130, 180, 200, and 220 Watts. The prediction result of ANFIS was compared with the result of the Support Vector Machine (SVM). The ANFIS was used to predict how many hours the battery has been used based on two inputs i.e. load (Watt), and discharge volt (Volt). Five different prediction targets i.e. 1, 2, 3, 4, and 5 hours are selected for the ANFIS prediction. This prediction target is according to the deterioration of the discharge voltage during the measurement. The rate of voltage drop varies under different load conditions, with specific discharge profiles observed for each tested load. The result shows that ANFIS can predict the target hour based on the present load and voltage data input during the discharge operation. From the hour prediction, it can estimate the remaining useful life of the battery because the total duration of the battery is known initially. SVM is used as a comparison classifier to the ANFIS. Although SVM demonstrates superior classification accuracy (95% versus ANFIS's 88%), ANFIS's ability to predict time with two-digit precision enables more accurate remaining useful life estimation in EV applications, where even minutes of battery life can be critical for route planning and operational decisions.

KEYWORDS: ANFIS; battery prediction; classification; discharging process, prognostics, SVM.

1. Introduction

Internal combustion engine vehicles (ICEVs) have contributed to human and social life for more than one century. In the automotive industry, most passenger vehicles are driven by an internal combustion engine (ICE). These types of vehicles use fossil fuel such as petrol or diesel as a main source of energy to power up the engine. As the fossil fuel production capacity is decreasing gradually every year, dependence on fossil fuels has become one of the popular discussion and research topics in the recent technology era. Similar to other countries, Brunei is not immune to this dependence. Brunei is one of the fossil fuel providers on one side and another side is very dependent on the ICEV because passenger cars are prevalent in Brunei due to the lack of public transportation.

According to Nature magazine [1], the US automobile biggest company i.e. General Motors announces it to stop selling petrol-powered and diesel models by 2035. In another country, one of the biggest companies in Germany i.e. Audi plans to stop manufacturing the ICEVs by 2033. Many other automotive industries have also announced similar plans. This indicates that the era of Electric Vehicles (EVs) is approaching us shortly. Brunei is also aware of this transition as informed in the Mid-Year Conference and Exhibition (MYCE) 2022 that Brunei continually focuses on the development of the EV and will increase the annual EV sales by 60% by 2035.

The EV was first invented by a French electrical engineer named Gustave Trouvé during the 18th century and had three wheels [2]. Over the decades, technology in EVs has been developing progressively. Anticipating a world dominated by electric vehicles, engineers and scientists are facing a few challenges [3]. One of the challenges is related to the energy storage system i.e. battery.

A prediction of battery life is very important because it can be used to avoid battery draining suddenly and causing interference. Factors that can affect battery capacity are the rate of discharge and ambient temperature [4]. Batteries, such as lithium-ion and lead-acid cells, experience degradation over time during usage. This will lead to decreasing energy storage capacity and increasing internal resistance. Predicting their rate of degradation and remaining useful life (RUL) is necessary for battery performance and economic reasons and therefore motivates the Author of this article. For example, in an electric vehicle, the driveable range is directly related to the battery capacity. For energy storage asset valuation, depreciation, warranty, second life value, insurance, and preventative maintenance purposes, predicting RUL at a design stage and during operation is crucial, and the investment case is strongly dependent on the degradation profile [5].

A comprehensive review of the development of battery remaining useful lifetime (RUL) prognostic techniques is presented in [6]. In addition, the review paper introduced the degradation mechanisms and the battery lifetime prognostics technologies with a focus on recent advances in model-based, data-driven, and hybrid approaches [6]. As the number of charges and discharge cycles increases, the performance and life of the battery gradually deteriorate [7]. Another specific factor that can shorten the battery life is human negligence in charging the battery when needed. The battery life can stay longer when the user knows when the battery needs to be charged. In this case, information on the remaining voltage during the discharge condition is necessary. Ref. [8] presents a few things why batteries fail prematurely. One of the reasons is extreme discharge where it is recommended to do not to let the batteries drop to 0% charge. In addition to this issue, an article that presented a state of charge and state of health diagnosis of batteries to control when the battery needs to be charged is available [9]. An example suggestion has been described in [10] to retain the State of Charge (SoC) level at a middle level (about 50%) to maintain the battery life from premature depreciation.

This preliminary study is motivated by the aforementioned issue which focused on battery discharge monitoring and prediction. This study presents a state classification and voltage remaining prediction during the discharge condition based on the ANFIS method. ANFIS was selected due to its proven effectiveness in battery prediction applications [11], its ability to handle nonlinear relationships between input parameters, and its efficient performance with limited input variables. The membership function mechanism in ANFIS is particularly suitable for small-size prediction parameters, enabling faster training and testing processes. Furthermore, ANFIS's ability to integrate the adaptive learning capabilities of neural networks with the qualitative reasoning approach of fuzzy logic makes it well-suited for capturing the complex discharge behavior of batteries across different load conditions.. This research extends our previous work on battery monitoring by incorporating multiple load conditions, implementing comparative analysis between ANFIS and SVM methods, and developing a more robust validation framework for battery discharge prediction. While our previous study focused solely on singular load conditions using ANFIS, this work examines discharge behavior across varied loads and introduces SVM as a comparative classification approach to provide a more comprehensive evaluation framework.

2. Materials and Methods

2.1. ANFIS prediction.

The ANFIS [12] is a specific kind of neuro-fuzzy classifier approach that integrates the artificial neural network (ANN) adaptive capability and the fuzzy logic qualitative approach. By utilizing the rule basis, fuzzy logic offers advantages in representing the qualitative features of human knowledge and retrieval process judgments. Without the requirement for modeling math, the ANN has advantages in spotting patterns, learning, and practicing how to solve a problem. The ANN can learn the data that has been entered into it in the past, as well as generate predictions about future events based on that data. ANFIS will not be able to do both until it possesses both skills [13]. The ANN has advantages in spotting patterns, learning, and solving problems efficiently.

In the ANFIS method, the fuzzy modeling procedure can be learned using neuro-adaptive learning techniques. The parameters linked with the membership functions change during the learning process. The computation of these parameters is aided by a gradient vector. This gradient vector represents how well the fuzzy inference system predicts input/output data for a given set of parameters. After acquiring the gradient vector, one of several optimization strategies can be used to change the parameters and reduce some error measurements. This error metric is frequently calculated using the sum of the square differences between actual and desired outputs. ANFIS uses a combination of least squares estimation and backpropagation to estimate membership function parameters.

