Research Article

Arduino-based battery monitoring system with state of charge and remaining useful time estimation

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Abstract
This paper presents a battery management system for lead-acid battery banks used in e-vehicle. It is incorporated with a diagnostic, measurement, and monitoring system for improving Lead-acid battery performance up to its efficiency and conservation. This matter calls the need for research on traction batteries as an insatiate demand exists for smaller vehicles with lightweight and portable equipment. It is extensive that batteries are strictly assessed and diagnosed before having them rented or exchanged for their condition to be highly 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. This study paves the approach for the comprehensive and continuous progress of battery identification, monitoring, and diagnosis that is a thorough advancement in the E-Vehicle industry.

Keywords
Battery management system, Lead-acid, Arduino-based management system, Electric vehicle, State of charge, State of health, Remaining useful time, Discharge rate.

1.Introduction
The utilization of commercial transportation is a facet of economic growth that the nation continues to progress. With developing technologies of transportation in the Philippines, e-vehicles turned into a trend started last 2015, attracting manufacturers for production [1]. Alongside the thriving industry for e-vehicles, the traction battery industry, as the heart of its construction, will also be prominent. The battery in an e-vehicle structure is the complement part of the fuel tank on a conventional vehicle. Traction batteries are the alter for gasoline.

The Lead-acid battery is the type of traction battery that is commonly used in the Philippines based on the statistics analyzed by the Electric Vehicle Association of the Philippines (eVap), the production of e-vehicles that use lead-acid batteries are greater than those vehicles that use lithium batteries. It is practical considering it is low-cost in comparison to other types [2]. In addition, it is uncomplicated to assemble as its construction of lead plates and electrolyte that is made of diluted sulfuric acid [3].

Electromechanical batteries are constructed in distinction to electrical analogy through means of having a prominent network of electrical components such as electromotive forces and passive components.

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The construction of the cell is formed by two schemes: design each part as an electrical element or set up the cell behavior as a black box. The approach of a black box is the analysis of the terminal's measurements [4]. Battery modeling can be collected from artificial intelligence which fuzzy logic is utilized to layout discharging of lead-acid batteries. The data of discharging are acquired through controlling the network among the battery's open-circuit terminal voltage, the output currents, and the state of charge [5].

Battery identification and diagnosis is a technology that is still not accessible to e-trike owners and e-trike battery shops in the Philippines. It is significant for batteries to be diagnosed before engaging them into business for maintaining their good quality. Even this, owners of e-trike and e-trike battery shops are only capable of diagnosing the battery by visual observation for any physical deformity and using a common voltmeter for checking the battery's health. State of Charge (SOC) is commonly confused with State of Health (SOH). Both stated techniques are inadequate assessment and resolution-making would be at risk.

As a solution, the researchers of the study proposed a system that exerts a profound understanding regarding the parameters to scrutinize in diagnosing a battery like the Lead-acid battery. The researchers specifically aims to: (1) design and develop an electronic circuit for the Arduino-based data acquisition system for the battery's no-load voltage, load voltage, current, and temperature, and (2) develop an Arduino-based identification and diagnostic system that stores and validates battery performance through information storage for the initialization, reading, and writing of the battery's performance history used for the battery.

A Management System solution is proposed to showcase how important measuring and monitoring the battery SOH and SOC for life span predictions. Nowadays, lead-acid batteries for e-vehicle are widely used because of their versatility and low cost but degrade their performance without proper management, measurement, and monitoring. As the lead-acid battery ages, its SOH and SOC are susceptible to a lot of factors affecting its life span. The software development of the proposed system used the application of Arduino IDE for programming the microcontroller of the system, MySQL for database, and Python for the system user interface. The microcontroller is programmed to acquire real-time parameters with computational analysis in obtaining the battery's internal resistance, SoC, SoH, Discharge Rate, and Depth-of-discharge (DOD). In addition to the indicator installed on the device, which includes the proposed system, with the data acquisition specification of the device the researchers developed a user interface to extract and interpret data from the SD card installed in the device.

The general objective of this study is to develop a smart Arduino-based e-vehicle battery management system with the remaining useful time prognosis deployed on an e-tricycle battery shop. Specifically, this study aims: (1) to design and develop an electronic circuit for the Arduino-based data acquisition system for the battery's no-load voltage, load voltage, current, and temperature, (2) to develop an Arduino-based identification and diagnostic system for batteries that stores and validates battery performance through information storage for the initialization, reading, and writing of the battery's performance history, and (3) predicting its remaining useful life in terms of time.

