Python-based E-Vehicle Battery Diagnostic with Service Life Prediction System through Data Analytics

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Abstract—**This paper presents a Python-based battery diagnostic system for lead-acid battery bank used in e-vehicle The study aims to incorporate management, measurement and monitoring system for the improvement of lead acid battery performance as far as its efficiency, capacity and conservation is concerned. It is of great importance that batteries are accurately assessed or diagnosed for the long cycle life to be maintained. The measurement of the battery's State-of-Charge and State-of-Health is derived from its load voltage, no-load voltage, load current and temperature during experimentation. The estimation of State-of-Charge, State-of-Health, Discharge Rate, and Remaining Useful Life are then derived by utilizing the concept of correlation and regression from the yielded real-time parameters recorded to the SD card module. Furthermore, the results of the diagnostic system show that the device operates real-time and accurate regarding predictions on Remaining Useful Life. The system provides recommendations or solutions for any abnormal state the battery encounters.**

Keywords— **Python-based; diagnostic system; State-of-Charge; State-of-Health; Remaining Service Life; Correlation; Regression; Discharge Rate; E-Vehicle**

I. Introduction

Battery state estimation is one of the most important functions of a Battery Management System. It is the real-time estimation of battery states, such as the state-of health (SOH) and state-of-charge (SOC). Estimating of SOH and SOC can result to a different conclusion on the SOH of the batteries because of the independence between the capacity and internal resistance [1]. Using the data gathered from data extractor, the health condition of the battery can be calculated, however, life of a battery is a wide idea of representing the health of the battery. E-trike owners and e-trike battery shops are only capable of visual inspection for any physical defects like wears and tears, and by means of a voltmeter for assessing the health of the battery, wherein SoC is confused with SOH.

As a solution, the researchers of the study proposed as system that would have a deep understanding about the parameters to consider upon diagnosing an e-trike battery like the lead acid battery. The researchers specifically aims to: (1) develop a MySQL Database for storing, retrieving, and displaying initial measured and computed parameters like no-load voltage, load current, temperature, internal resistance, State-of-Health, State-of-Charge, and estimated Remaining Useful Life and estimated Remaining Useful Time and (2) develop battery monitoring and prognosis system using python for the analysis of the battery's condition with mathematical equations for tracking the battery's condition with graphical representations and predicting its remaining useful life in terms of time. Unlike with the previous researches which solely focus on battery diagnosis from data acquired using SD card technology, this study includes recommendations and report which allows the battery owner to easily understand what the battery went through. It also includes voltage correction technique using temperature, a historical graph of the battery's current, voltage, State-of-Charge and State-of-Health of all battery kinds; brand new or used. Furthermore, this study determines the battery's End-of-Life based on daily and weekly utilization and not only with its cycle of charge and discharge.

This study deals the diagnostic system processes the life span prediction using a mathematical model and the battery's history. However, the standards being followed by the researchers is just the battery's data sheet and the measured parameters by a real-time measuring device. The proposed system includes display of measured parameters, the produced critical parameters and the estimation of the battery life by means of time. The system shows a warning if the battery parameters undergo a large difference error in predicted parameters to the measured and calculated parameters. The interface is programmed to provide a graphical report of the battery's diagnosis that will be displayed or printed.

This study will yield convenience to the utilization and diagnosis of traction batteries. The success of the study will be the main source of the e-trike battery shops for better battery diagnosis and business judgement. Owners will not rely to the battery physique or to voltmeter alone for diagnosis for there are specific parameters such as load voltage, no-load voltage, working current and temperature to be measured The result of the study is perceived to help better assessment of battery status in terms of efficiency, capacity and conservation.

This research paper is organized as follows: Section II pertains to related studies, Section III defines the methods and materials used by the researchers, Section IV presents the data and results of the study, Section V declares the conclusion and Section VI enumerates possible future works of the research.

II. Related works

Estimation of battery's end-of-life is a crucial parameter in battery diagnosis. Numerous of study have been proposed to produce accurate results. Wherein different combination of parameters considered to be variables.