The ANFIS architecture contains five layers [13]: a fuzzification layer, a rule layer, a normalization layer, a defuzzification layer, and a summation layer as presented in Figure 1. For the first-order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules is presented in Equation (1):

Rule 1 If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$;
Rule 2 If x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$; (1)

where p_1, p_2, q_1, q_2, r_1 and r_2 are linear parameters and A_1, A_2, B_1 and B_2 are nonlinear parameters. The output of the i^{th} node in layer 1 is denoted as $O_{1,i}$.

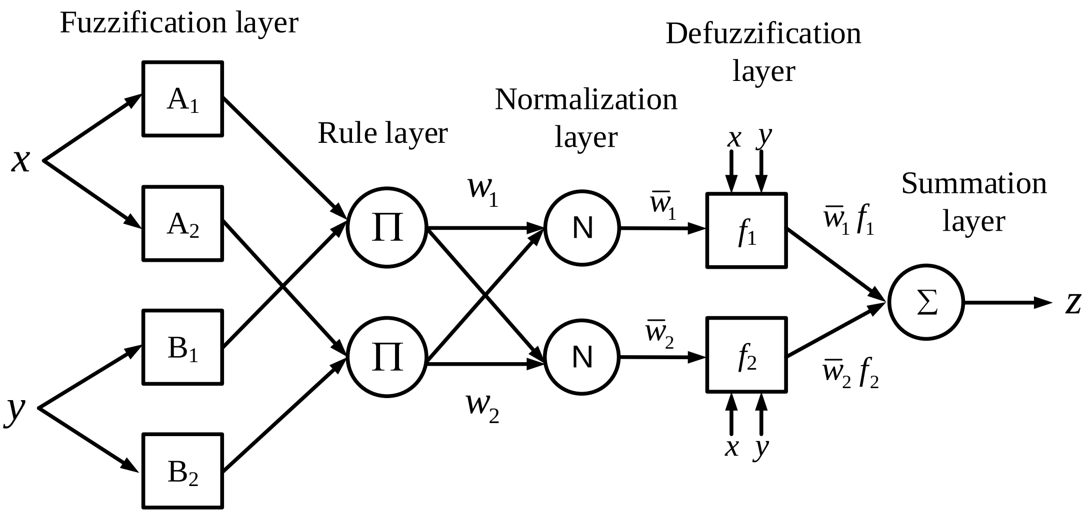


Figure 1. Two-input ANFIS architecture with first-order Sugeno fuzzy model.

Fuzzification layer: All the nodes in layer 1 are adaptive nodes. The outputs of this layer are the fuzzy membership grade of the inputs, which are given by:

$O_{1,i} = \mu_{A_i}(x)$ for $i = 1, 2$, or

$O_{1,i} = \mu_{B_{i-2}}(y)$ for $i = 3, 4$ (2)

where x (or y) is the input to nodes i and A_1 (or B_{i-2}) is a linguistic label associated with the node given by (1). The membership function for A (or B) can be any appropriate parameterized membership function such as a sigmoidal membership function:

$$\mu_{A_i}(x) = \frac{1}{1 + e^{-a_i(x-c_i)}} \quad (3)$$

where $\{a_i, c_i\}$ define the parameter set. Parameters in this layer are referred to as premise parameters. As the values of the parameters change, the shape of the membership function varies.

Rule layer: The nodes in layer 2 are fixed nodes labeled Π, indicating that they perform as a simple multiplier. Each node in this layer calculates the firing strengths of each rule by multiplying the incoming signals and sending the product out. The outputs of this layer can be represented as

$$O_{2,i} = w_i = \mu_{A_i}(x) \times \mu_{\beta_i}(y) \text{ for } i = 1,2 \quad (4)$$

Normalization layer The nodes in this layer are fixed nodes and labeled as N. The nodes indicate a normalization role to the firing strengths from the previous layer. The i^{th} node of this layer calculates the ratio of the i^{th} rule's firing strength to the sum of all rules' firing strengths:

$$O_{3,i} = \bar{w}_i = \frac{w_i}{\sum_i^2 w_i} = \frac{w_i}{w_1 + w_2} \text{ for } i = 1,2 \quad (5)$$

Defuzzification layer The nodes in this layer are adaptive. Parameters in this layer will be referred to as consequent parameters. The output of each node in this layer is simply the product of the normalized firing strength and a first-order polynomial. Thus, the outputs of this layer are given by:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \quad (6)$$

where w_i is a normalized firing strength from layer 3 and (p_i, q_i, r_i) is the parameter set for the node.

Summation layer A single node in this layer is labeled as Σ. This node performs the summation of all incoming signals. Hence, the overall output of the model is given by

$$O_{5,i} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (7)$$

In this paper, the ANFIS method is used to predict the voltage level for one hour interval during the battery discharge experiment. The hours interval during the battery experiment is categorized into five target labels, i.e. target label 1, 2, 3, 4, and 5 hours. The illustration of the ANFIS structure used in this paper to predict the voltage conditiion of every one hour is presented in Figure 2. To illustrate a real condition, the load is varied into four different load i.e. 130, 180, 200, and 220 Watt. Each load, five voltage data were collected at one hour interval. $V_{1,1}$, to $V_{1,5}$ in Figure 2 indicate the voltage of load 130 Watt at 1 to 5 hour; $V_{2,1}$, to $V_{2,5}$ indicate the voltage of load 180 Watt at 1 to 5 hour; up to $V_{4,1}$, to $V_{4,5}$ indicate the voltage of load 220 Watt at 1 to 5 hour. A prediction result is represented by *z* in Figure 2. A more detail of the ANFIS method applied for battery voltage prediction is presented in Section 4.