The study only considered the sets of lead-acid batteries in an E-bike Shop used for public utilization in Bacoor, Cavite, Philippines. The output of the study was proposed to e-trike battery shops and even e-trike owners who offer battery renting and/or swapping. This study was focused on the identification, diagnosis, and monitoring of lead-acid batteries that are available within the area. This study dealt with the use of SD Card technology for security over authentication in each-and-every battery available. The goal of the proposed SD Card Identification System is to be able to store large amounts of data from the analog signal over a long period of time so that it can stay unattended for a long time. Physical battery defects, such as wears and tears or smudges, are not considered as factors for diagnosis and monitoring. This study required manpower to ensure the security of data from the SD Card till it makes to the database on the shop owner's personal computer.

The success of the study will be a source for the e-trike battery shops for improved diagnosis of battery and business exhortation. In addition to that, it will provide a reference for the continuous progress of Lead-acid battery identification and diagnosis that is a profound upgrade for the e-vehicle industry.

This paper is organized as follows: Section 2 pertains to the gaps and limitations of the related researches, Section 3 defines the materials and methods used by the researchers, Section 4 explains the detection and database results of the study, and Section 5 declares the conclusion and enumerates possible future works of the research.

2. Related works

Recognizable battery degradation assessments have emerged even before the creation of electric vehicles. Various methods and variables were introduced for the estimation of measurements of the battery's SOC and SOH. In [6], researchers introduce a method that adopts known cell-balancing circuits for individual estimation of cell's voltage and current from a battery bank or battery string terminal. The methods include control strategies and algorithms by manipulating balancing circuits to observe battery subsystems. It is concluded that a large balancing current circuit is ideal for accurate measurement.

Diao et al. [7] determined if batteries have reached their limit by using internal resistance to evaluate the state of health (SOH). However, due to capacity independence from the internal resistance, it can bring about contradicting outcomes for the SOH of the battery. The SOH is more accurately defined as the present battery status with relation to the capacity and power SOH, in which degradation, internal resistance, and inconsistency of capacity are all considered. With the use of this method, a clear advantage can be seen by analyzing data and by comparing it to other methods.

Liu et al. [8], researchers utilized probability distribution and adopted the concept of Monotonic echo sate Networks or MONESNs algorithm for tracking nonlinear degradation patterns of battery-RUL estimation. A correlation model between health index and battery capacity is developed. Two sets of data of lithium-ion batteries are used to prove the efficiency of the proposed method.

Hou et al. [9] propose calculation and monitoring of the electric vehicle's SOH, SOC, and state of function (SOF). The estimation of SOC shows that the maximum error is 0.334%. The present maximum capability to minimize the error of the SOC estimation will therefore be redefined. Furthermore, this article states that the SOF is established based on the SOC and the SOH will yield the system's driving power.

You et al. [10] an illustration about the recurrent neural network (RNN) which is very suitable in working with sequential data like the ratio of current and voltage during the charge cycle is carefully constructed. There are many advantages with the use of long-short term memory neural networks as the improved variant of the standard recurrent neural network. For the former data's neural network, the performance of a battery is used to gather samples and is necessary to minimize the noise effect.

Yang et al. [11] introduce a dynamic Peukerts law-based SOH estimation of batteries. The estimation method is correlating Peukerts coefficient to the battery's capacity loss. It is computed that the Peukerts coefficient is a function of the battery's capacity loss. They experimented with seven samples using one type of battery and compared the results using the proposed method to the same number of sample history data of the same battery type. The proposed method is eligible for direct SOH estimation with missing data.

Dong et al. [12] estimation for short-term SOH and long-term RUL was proposed using Brownian Motion and Particle Filter. This study utilizes the degradation modeling using Brownian Motion with drift and scale and Particle Filter is used for estimation of the drift parameters. Two sets of different capacity of battery degradation in terms of distance traveled were experimented for validating the results of the method. The proposed forecasting of the mentioned two parameters was verified to be accurate. The limitation of the method is that the parameters are initialized off-line with the use of available measurements.

Qu et al. [13] proposed a model for estimation of SOH and prediction of RUL using a synergy of long short-term memory (LSTM) network and particle swarm. The optimization of key parameters of the particle swarm was employed. In forecasting of RUL of the lithium-ion batteries, the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) method is utilized to denoise raw data for extracting the downtrend of SOH. Real-life datasets from NASA of the lithium-ion batteries life cycle were used for validation. The results from the experimentation present that the proposed method is better than the predictions of RNN, LSTM, and RVM in monitoring SOH and prediction of RUL of lithium-ion batteries. The application of an accurate and low computational demanding state-of-health (SOH) estimation algorithm represents a key

challenge for the battery management systems in electric vehicle (EV) applications. Stroe and Schaltz proposed the suitability of the incremental capacity analysis (ICA) technique for estimating the capacity fade and subsequently the SOH of LMO/NMC-based EV Lithium-ion batteries. During the eleven months of testing, ageing results were collected and they were able to accurately relate the capacity fade of the studied batteries to the evolution of the voltage value, which corresponds to one of the incremental capacity (IC) valleys, obtained using the ICA technique [14].