In [2], the researchers proposed a system of State-of-Health battery estimator. Verified based on the large amount of experimentations at three different temperatures performed. The results are precise and strong. It also shows that SBPM-based estimator is far more reliable compared to other schemes as far as analytical integration of temperature effects is concerned. The study considers more of temperature extents. Like temperature dependency of different SOH estimator.

Gae-Won *et al,* proposed a snapshot-based model that is constructed by the use of recurrent neural network (RNN) that handles sequential data with the ratio of current and voltage during the charge cycle. The used of long-short term memory (LSTM) neural network as the improved variant of the standard recurrent neural network. The neural network of former data the performance of a battery is used. [3]

In [4], the study stated that battery Lead - acid is the largest photovoltaic (PV) storage technology in the country. The charging and discharging statuses of batteries directly affect the battery degradation and the decrease of battery useful life. The new iterative 2- model approach to explicit battery deterioration modeling of optimal procedure of PV systems is also presented. The approach proposed includes two new models: the economic model and the model for degradation that were incrementally resolved for the optimal solution. A linear program optimization problem that computes the ideal hourly battery usage profile, based on the assumed value of the degradation cost of the battery. In turn, the battery deterioration model provides costs based on the profile of battery usage, the temperature and the qualities of battery use. The designs are incrementally solved to achieve optimal use of batteries in view of deterioration of batteries. The application of the suggested approach was also shown to evaluate the maximal storage size and financial battery life. Seasonal variations of assessment also examined the advantages and capabilities of the suggested approach when considering PV generation and irradiation differences.

Wei *et al,* proposes a method of diagnosis of state-of-health and remaining useful life prediction of lithium-ion batteries using particle filtering and support vector regression. SOH is determined from degrading parameters: impedance and capacity. Fitting parameters schemes are simulated for discharging the batteries to record degradation statistics. It is concluded here that the two degradation parameters show linear relationship. The proposed methods are concluded to be produce accurate measures of SOH and RUL prediction. [5]

In [6], the study proposes an integrated Deep Neural Network approach for the prediction of the remaining useful life of lithium-ion battery. A twenty-one-dimensional extraction integrated with autoencoder model is used to present battery degradation, from it the model of remaining useful life estimation is derived. The proposed method was tested to the set of data from the cycle life of lithium-ion batteries from NASA. Results are compared with shallow models as regressions and vector machines to show the efficiency.

II. Methodology

The diagnostic system acquires data from the SD card, battery specifications and the measured parameters are all transferred to the database. The calculation and prediction of remaining life of the battery in time was done by a mathematical model with the help of the measured value and the history of the battery. Finding the SOC and the SOH of a battery are also to take place where the output of mathematical model and the prediction using its history is combined to produce a definite and more accurate value for these two critical parameters.

The system uses the application of MySQL for its database, XAMPP as its server, and PyCharm for developing the user interface.

A. *System Framework*

The data from the SD card module, battery specifications and the measured parameters were all uploaded to the database. The transfer of data is presented in Figure 1. The calculation and prediction of remaining life of the battery in time was done by a mathematical model with the help of the measured value and the history of the battery. The proposed interface generates report that includes the battery performance history in graph format for easy interpretation with recommendation of usage to prevent early deterioration

B. *Computational Analysis*

The voltage, current and temperature of the battery will be taken initially. For the voltage, multiple data were taken and corrected by a measuring device using the offset voltage. The voltage correction using the offset voltage was done thru the battery's temperature. For a new battery, its initial data is stored on an SD card and, later, will go through a data extractor for the generation of its State-of-Health and State-of-Charge. Same thing goes for a previously registered battery.

When the required initial data are complete, monitoring then starts for the battery's voltage and current. Monitoring the battery's voltage and current has two conditions to determine its State-of-Health and State-of-Charge.

The battery is at full charge state when its measured voltage is the same as the max voltage. The data about the max voltage is stored in the SD card when the initial data gathering took place. The battery is known to be at full capacity when its max voltage, upon initial data gathering, is equal to the rated voltage.