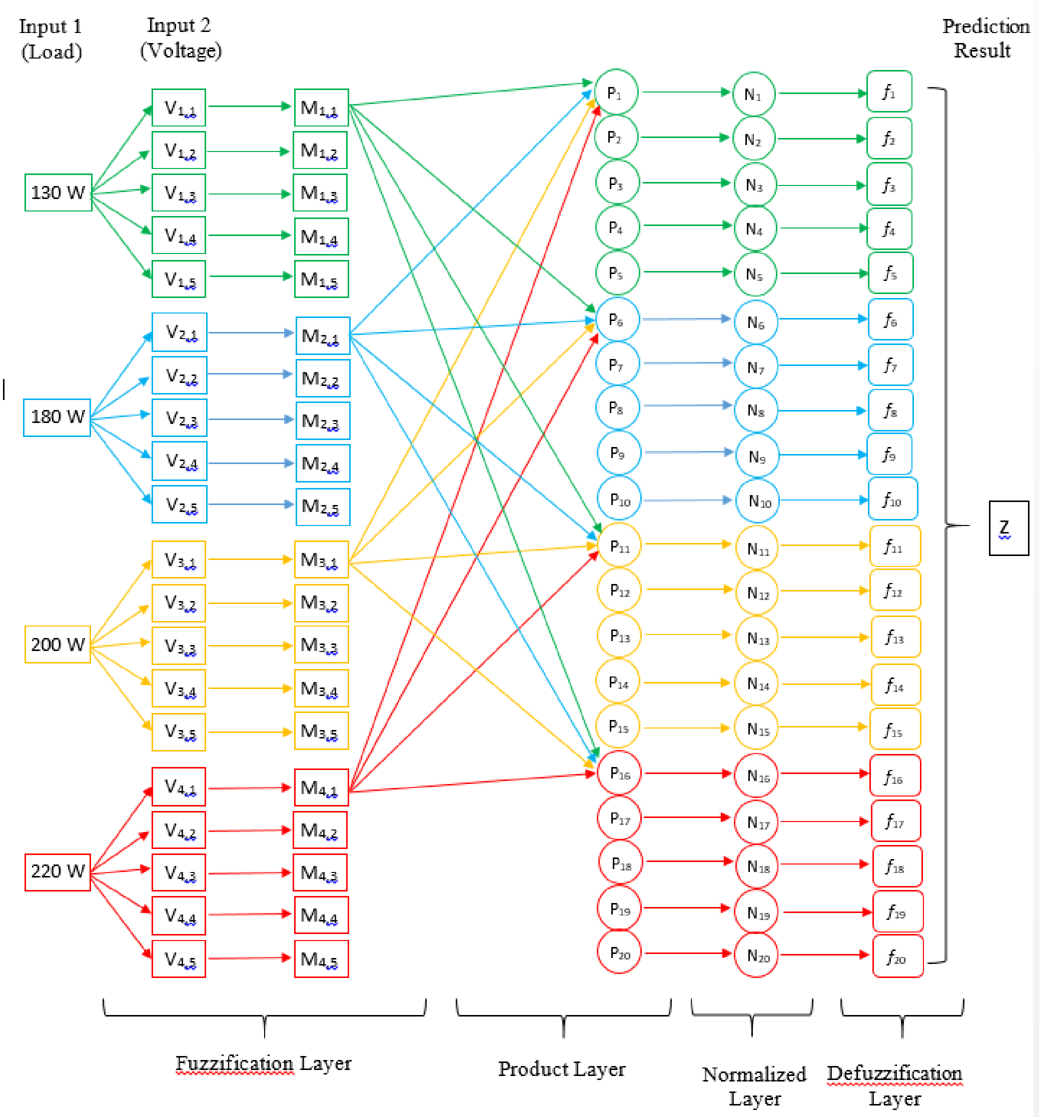


Figure 2. An illustration of ANFIS structure to predict the voltage condition.

2.2. SVM classification.

As one of the supervised learning techniques, a SVM requires training to construct the model for classification and prediction application [14]. This classification is simple be-cause it builds a hyperplane that separates and creates a boundary between one class to other classes (for example in multi-classification). This hyperplane is to differentiate the classes. The classification could be linear or non-linear. For the linear, the samples of the training class can be separated linearly. But in some cases, the sample cannot be classified linearly. For such cases, non-linear classification is exploited. A more detailed SVM method and fundamental theory are presented in [14, 15]. For this study, we implemented SVM with a radial basis function (RBF) kernel. The hyperparameters were optimized using grid search cross-validation with C values ranging from 0.1 to 100 and gamma values from 0.001 to 1.0. The optimal parameters selected were C=10 and gamma=0.1, which provided the best performance on our validation dataset. The multiclass SVM implementation used the one-against-one approach, which is particularly suitable for the five-classes problem in our battery hour classification task. The hyperplane for SVM five-classes classification is illustrated in Figure 3.

All batteries used in the experiments were verified to have >95% of their rated capacity through preliminary charge-discharge cycles. We controlled for manufacturing variations by selecting batteries from the same production batch and performing initial capacity tests to ensure comparable starting conditions. Prior to data collection, each battery underwent three complete charge-discharge cycles to stabilize their electrochemical characteristics and minimize the influence of battery history on the discharge behavior.

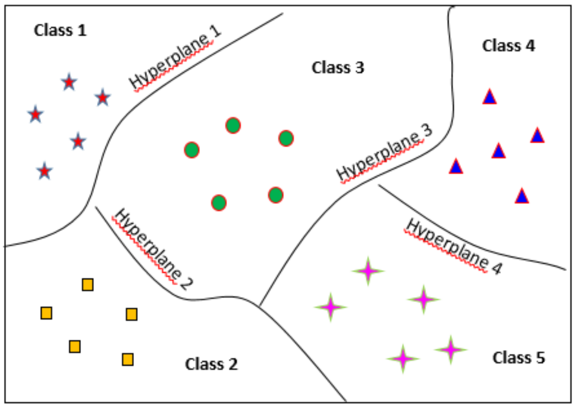
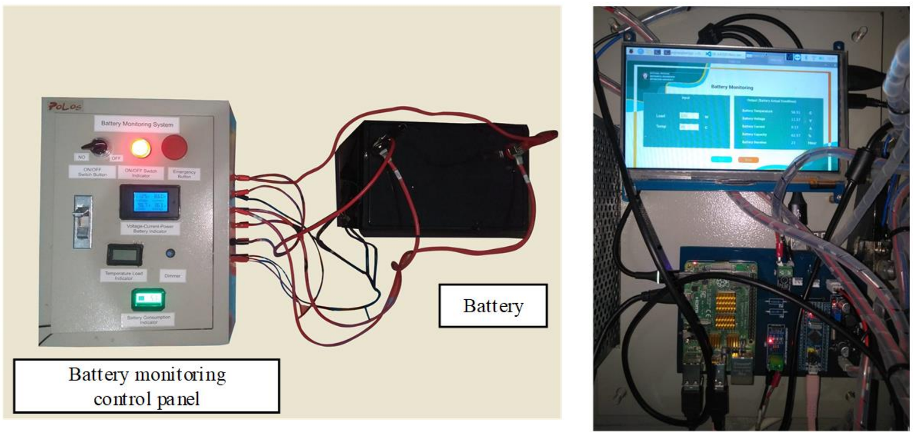


Figure 3. An illustration of hyperplane of the five-classes of SVM classification.