Topan et al. [15] avoiding battery failure and keeping the battery lifespan, a system should be controlled by considering several parameters of Battery Management System (BMS) such as State of Charge (SOH) and State of Health (SOH). The State of Charge in Battery Management System provides the percentage of battery capacity, while the State Of Health measures the battery health. Polarization characteristic, dynamic behaviour of the battery and estimation through Kalman Filter (KF) are defined by the use of Thevenin battery model. Parameters in the model were accumulated using Recursive Least Square.

Dung et al. [16] Dung proposed an SOH estimation system based on time constant-ratio measurement. Time-constant represents the response speed of terminal voltage during charging and discharging and the change of internal chemical reactions. There have been different issues regarding traditional SOH estimations. The first SOH estimation is a full-charge-capacity (FCC) estimation. Unfortunately, to access FCC information, it required a long-term charging and discharging tests and therefore failed on estimation speed. The second estimation is internal impedance estimation. However, this SOH estimation may cause large error because of environmental impedance. Dung proposed a time-constant-ratio measurement to improve issues on different SOH estimations that were mentioned.

3.Methodology

In this research, the battery management system was deployed in a battery rental shop for public transportation. *Figure 1* shows the block diagrams of the entire system. Batteries, with and without the proposed device for identification and measurement, are subjected to be manually operated by the personnel of the battery shop. The specifications of new batteries are stored in the database by the user interface, from the user interface a new SD card will undergo decoding for the battery specifications. The SD card module is applied as the battery identification that collects data for every charging and discharging of the battery. The measuring system is an Arduino-based circuitry designed as a voltmeter, ohmmeter, ammeter, and thermometer. In the diagnostic system, the data from the SD card module, battery specifications and the measured parameters were all transferred to the database of the system. The computation and prediction of the remaining useful time of the battery were taken from a mathematical model using the measured values. The monitoring system comprises a display of real-time measured parameters, the produced critical parameter, the SOC and the estimation of the battery useful time by means of hours and minutes. The data acquired from the Lead-acid battery over time is also presented in the display to show the performance of the battery in every charging and discharging cycle. The *Figure 2* is the system architecture that illustrates the connectivity of the technology to be used in this study.
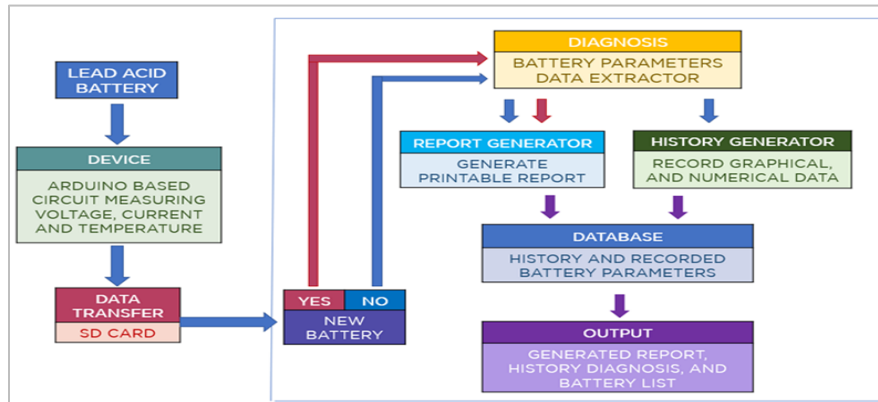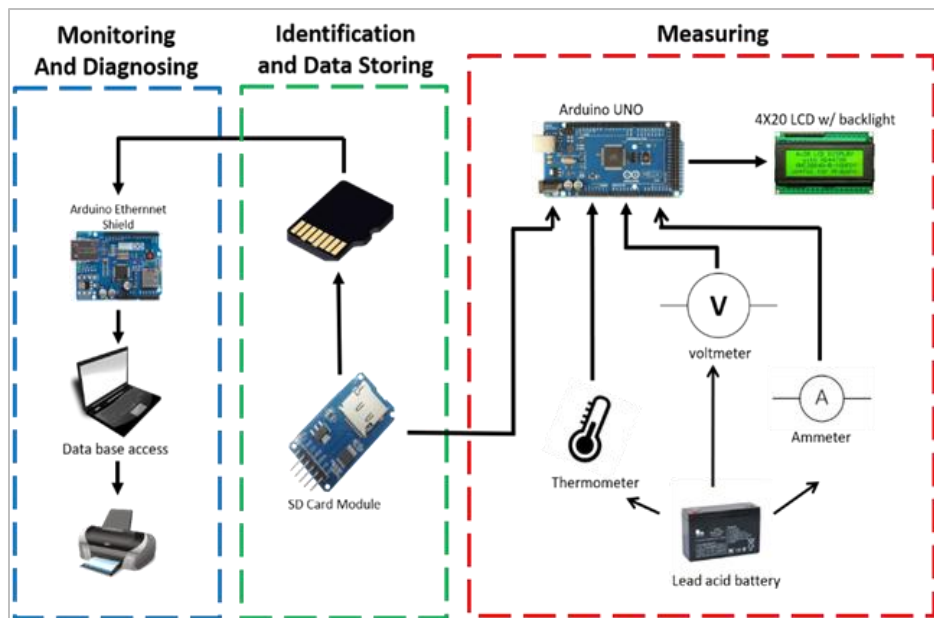