The rated voltage is provided by the manufacturer of the battery. Commonly, it is seen on the battery's data sheet. At full charge, the battery's State-of-Health is equal to its State-of-Charge. At full discharge, the battery's State-of-Charge is determined using the measured voltage, rated voltage and minimum voltage. Mathematically,

$$SOC = \frac{V - Vmin}{Vrated - Vmin} \quad (1)$$

The battery is at full discharge state when the measured voltage is lower than the minimum voltage. The data about the minimum voltage is stored in the SD card when the initial data gathering took place. In here, the battery's State-of-Health is equal to its Depth-of-Discharge. Meaning to say, the overall discharge that happened is the battery's remaining health, on that instance. Then, new data for the max voltage is recorded. Mathematically,

$$\mathrm{Vmax} = \mathrm{DOD}(\mathrm{Vrated} - \mathrm{Vmin}) - \mathrm{Vmin}, \quad (2)$$

$$SOH = \frac{Vmax - Vmin}{Vrated - Vmin} \quad (3)$$

Equation 2 came from Equation 3, wherein SOH is DOD The Depth-of-Discharge is determined thru the hourly current reading on the battery. The battery's discharging state is measured using the SOC formula,

$$\mathrm{SOC} = \mathrm{SOH} - \mathrm{DOD} \quad (4)$$

$$Q = (I)(t) \quad (5)$$

Wherein DOD is Equation 5. The Depth-of-Discharge is the measurement of the battery's current every hour whether the e-vehicle is in motion or at rest.

Whenever the battery is discharging, the measured current displayed will have a negative. On the other hand, the measured current, when charging, will display a positive sign. Hence, charging is inversely related to the DOD.

Furthermore, the battery's State-of-Health is determined when the battery is either full-charged or full-discharged. The battery's State-of-Charge is, then, determined by either open circuitry or discharging by voltage or current.

C. *EOL Estimation*

The process of the estimation is presented on Figure 2. To initialize the process, battery's data from SD card must be retrieved. The data to be acquired are the battery's State-of-Health, both initial SOH and final SOH, Maximum Voltage (Vmax), Load Voltage, Current and Temperature. For a new battery, no previous data has been gathered, its End-of-Life is measured using the final SOH and Day 1 SOH. For a used battery, from previous data gathering, its EOL is measured using Total Recorded Degradation and Total Recorded Days. The total recorded degradation is the overall reduction of SOH on the battery while total recorded day is number of days that the battery has been used. Once EOL is determined, it is then forwarded to the database for analysis and generation of report. The generated report displays the remaining number of days of the battery and how the battery was utilized.