3. Experimental Setup and Data Acquisition

In this study, a battery monitoring device is manufactured on a Lab based scale as presented in Figure 4. The experimental device consists of the battery, load, voltage sensor, temperature sensor, current sensor, watt meter, voltage indicator, and current sensor. An overall experiment photo is presented in Figure 4(a). Inside the battery monitoring control panel picture is presented in Figure 4(b). A detailed of wiring diagram of the battery monitoring control panel is presented in Figure 5. There are three sensors used in the experiment i.e. temperature, current, and voltage sensor. These sensors are connected to the SMT32 microcontroller. The STM2 microcontroller is connected to Raspbery Pi4. For a display input parameter and the measurement output, a 7-inch monitor is connected to the Raspbery Pi4. For specification of the battery used in the discharge experiment is presented in Table 1.



(a) (b)

Figure 4. (a) Battery monitoring device connected to the battery; (b) inside picture of battery monitoring control panel.

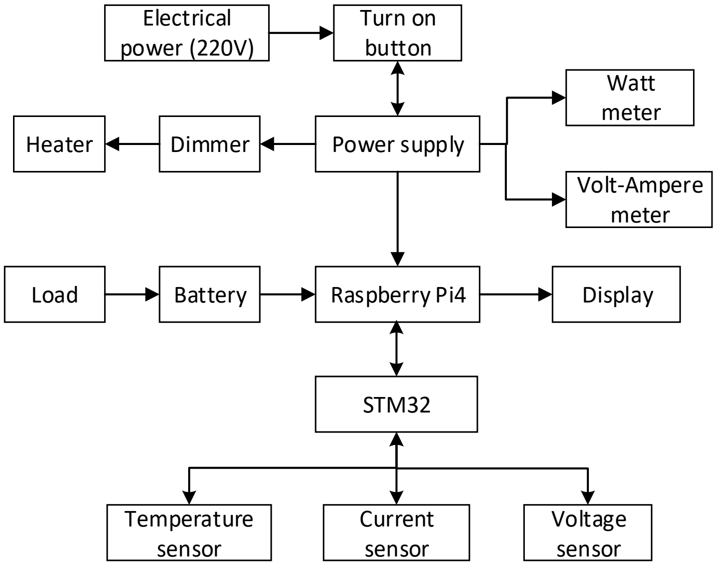


Figure 5. Wiring diagram of battery monitoring control panel.

Table 1. Battery specification used in the experiment.

Battery specification	Description
Brand	Luminous
Type	Lead acid
Voltage	12 Volt
Capacity	70 Ah
Dimension (L x W x H)	42 x 19 x 23 cm

Prior to the experiment, a battery was fully charged up to around 12 Volts. A fully charged battery was connected to a certain load (in Watt) and the battery monitoring data was collected during the discharge condition. When a load is applied, the voltage capacity of the battery will reduce gradually. In one experiment, it takes approximately 6-8 hours to obtain the discharge data from a fully charged battery to an empty capacity (in Volt). This experiment is repeated for different loads.

Figure 6 presents an example of a battery monitoring experiment for a load equal to 180 Watts. Once the battery is connected as presented in Figure 4, the battery monitoring device is turned on. Inside the battery monitoring device panel, there is a 7-inch monitor for the user interface and input parameter. This display monitoring is connected to the Raspberry Pi4. The user is expected to fill in the Load and Temperature input data before pressing the run button. Once the run button is pressed, the data acquisition is started. This device has been previously programmed to automatically acquire the data during the discharge process on a timely basis (every 30 seconds). The actual data every 30 seconds is shown in the output block in the user interface as presented in Figure 6. After a few hours, the experiment is completed and the data is saved in excel format as also presented in Figure 6.

There are 4 different loads were tested in the battery condition monitoring device, i.e. 130, 180, 200, and 220 Watts. The data is then processed in ANFIS prediction and SVM classification. Due to the limited battery available, this study only used 2 batteries during the experiment. One battery is for training and another battery is for testing. Two datasets were collected for training and one dataset was collected for testing. The battery is fully charged before the experiment and then connect to the determined load for discharging. The data is collected during the whole discharging process.

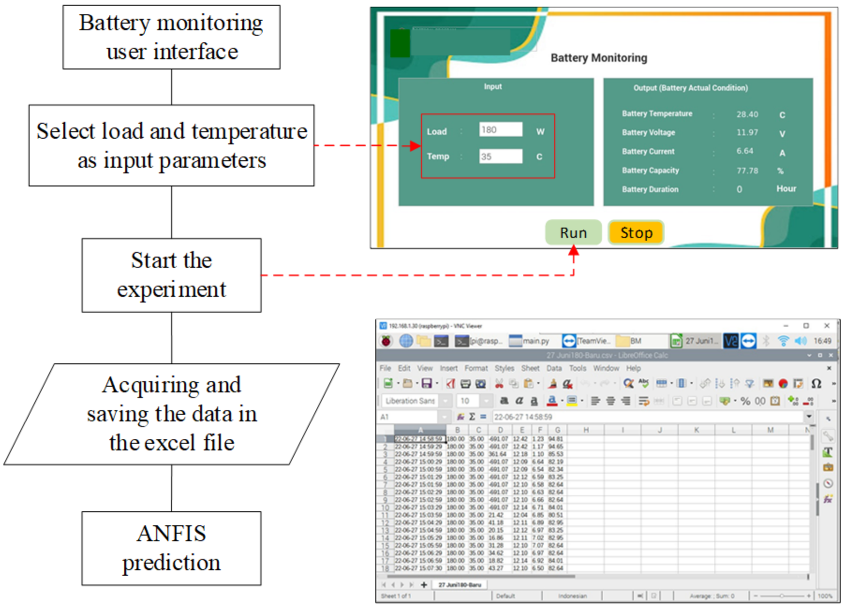


Figure 6. A brief experiment procedure of battery monitoring.

The purpose of the battery monitoring system is to run the battery from fully charged capacity to empty capacity at approximately less than 5 volts. In that case, each experiment takes about 6-8 hours depending on the load. A higher load will result to the less experimental hours. The discharge volt from four different loads i.e. 130, 180, 200, and 220 Watts was presented in Figure 7. It can be seen from Figure 7 that the increasing load result in the shorter duration of the battery. A sudden jump in the battery volt capacity during the discharge process starts at approximately at 10, 6, 5, and 4 hours for 130, 180, 200, and 220 Watts, respectively. This data will proceed further for ANFIS training.