Figure 1 System block diagram

Figure 2 System architecture

3.1 Research locale

Shops in Bacoor, Cavite, Philippines that offer rental and/or swapping of lead acid batteries were located. For that opted location, the study device was used on battery banks used in e-trikes for testing and battery diagnosis. The acquired data and evaluation would be disclosed to the owners of the business.

3.2 Hardware development

The hardware development consists of measuring and identification technology. In the measuring section, an Arduino-based circuitry is used to be the equipment to measure real-time parameters of the battery. Initial diagnosis will undergo the Arduino-based voltmeter, ohmmeter, ammeter, and thermometer circuits that will be stored in the integrated microSD card module. The integration of the microSD card module functions also as the unique identification for the system. It will be given a serial number for a set of the battery bank. The flow chart illustrated in *Figure 3* is the process of data transfer in the device.
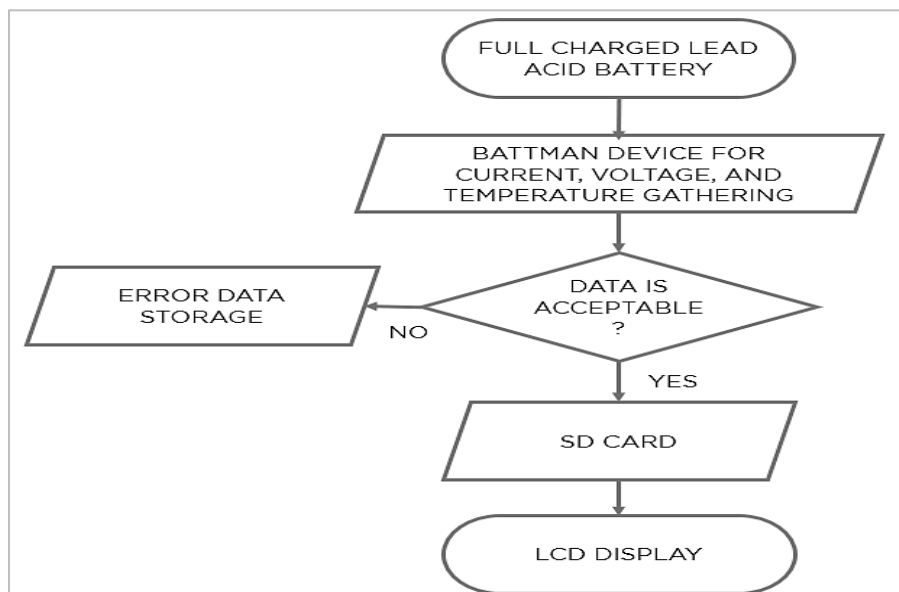

Figure 3 Data transfer in the device

3.2.1 Identification system

Batteries, with and without the proposed device for identification and measurement, are subjected to be manually selected by the owner of the battery shop. The specifications of new batteries (without the device) are stored in the database then, from the user interface a new SD card will undergo decoding for the battery specifications. The SD card module served as the identifier of the battery that also records data every charging and discharging.