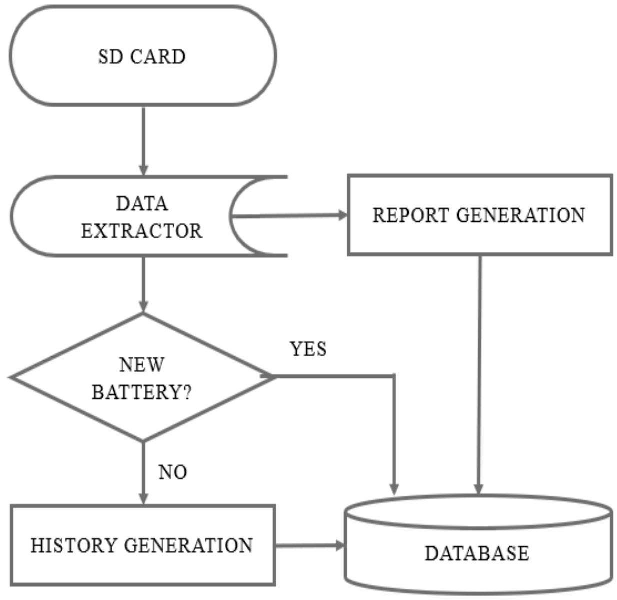


Figure 1 Data Transfer to the Graphic User Interface

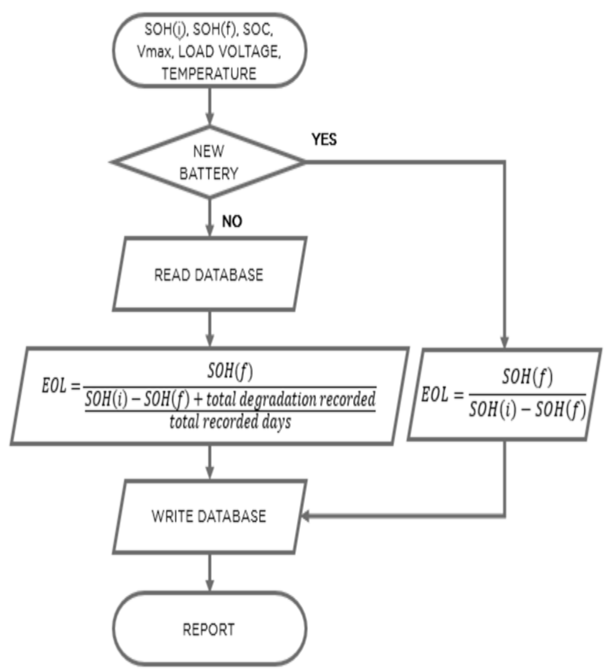


Figure 2 Framework for End-of-Life Estimation

III. RESULTS AND DISCUSSION

A. . Graphical User Interface

This section presents the lay-out of the user interface. Figure 6 shows the flow chart of the interface.

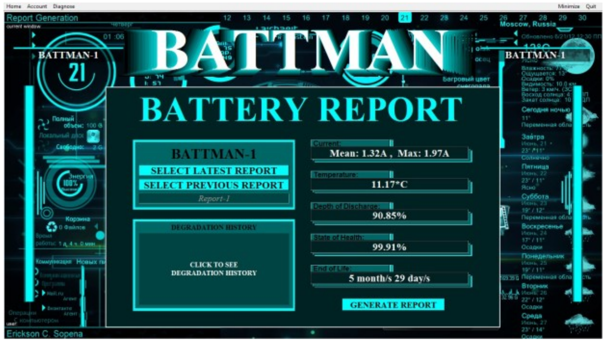


Figure 3 Report Generation Window

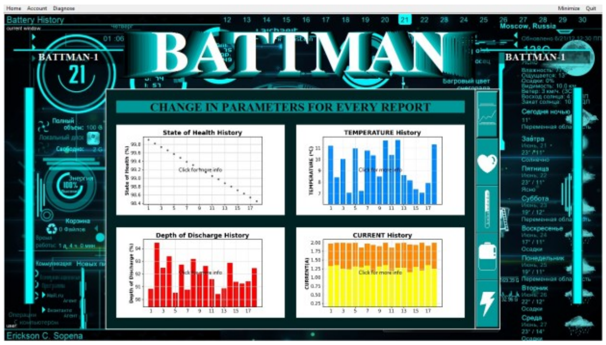


Figure 4 Battery History Window

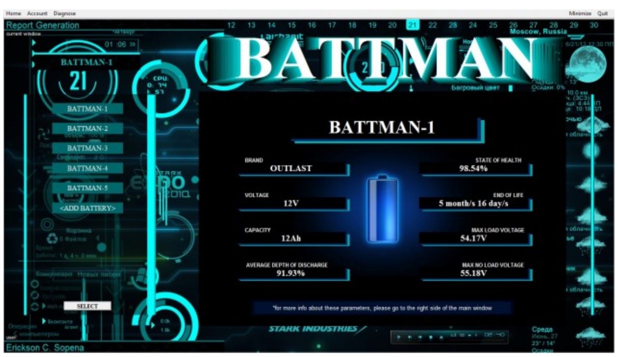


Figure 5 Battery Selection Window

B. . Data Report and Analysis

The TABLE IV. is the sets of data of Days Used and Predicted Remaining Service Life. Used Days is the number of days passed from the purchase date. Predicted EOL is defined as the number of days till the battery wears out. The prediction is based on the current remaining SOH which is determined thru the battery's load load-voltage, no-load voltage, mean current, maximum current, maximum temperature and DOD. From the five sample batteries, five sets of data gathering/report were taken out based on different age.