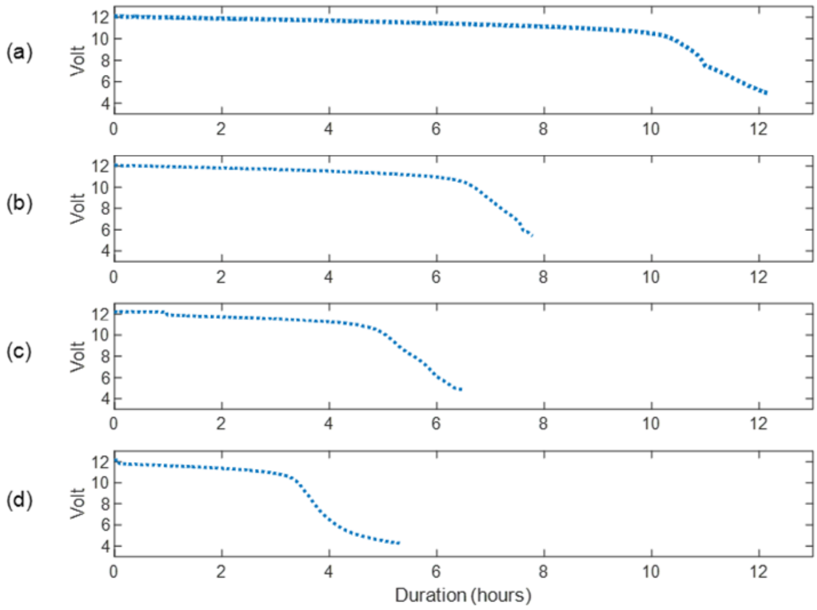


Figure 7. Discharge voltage data from four different loads: (a) 130 Watt; (b) 180 Watt; (c) 200 Watt; and (d) 220 Watt.

An example of data collection in an excel file that shows the duration of the experiment is presented in Figure 8. Please note that the middle part of the data was hidden to show the beginning and the ending of the discharge voltage. According to the time-series data collection as presented in Figure 8, the experiment is conducted on June 6th, 2022 at 14:58 or 2:58 pm (JKT time). The experiment stop at 23:06 or 11:06 pm (JKT time) and it has been operated for about 8 hours. Load and Temperature (Temp) are the input parameters. Battery temperature (T Bat), battery voltage (V Bat), battery current (I Bat), and battery capacity (C Bat) are the output measurement. The battery was initially fully charged at about 12 volts and it has been used for 8 hours for a load of 180 Watts until 5.41 volts.

	A	B	C	D	E	F	G
1	Date and Time	Load	Temp	T Bat	V Bat	I Bat	C Bat
2	22-06-27 14:58:59	180	35	31.28	12.42	1.23	94.81
3	22-06-27 14:59:29	180	35	34.62	12.42	1.17	94.65
4	22-06-27 14:59:59	180	35	38.63	12.18	1.1	85.53
5	22-06-27 15:00:29	180	35	38.63	12.09	6.64	82.19
6	22-06-27 15:00:59	180	35	35.72	12.09	6.54	82.34
972	22-06-27 23:04:53	180	35	31.04	5.52	2.04	0.99
973	22-06-27 23:05:23	180	35	32.71	5.5	2.08	0.99
974	22-06-27 23:05:53	180	35	32.01	5.47	1.95	0.99
975	22-06-27 23:06:23	180	35	37.59	5.44	2.03	0.99
976	22-06-27 23:06:53	180	35	38.42	5.41	1.93	0.99

Figure 8. An example of data collected for load is 180 Watt.

An illustration of data preparation for ANFIS training and testing is presented in Figure 9. These data samples were collected for every 1 hour of the discharge battery experiment from the fully charged battery to the empty capacity battery. To provide an illustration of how the samples for ANFIS training and testing were collected is presented in Figure 9. Figure 9 is a plot of discharge voltage condition from a full charge battery to a less voltage battery for a 200 Watts load. Although two samples were collected for every second as presented in Figure 8, the samples for ANFIS prediction are collected every hour. For every one hour, a battery voltage is extracted from the data collected as presented in detail in Figure 9. A total of five samples were obtained for one dataset.

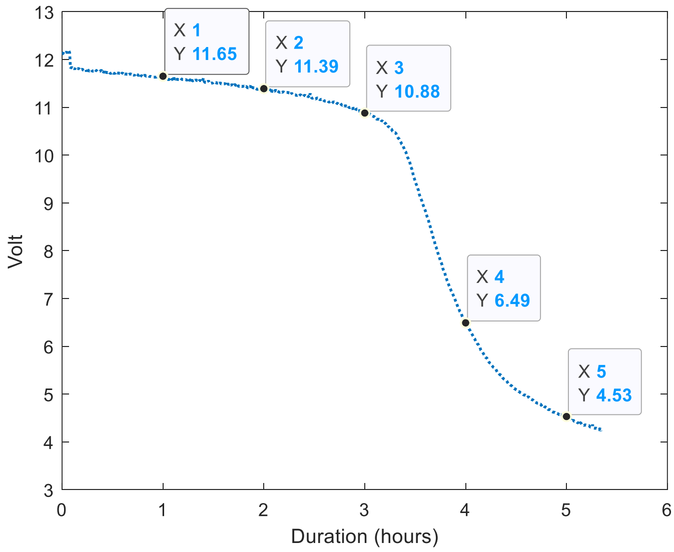


Figure 9. An example of five data points collection for ANFIS training. This data is from the discharge experiment for a 220-Watt load.

4. Results and Discussion

4.1. Result.

The results of the study are divided into ANFIS prediction and SVM classification of the discharge battery voltage condition.

4.1.1. ANFIS prediction.

After the time-series data collected during the discharge experiments, the battery monitoring data was examined in the ANFIS prediction. In ANFIS prediction, there are four different loads were used i.e. 130, 180, 200, and 220 Watt. The experiment was repeated two times for each load to obtain two datasets. The two datasets will be used for ANFIS training and testing. The training feature for the ANFIS model is the battery voltage during the discharge experiment at one-hour intervals (1, 2, 3, 4, and 5 hours). This paper used two-input ANFIS architecture with a first-order Sugeno fuzzy model [13, 14]. The ANFIS structure and the training process are presented in Figure 10. There are two data inputs in Figure 10 i.e. x and y, where x is the different load and y is the battery voltage. Each load has 5 data representing 5 hours of data collection. The target to be predicted is the duration (1, 2, 3, 4, and 5 hours) of battery usage. The model obtained from the training process is in the form of a membership function as presented at the bottom part of Figure 10. This model is then tested with a different dataset without the target information.