3.2.2 Measuring system

Measuring the battery's parameters was real-time and saved on the SD card contained in the prototype. The measuring system is an Arduino-based voltmeter, ohmmeter, ammeter, and thermometer circuit used for the diagnosis and estimation of battery life. In the measuring system, an Arduino-based voltmeter, ohmmeter, ammeter, and thermometer circuit capable of measuring the parameters needed in diagnosis and the battery end-of-life prediction is used. Two clips were connected to the positive and negative terminals of the lead-acid battery for measuring no-load voltage, load voltage, internal resistance, and current of the battery. A thermal sensor was used for measuring the battery bank temperature and its surrounding.

3.3 Software development

The software development of the proposed system used the application of Arduino IDE for programming the microcontroller of the system, MySQL for database and Python for the system user interface. The microcontroller is programmed to acquire real-time parameters with computational analysis in obtaining the battery's internal resistance, SoC, SoH, Discharge Rate, and Depth-of-Discharge (DOD).

Figure 4 shows the data transfer on the device alone of SOC and SOH Measurement. With the process-flow presented measured real-time variables are also programmed to be shown on the LCD. Meanwhile, *Figure 5* is the illustration of the user interface flow chart. The user interface must be manipulated by personnel to choose whether to diagnose a battery bank that is already on the database (with device) or not. MySQL technology will be used for the development of databases. If a battery has an SD card module on it, then it is already subjected to diagnosis by taking its measured parameters and storing the data for monitoring.
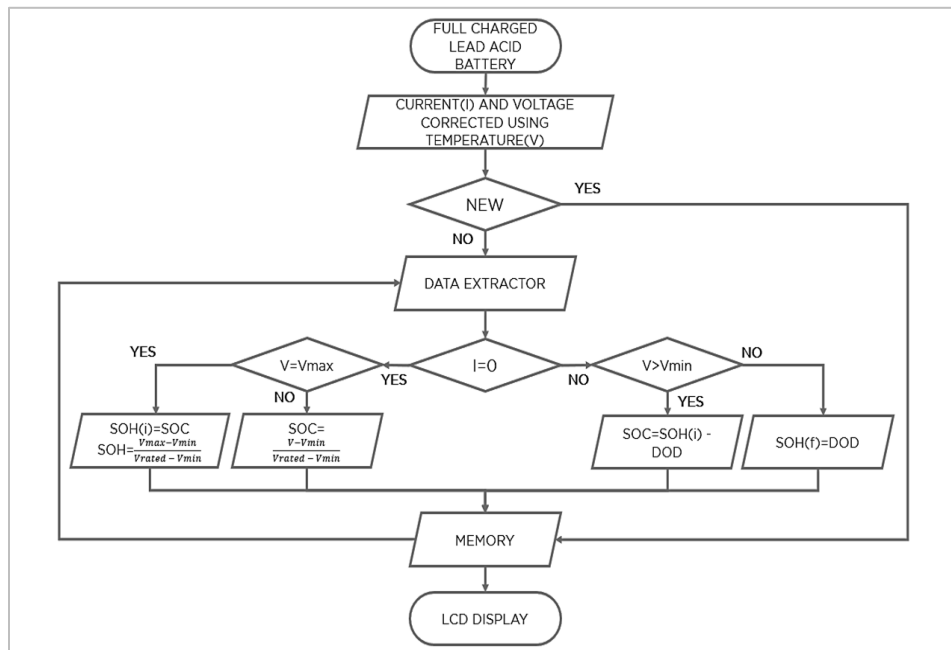