The calculated SOC and SOH by the interface were compared to the standard equation for calculating the said parameters presented in TABLE V and TABLE VI. Figure 2 and Figure shows graphical relation of the comparison with the data plotted in red line represents the accumulated data using the BATTMAN and the data in the blue line which is manually computed from the raw data gathered using multimeter based on standard equation. The error in SOH approximates to 0.65 and the error in SOC approximates to 0.56.

TABLE IV.
DATA REPORT: Predicted EOL of Different Tested Batteries

Battery	Report Number	Report Date	Days Used	Predicted EOL
BATTMAN-N2	48	23-Jun-20	7	169
	54	24-Jun-20	8	167
	60	27-Jun-20	11	162
	66	29-Jun-20	13	160
	72	2-Jul-20	16	155
BATTMAN-1M	46	22-Jun-20	30	147
	58	26-Jun-20	34	141
	67	29-Jun-20	37	136
	74	3-Jul-20	41	130
	77	5-Jul-20	45	127
BATTMAN-2M	49	23-Jun-20	60	117
	61	27-Jun-20	64	111
	70	30-Jun-20	67	106
	75	3-Jul-20	71	101
	78	5-Jul-20	73	98
BATTMAN-3M2	45	22-Jun-20	90	78
	51	25-Jun-20	93	73
	57	26-Jun-20	94	70
	63	28-Jun-20	96	67
	69	30-Jun-20	98	64
BATTMAN-4M	52	25-Jun-20	120	57
	64	28-Jun-20	123	52
	73	2-Jul-20	127	45
	76	3-Jul-20	128	43
	79	5-Jul-20	130	39

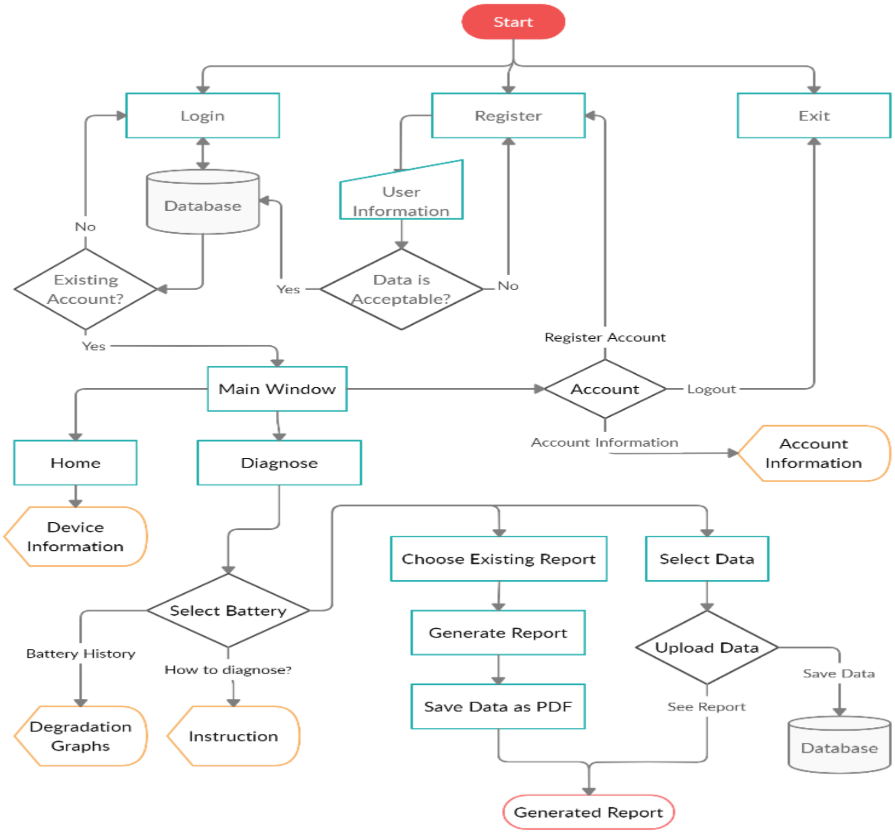
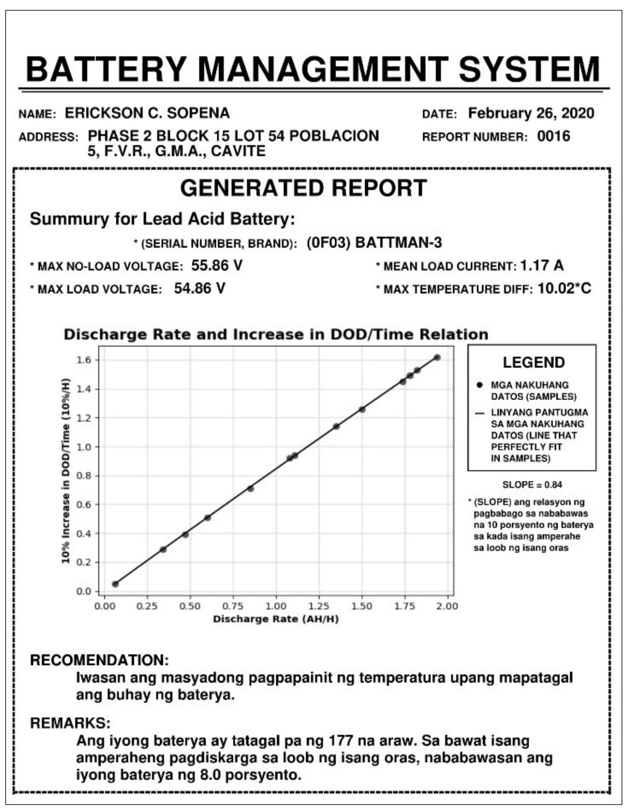