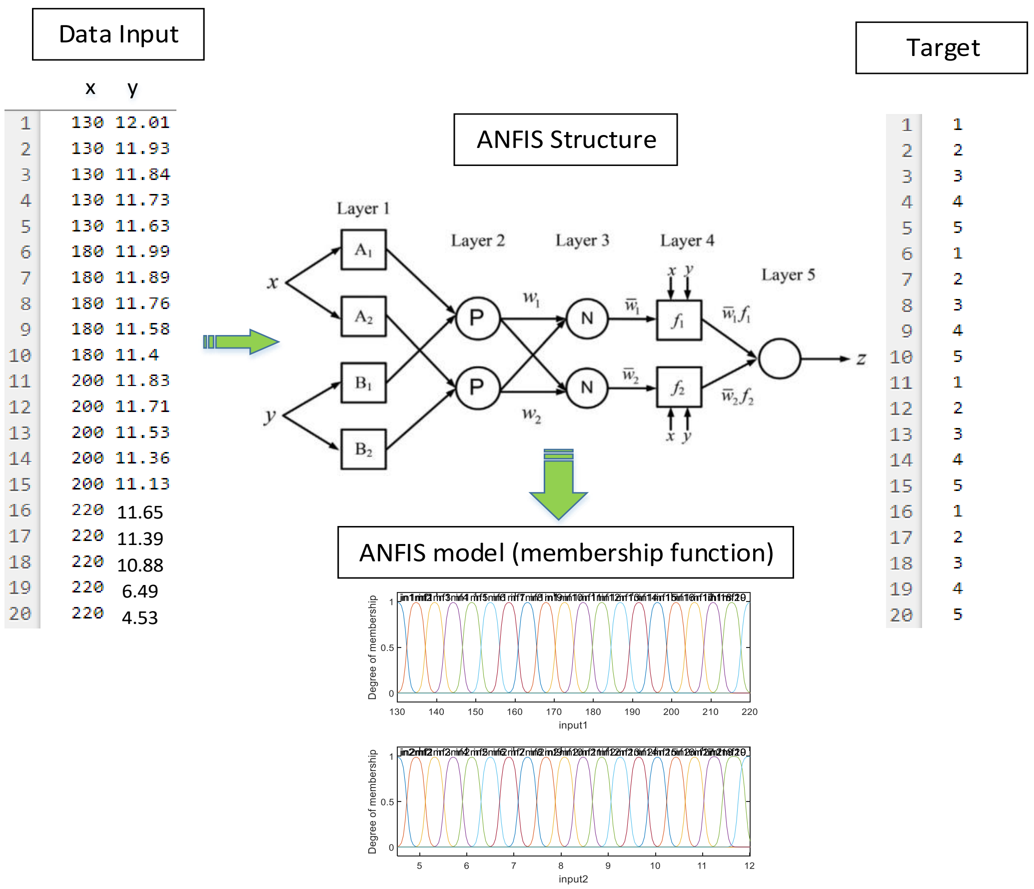


Figure 10. ANFIS training process.

The ANFIS prediction result is presented in Figure 11. The x-axis indicates the total number of samples for testing data i.e. 20 samples. These 20 samples consist of 4 different loads and each load consist of 5 samples. The y-axis represents the duration of the battery from 1 to 5 hours. The blue circle is the target and the red solid dot is the prediction.

The training data and the testing data of the ANFIS method were collected from each hour of discharge time. One hour is labeled as 1, two hours is labeled as 2, etc. A detail of training data and testing data were presented in Tables 2 and 3. Although the total duration of the experiment is more than 5 hours, this study used the 5 hours of data as a preliminary prediction study. The ANFIS prediction is also used for 1-hour intervals of battery usage capacity even though the interval can be changed later for future works for example at 30 minutes intervals.

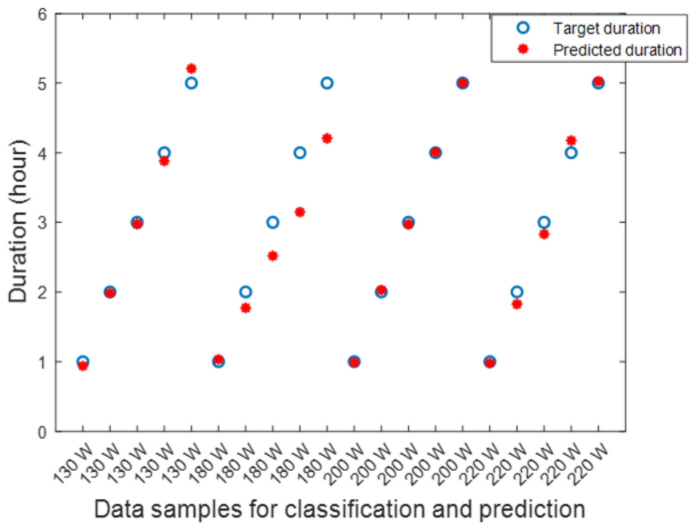


Figure 11. ANFIS classification results.

As presented in Tables 1 and 2, four different loads were used for the battery experiment. The discharge voltage values of the one-hour intervals were collected from four different loads. These data were then used for ANFIS prediction. It can be seen from Tables 1 and 2 that the discharge voltage values were different between the training and testing data. It is because the data were collected from different batteries. The authors collected all the data training from one battery until the battery run out and conduct a similar experiment from another brand new battery for collecting the testing data. Please note that the battery type used in the training and the testing is a similar type of battery.

It can be seen visually from Figure 11 that the ANFIS is a potential prediction tool for battery remaining life. Detailed prediction accuracy of the ANFIS method for four different loads is presented in Tables 4-7.

As mentioned previously that the objective of this study is to predict the present capacity (i.e. discharge voltage value) of the battery based on historical data. Once the discharge voltage value was obtained from the ANFIS prediction and the total duration battery was also known, the remaining battery voltage will be easily calculated using the following Eq. (3).

$$R = T - P, \tag{3}$$

where R is the remaining battery time (hours), T is the total battery duration (hours), and P is the predicted hours of battery usage. This calculation provides an estimate of the remaining useful life in the same time units.

Table 2. Training features for ANFIS prediction.

Load (Watt)	Discharge voltage	Label (discharge hour)
130	11.98	1
130	11.92	2
130	11.77	3
130	11.69	4
130	11.56	5
180	11.97	1
180	11.86	2
180	11.71	3
180	11.53	4
180	11.33	5
200	11.94	1
200	11.75	2
200	11.56	3
200	11.25	4
200	10.17	5
220	11.65	1
220	11.39	2
220	10.88	3
220	6.49	4
220	4.53	5

Table 3. Testing features for ANFIS prediction.

Load (Watt)	Discharge voltage	Label (discharge hour)
130	12.04	1
130	11.91	2
130	11.78	3
130	11.69	4
130	11.58	5
180	11.96	1
180	11.83	2
180	11.68	3
180	11.51	4
180	11.26	5
200	11.84	1
200	11.68	2
200	11.51	3
200	11.26	4
200	10.74	5
220	11.63	1
220	11.39	2
220	11.06	3
220	7.88	4
220	4.13	5

4.1.2. SVM classification.

Datasets of training and testing features presented in Tables 2 and 3 were also used in the SVM method. Differing from the ANFIS method where the prediction is on the detail about the discharge of hours spent, the SVM method was used for classification only. A multiclass function of SVM that is available in MATLAB 2022b namely fitcecoc was used to build the SVM model. The classification result is presented in Figure 12.