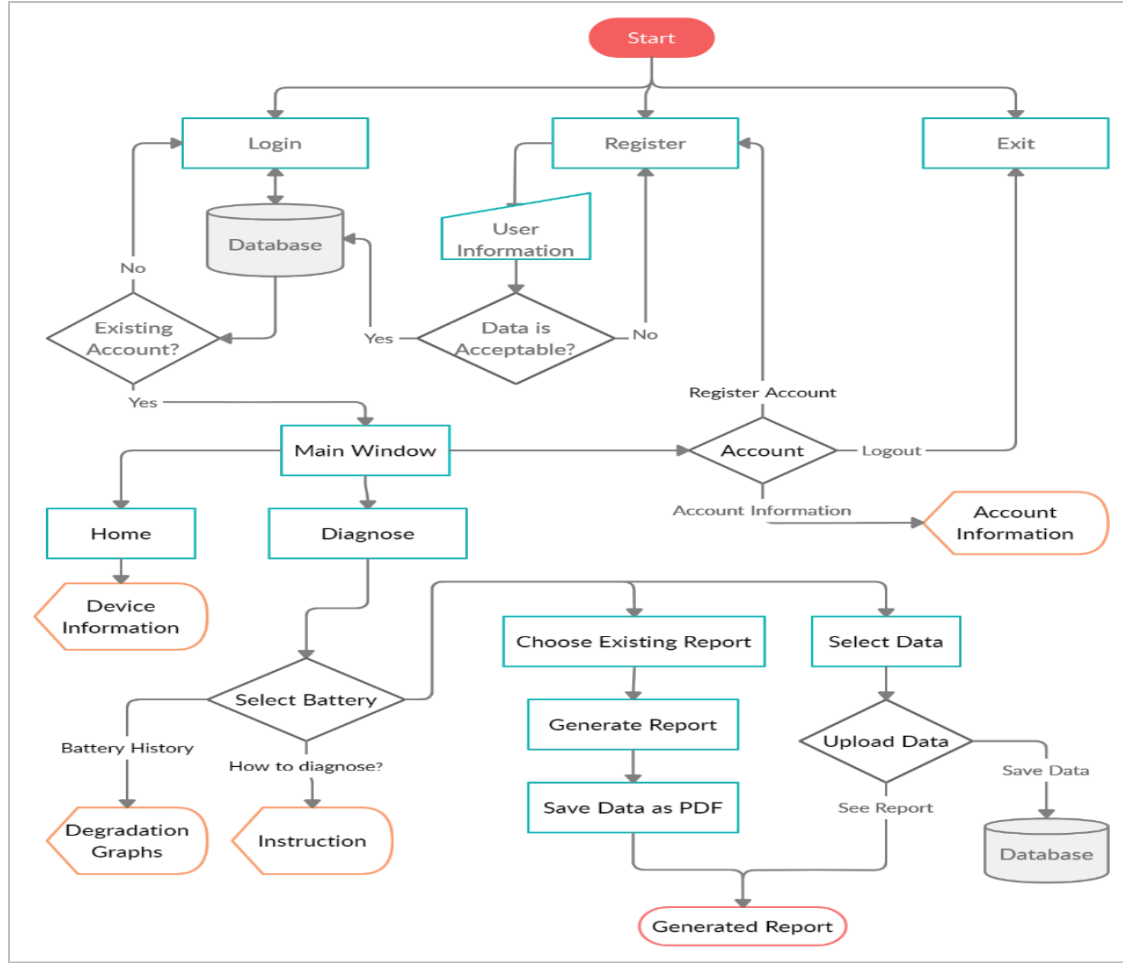**Figure 4** Measurement of SOC and SOH flow chart

Figure 5 User interface flow chart

3.4 Computational analysis

The researchers classify the health of the battery as they know critical parameters, the SOC and SOH. SOC is the ratio of the charge remaining to the battery to its fully charged state. In alternative, SOC is the percentage of the charge remaining in the battery to the maximum charge of the battery. To calculate the SOC:

$$SOC = (Q_R / Q_M) \times 100\% \qquad (1)$$

where,
SOC, State-of-Charge of the battery
Q_R, Remaining Charge in the battery
Q_M, Maximum Charge of the battery

$$SOC = SOC_o - \left(\frac{1}{Cn} \int_{t1}^{t2} Idt \right) \times 100\% \qquad (2)$$

where,
SOC_0, Initial State-of-Charge of full charge battery

The initial state of charge (SOC_o) of new fully charged batteries can be simply computed considering the new battery will pass its maximum capacity. Fully charged new battery SOC_o is equal to 100% since Q_R is same as Q_M, as declared in Equation 1.

$$SOC_o = (Q_M / Q_M) \times 100\% \qquad (3)$$
$$SOC_o = 100\% \qquad (4)$$

The SOC can be computed also using cell voltage (V_{CELL}) and the standard battery voltage prior from having internal resistance (V_O), expected from the direct proportionality of charge and voltage.

$$SOC_V = \frac{V(cell)}{Vo} \times 100\% \qquad (5)$$

$$V_{CELL} = V_{BAT} - V_{INTERNAL\ RESISTANCE} \qquad (6)$$

where,
V_{CELL}, Cell Voltage
V_{BAT}, Battery Voltage (12 V)
V_{IR}, Battery Voltage having Internal Resistance

The battery voltage will increment for a certain value (**α,** normally 0.003V) to each cell of a battery bank

when the battery temperature is below the ambient temperature and reciprocally, where n is equal to the number of cells.