Figure 3 Development of User Interface Workflow



BATTERY MANAGEMENT SYSTEM

NAME: ERICKSON C. SOPENA DATE: February 26, 2020

ADDRESS: PHASE 2 BLOCK 15 LOT 54 POBLACION 5, F.V.R., G.M.A., CAVITE REPORT NUMBER: 0016

GENERATED REPORT

Summury for Lead Acid Battery:

* (SERIAL NUMBER, BRAND): (0F03) BATTMAN-3
* MAX NO-LOAD VOLTAGE: 55.86 V
* MEAN LOAD CURRENT: 1.17 A
* MAX LOAD VOLTAGE: 54.86 V
* MAX TEMPERATURE DIFF: 10.02°C

RECOMENDATION:

Iwasan ang masyadong pagpapainit ng temperatura upang mapatagal ang buhay ng baterya.

REMARKS:

Ang iyong baterya ay tatagal pa ng 177 na araw. Sa bawat isang amperaheng pagdiskarga sa loob ng isang oras, nababawasan ang iyong baterya ng 8.0 porsyento.

Figure 3 Printed Report

TABLE V.
Comparison of the SOH of Different Tested Batteries

State of Health (SOH)			
BATTERY	***RESULT using BATTMAN***	***MANUAL based on Standard Equation***	***% ERROR***
BATTMAN-1	98.54	98.16	0.39
BATTMAN-2	99.04	98.43	0.62
BATTMAN-3	99.09	98.34	0.76
BATTMAN-4	99.77	98.77	1.01
BATTMAN-N1	97.88	98.23	0.36
BATTMAN-N2	97.27	96.46	0.84
BATTMAN-1M	94.14	93.25	0.95
BATTMAN-2M	90.98	90.57	0.45
BATTMAN-3M1	88.2	87.5	0.8
BATTMAN-3M2	86	85.52	0.56
BATTMAN-4M	84.48	84.13	0.42