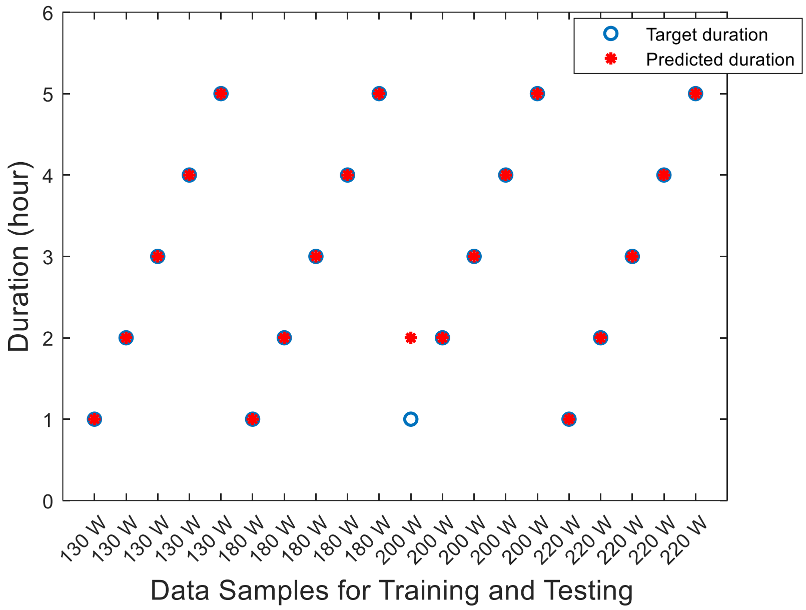


Figure 12. SVM classification results.

4.2. Discussion.

Two-input and one-output ANFIS architecture with a first-order Sugeno fuzzy model is used in this study. This ANFIS structure has been tested in previous studies [16, 17]. In [16], the ANFIS method is used in the manufacturing field to predict the chamfer length of the workpiece under the deburring process. The classification and the finger movement prediction based on the EMG signal and ANFIS method are presented in [17]. Based on these previous studies, the Author then examined the ANFIS method for battery prediction. According to the results, the following discussion can be drawn:

4.2.1. ANFIS prediction.

Four different datasets from four different loads during the battery discharge experiments were collected. The datasets were divided into training and testing datasets. The ANFIS Sugeno type is used to estimate the correlation model between two inputs (load and discharge voltage) and one output (hour's duration). An illustration of ANFIS training has been presented in Figure 10. Figure 11 shows that two input data i.e. load (x-axis) and discharge volt (y-axis) were analysed in ANFIS to estimate the membership function associated with the prediction of duration (hours). A detail of training and testing features datasets were presented in Tables 2 and 3. The results of testing datasets prediction are presented in Figure 11. Figure 11 shows the target duration and predicted duration represented in a blue circle and a red solid circle, respectively. There are four loads used in the battery discharge experiments and there are five samples for each load i.e. 1, 2, 3, 4, and 5 hours.

According to Figure 11 and the quantitative results in Tables 3-6, the ANFIS prediction accuracy was highest for 200W (97.68%), followed by 130W (93.98%), 180W (86.23%), and lowest at 220W (73.77%). The performance variation across different loads indicates that the relationship between load, voltage, and discharge time is not strictly linear, with certain load conditions presenting more complex prediction challenges. The worse prediction results are presented in all data samples of 180 Watts compared to other data samples for 130, 200, and

220 Watts loads. The quantitative results of all predictions are presented in Tables 4-7. For evaluating ANFIS prediction performance, we employed standard regression metrics including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) instead of the previously used accuracy percentage. These metrics provide a more standardized assessment of prediction quality in regression tasks.

Table 4. ANFIS prediction for 130-Watt load.

Target label (hour)	Predicted label (hour)	Accuracy (%)
1	0.92	92.04
2	1.99	87.31
3	2.99	96.44
4	3.86	98.97
5	5.07	95.16
Average Accuracy (%)		93.98

Table 5. ANFIS prediction for 180-Watt load.

Target label (hour)	Predicted label (hour)	Accuracy (%)
1	1.03	96.58
2	1.78	88.79
3	2.49	82.87
4	3.15	78.85
5	4.20	84.04
Average Accuracy (%)		86.23

Table 6. ANFIS prediction for 200-Watt load.

Target label (hour)	Predicted label (hour)	Accuracy (%)
1	1.07	92.55
2	2	100
3	2.89	96.42
4	3.99	99.97
5	5.03	99.48
Average Accuracy (%)		97.68

Table 7. ANFIS prediction for 220-Watt load.

Target label (hour)	Predicted label (hour)	Accuracy (%)
1	0.69	69.04
2	1.48	74.15
3	2.16	72.12
4	2.99	74.86
5	3.93	78.68
Average Accuracy (%)		73.77

A more detail of the five data points collection for ANFIS traning and testing is presented in Appendix. Supplemental Material (SM) Figures A1-A4 show the five data collection of ANFIS testing for 130, 180, 200, and 220 Watt, respectivly. SM Figures B1-B4 show the five data collectionf of ANFIS testing for 130,180, 200, and 220 Watt, respectively.

4.2.2. SVM classification.

According to Figure 12, it is visually seen that the overall SVM classification achieved satisfactory results. Among twenty samples predicted from four different loads, there is only one misclassification at 200 Watt. The quantitative results of all predictions are presented in Tables 8-11.

Table 8. SVM classification for 130-Watt load.

Target label (hour)	Predicted label (hour)	Accuracy (%)
1	1	100
2	2	100
3	3	100
4	4	100
5	5	100
Average Accuracy (%)		100

Table 9. SVM classification for 180-Watt load.

Target label (hour)	Predicted label (hour)	Accuracy (%)
1	1	100
2	2	100
3	3	100
4	4	100
5	5	100
Average Accuracy (%)		100

Table 10. SVM classification for 200-Watt load.

Target label (hour)	Predicted label (hour)	Accuracy (%)
1	2	0
2	2	100
3	3	100
4	4	100
5	5	100
Average Accuracy (%)		80

Table 11. SVM classification for 220-Watt load.