$$SOC_V = \frac{V(measured) \pm n(\alpha)}{Vo} \times 100\% \qquad (7)$$

From Equation 2 and Equation 5, where $SOC_V = SOC_o$, an equation would be derived:

$$SOC = (\frac{V(measured) \pm n(\alpha)}{Vo} - \frac{1}{Cn}\int_{t1}^{t2} Idt) \times 100\% \quad (8)$$

where,

$V_{Measured}$, Voltage measured by BattMan
N, Number of Battery/Cell
α, Voltage increment (at 0.003 V)

The initial discharge ($Q_{INITIAL\ DISCHARGE}$) is equal to 0 for new fully charged battery so that,

$$Q(Discharge) = \int_{t1}^{t2} Idt \qquad (9)$$

Using Equation 9 to Equation 8, C_n is the original capacity (Q_O),

$$SOC = (\frac{V(measured) \pm n(\alpha)}{Vo} - \frac{Q(discharge)}{Q(o)}) \times 100\%$$
$$(10)$$

where,
Q_O, Original Charge Capacity of the battery

The remaining useful time of the battery is calculated in terms of hours and minutes. The $t_{average}$ is equal to the average operation time of the battery that is normally 6 hours.

$$t_{remaining} = t_{average} \times SOC \qquad (11)$$

where,

$t_{remaining}$, Remaining time of the battery in hours and mintes
$t_{average}$, Average Operation of the battery

Another parameter to be calculated for assessing the health of the battery is the SOH. There are various ways to calculate the SOH such as using internal resistance, voltage, or charge.

$$SOH_R = [1 - \frac{R(eol) - R(internal\ resistance)}{R(eol) - R(o)}] \times 100\%$$
$$(12)$$

where,
R_{EOL}, End-of-Life Resistance of the battery
R_{IR}, Rated Internal Resistance of the battery

The **SOH_R** is the state of health internal resistance of the battery, R_{EOL} is the resistance of the battery to reach its end of life, and R_O is the rated internal resistance of the battery.

$$SOH_R = (\frac{V(noload) - V(load)}{R(eol)xI(measured)} \times 100\% \qquad (13)$$

The degradation of the battery is the decrease of the SOH over a period of time.

3.5Device setup
Figures 6 to 9 present the different views of the developed device for the proposed battery management system by the proponents. Dimensions are measured in terms of inches (in). The following figures show the integration of the material into a compact device.
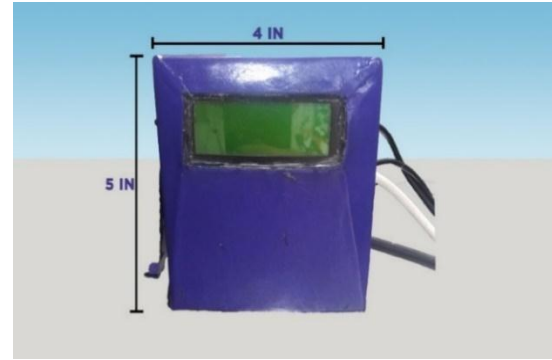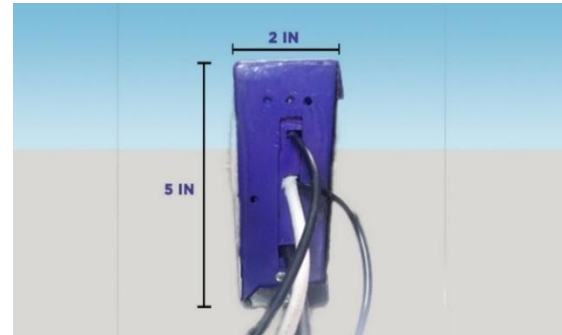