TABLE VI
Comparison of the SOC of Different Tested Batteries

State of Charge (SOC)			
BATTERY	***RESULT using BATTMAN***	***RESULT USING STANDARD EQUATION***	***% ERROR***
BATTMAN-1	96.73	97.59	0.88
BATTMAN-2	97.23	97.73	0.51
BATTMAN-3	97.29	98.16	0.89
BATTMAN-4	98.04	98.34	0.31
BATTMAN-N1	96.05	96.39	0.35
BATTMAN-N2	95.45	95.75	0.31
BATTMAN-1M	92.25	92.7	0.49
BATTMAN-2M	89.04	89.39	0.39
BATTMAN-3M1	86.2	86.88	0.78
BATTMAN-3M2	89.04	89.5	0.51
BATTMAN-4M	82.38	82.96	0.7

E. Report Generation

The system includes a functionality of report generation. It presents graphical history of performance from the data gathered and presents recommendation based on the consumption acquired by the interface. Figure 5 is a report generated as a PDF file for printing preference.

IV. CONCLUSION

In determining the battery's End-of-Life, parameters like no-load voltage, load voltage, mean current, maximum current, maximum temperature, DOD and Charge-Discharge cycle should be carefully measured. Large battery consumption or DOD will occur if the discharge current is low. It shows in the data that DOD doesn't affect the battery life since the discharged current is low. However, based on the data, with low discharge current and low DOD, the battery's SOH continues to decrease due to its charge-discharge cycle. With this, SOH will still decrease no matter how efficient the battery is used. If the battery is discharged with high current, the decrease in SOH is great and evident. The data shows that battery ageing doesn't affect the decrease in SOH. Basically, the battery gets consumed easily as the SOH decreases continuously. In addition, the increase in charge-discharge cycle of the battery contributes to the decrease in SOH. The temperature, when high, affects battery consumption and may also cause serious damage like overheating. High discharge current was found to consume the battery easily.

V. FUTURE WORK

For further research related to this study, here are some of the recommendations from the proponents: (1) Estimation of Remaining Useful Distance. The study only developed a program capable of predicting the EOL in terms of Time and not what's left to travel, (2) testing of different battery capacities. Different manufacturers have been emerging from the trend of e-vehicles, (3) Real-time data acquisition to database using IoT, (4) Coordinate tracker for e-e-vehicle to be monitored, and (5) it would be better and more convenient if the user can monitor it via the internet through a website or app.

REFERENCES

[1] W. Diao, JiuchunJiang, C. Zhang, H. Liang and M. Pecht, "Energy state of health estimation for battery packs based on the degradation and inconsistency," *ScienceDirect - Energy Procedia,* vol. 142, pp. 3578-3583, 2017.

[2] X. Hu, J. Jiang, D. Cao and B. Egardt, "Battery Health Prognosis for Electric Vehicles Using Sample Entropy and Sparse Bayesian Predictive Modeling," *IEEE Transactions on Industrial Electronics,* vol. 63, no. 14, pp. 2645 - 2656, 2016.

[3] G.-W. You, S. Park and D. Oh, "Diagnosis of Electric Vehicle Batteries Using Recurrent Neural Networks," *IEEE Transactions on Industrial Electronics* , vol. 64, no. 6, pp. 4885 - 4893, 2017.

[4] A.-S. Hamedi and A. Rajabi-Ghahnavieh, "Explicit degradation modelling in optimal lead–acid battery use for photovoltaic systems," *IET Generation, Transmission & Distribution,* vol. 10, no. 4, pp. 1098-1106, 2016.

[5] J. Wei, G. Dong and Z. Chen, "Remaining Useful Life Prediction and State of Health Diagnosis for Lithium-Ion Batteries Using Particle Filter and Support Vector Regression," *IEEE Transactions on Industrial Electronics,* vol. 65, no. 7, pp. 5634-5643, 2018.

[6] L. Ren, L. Zhao, S. Hong, S. Zhao, H. Wang and L. Zhang, "Remaining Useful Life Prediction for Lithium-Ion Battery: A Deep Learning Approach," *IEEE Access,* vol. 6, pp. 50587-50598, 2018.

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