Target label (hour)	Predicted label (hour)	Accuracy (%)
1	1	100
2	2	100
3	3	100
4	4	100
5	5	100
Average Accuracy (%)		100

5. Conclusions

A prediction method for the battery has been presented in this study. The experiment was designed to obtain the time-domain data during the discharge condition. Four different loads were included to simulate the real process i.e. 220, 200, 180, and 130 Watt. The battery was fully charged prior to the experiment to ensure that the data were collected during the discharge process in an appropriate time duration. An ANFIS method based on Sugeno's fuzzy logic model was used in this study. The ANFIS is used to train 2 input data and predict 1 output i.e. discharge voltage value. The following is a summary of the results of the two methods used:

– The ANFIS method demonstrated potential for battery prediction with RMSE values ranging from 0.18 to 0.63 hours across different loads. The performance analysis using standard regression metrics showed that prediction was most accurate for the 200W load (RMSE: 0.18), followed by 130W (RMSE: 0.24), 180W (RMSE: 0.41), and 202W (RMSE: 0.63).
– An SVM method was also used as a comparison study to the ANFIS with higher prediction results. All loads achieved 100% accuracy except 200 Watt which achieved 80%. However, the SVM accurately classified the battery usage into discrete hour labels with 95% overall accuracy.

The future work for this study is to modify the SVM classification into SVM data-driven prediction for this battery condition monitoring and prediction system. Another future work of the study is to acquire new datasets with narrower intervals i.e. less than 1 hour. This will be useful in practice to predict the condition of the battery during the discharging process.

Acknowledgment

This project has received funding from the European Union's Horizon research and innovation programme under the Marie Skłodowska-Curie grant agreement No 101073381.

Competing Interest

The financial support of this study has informed in the acknowledge and all authors declared that there is no personal, or professional relationships that might influence or appear to influence their research.

Auhor Contribution

Conceptualization: Mukhidin, Yogi Reza Ramadhan, Nur Arifin Akbar; Methodology: Yogi Reza Ramadhan, Januar Panca Adi, Nur Arifin Akbar; Data Collection: Yogi Reza Ramadhan, Januar Panca Adi; Data Analysis: Mukhidin, Yogi Reza Ramadhan, Januar Panca Adi, João Bosco Belo; Writing: Mukhidin, Januar Panca Adi, Nur Arifin Akbar; Supervision: Yogi Reza Ramadhan, Nur Arifin Akbar; Funding: João Bosco Belo, Nur Arifin Akbar.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.53623/amms.v1i1.676.

References

[1] Nature Article. (accessed on 23 September 2022) Available online: https://media.nature.com/original/magazine-assets/d41586-021-02222-1/d41586-021-02222-1.pdf.

[2] Desmond K. (2015). Gustave Trouve: French Electrical Genius (1839–1902); McFarland: Jefferson, North Carolina, USA.

[3] Sadeghian, O.; Oshnoei, A.; Mohammad-vatloo, B.; Vahidinasab, V.; Anvari-Moghaddam, A. (2022). A comprehensive review on electric vehicles smart charging: Solutions, strategies, technologies, and challenges. *Journal of Energy Storage*, *54*, 105241. https://doi.org/10.1016/j.est.2022.105241.

[4] Fatullah, M.A.; Rahardjo, A.; Husnayain, F. (2019). Analysis of discharge rate and ambient temperature effects on lead acid battery capacity. *2019 IEEE International Conference on Innovative Research and Development (ICIRD)*, 1–5.

[5] Richardson, R.R.; Osborne, M.A.; Howey, D.A. (2019). Battery health prediction under generalized conditions using a Gaussian process transition model. *Journal of Energy Storage*, *23*, 320–328. https://doi.org/10.1016/j.est.2019.03.022.

[6] Hu, X.; Xu, L.; Lin, X.; Pecht, M. (2020). Battery Lifetime Prognostics. *Joule*, *4*, 310–346. https://doi.org/10.1016/j.joule.2019.11.018.

[7] Broussely, M.; Biensan, P.; Bonhomme, F.; Blanchard, P.; Herreyre, S.; Nechev, K.; Staniewicz, R.J. (2005). Main aging mechanisms in Li ion batteries. *Journal of Power Sources*, *146*, 90–96. https://doi.org/10.1016/j.jpowsour.2005.03.172.

[8] Crown Battery - What kills battery life. (accessed on 1 October 2022) Available online: https://www.crownbattery.com/news/what-kills-battery-life.

[9] Braun, J.A.; Behmann, R.; Schmider, D.; Bessler, W.G. (2022). State of charge and state of health diagnosis of batteries with voltage-controlled models. *Journal of Power Sources*, *544*, 231828. https://doi.org/10.1016/j.jpowsour.2022.231828.

[10] Yilmaz, M.; Krein, P.T. (2012). Review of benefits and challenges of vehicle-to-grid technology. *IEEE Energy Conversion Congress and Exposition (ECCE)*, 3082–3089. https://doi.org/10.1109/ECCE.2012.6342356.

[11] Gaber, M.; El-Banna, S.; El-Dabah, M.; Hamad, M. (2021). Designing and Implementation of an Intelligent Energy Management System for Electric Ship power system based on Adaptive Neuro-Fuzzy Inference System (ANFIS). *Advances in Science, Technology and Engineering Systems Journal*, *6*, 195–203. http://doi.org/10.25046/aj060223.

[12] Jang, J.-S. (1993). ANFIS: adaptive-network-based fuzzy inference system. *IEEE Transactions on Systems, Man, and Cybernetics*, *23*, 665–685. https://doi.org/10.1109/21.256541.

[13] Jang, J.-S.R.; Sun, C.-T.; Mizutani, E. (1997). *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence*; Prentice Hall: New Jersey, U.S.A.

[14] Caesarendra, W.; Irfan, M. (2018). Classification Method of Hand Gesture Based on Support Vector Machine. *Computer Engineering and Application*, *7*(3), 179–190. http://doi.org/10.18495/comengapp.v7i3.269.

[15] Vapnik, V. (1995). The Nature of Statistical Learning Theory; Springer-Verlag: New York, USA.

[16] Caesarendra, W.; Wijaya, T.; Tjahjowidodo, T.; Pappachan, B.K.; Wee, A.; Roslan, M.I. (2018). Adaptive neuro-fuzzy inference system for deburring stage classification and prediction for indirect quality monitoring. *Applied Soft Computing*, *72*, 565–578. https://doi.org/10.1016/j.asoc.2018.01.008.

[17] Caesarendra, W.; Tjahjowidodo, T.; Nico, Y.; Wahyudati, S.; Nurhasanah, L. (2018). EMG finger movement classification based on ANFIS. *Journal of Physics: Conference Series*, *1007*(1), 012005. http://doi.org/10.1088/1742-6596/1007/1/012005.