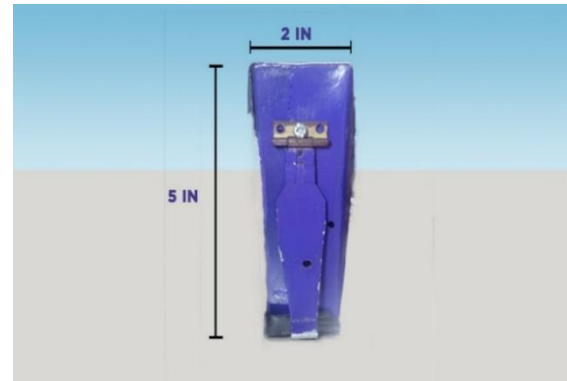**Figure 6** BattMan front view

Figure 7 BattMan right side view
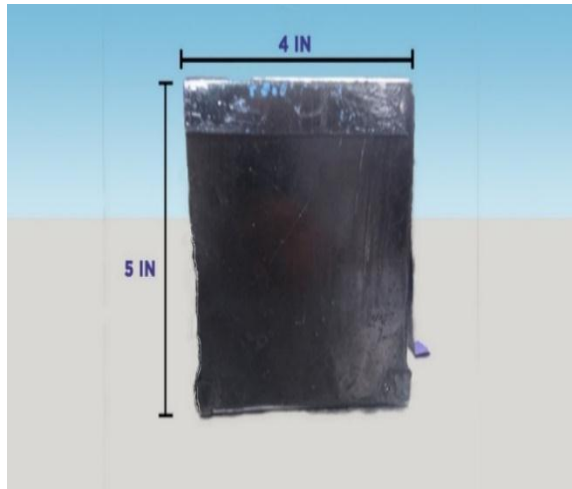

Figure 8 BattMan left side view

Figure 9 BattMan back view

4.Results
4.1Data and results

Table 1 and *2* are the two experiments between batteries using varied current. *Table 1* is the measurements with low current and *Table 2* is the measurements with high currents. The expected DOD upon experimentation from *Table 1* and *2* was 90%, 60% and 30%. However, strict monitoring on the

batteries became a challenge which is why the actual DOD gathered was slightly different than the expected. Listed also were the mean and maximum current from 1st cycle up to the 10th cycle.

Table 3 shows the third experimentation for State-of-Health and Depth of Discharge between BattMan 3M1 and BattMan 3M2. Also, the expected DOD upon experimentation was 90%, 60% and 30% but strict monitoring on the batteries was still a challenge due to enhanced quarantine protocol which made it almost the same as the second experimentation.

Table 4 shows the new sets of data like 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 voltage, no-load voltage, mean current, maximum current, maximum temperature, and DOD. From the five (5) sample batteries, five sets of data gathering/report were taken out based on a different age.

Table 1 First testing: state-of-health and depth of discharge

Battery		BATT MAN-N1	BATT MAN-N2	BATT MAN-N3
Decreased in SOH (%)	1st Cycle	0.09	0.09	0.09
	5th Cycle	0.09	0.08	0.09
	10th Cycle	0.08	0.09	0.09
Average DOD (%)		91.93	61.46	31.78
Average Current (A)		1.29	1.33	1.26

Table 2 Second testing: state-of-health and depth of discharge

Battery		BATTMAN-3M1	BATTMAN-3M2
	Report-1	0.14	0.18
	Report-2	0.14	0.16
Decreased in SOH (%)	Report-3	0.13	0.17
	Report-4	0.13	0.18
	Report-5	0.13	0.17
Average DOD (%)		60.46	91.18

Table 3 Third testing: state-of-health and depth of discharge

Battery		BATTMAN-3M1	BATTMAN-3M2
	Report-1	0.15	0.17
	Report-2	0.14	0.17
Decreased in SOH (%)	Report-3	0.14	0.18
	Report-4	0.14	0.16
	Report-5	0.13	0.13
Average DOD (%)		61.07	90.40
Average Current (A)		13.42	13.40

Table 4 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

4.2 Data of report

In addition to the indicator installed on the device with the data acquisition specification of the device the researchers developed a user interface to extract and interpret data from the SD card installed in the device. Stated technologies: MySQL and Python were used for interface development. The interface is programmed to diagnose the data for the prediction of EOL as presented on *Table 4*.

5. Discussion

Calculating the Remaining Useful Life of the e-vehicle battery in terms of cycle and time using SOHR is used, since the degradation of the battery is proportional to the number of cycles used. Cycles 1, 5 and 10 were chosen to serve as the initial, middle and final experimental setup. The first experimentation is to make a comparison of the battery's degradation; for BattMan1, BattMan2, and BattMan3, using low current. Each battery has a different average Depth of Discharge. In each battery, three (3) SOH samples were taken on different cycles. It is greatly observed that the Decrease in SOH is very little among the three batteries due to the small difference in current. Also, the big difference in the DOD among the three batteries didn't affect the Decrease in SOH.

The Second experimentation is about the measurement of battery degradation between BattMan1 and BattMan2 using high current. Just like the first experimentation, BattMan N1 had 60% DOD and BattMan N2 had 90% DOD. Both BattMan N1 and BattMan N2 are brand new but have undergone series of charge and discharge. For a better comparison of the said batteries, data were gathered simultaneously. It is observed that the SOH of BattMan N2 decreased greater than BattMan N1. With high current applied, the Decrease in SOH between the two batteries is different as well as DOD.

In the third experimentation, two used batteries (3-month old) were utilized. Both batteries also displayed different DOD like BattMan N1 and BattMan N2. The data gathered from the used batteries and the brand-new ones were almost the same. The measurement acquired was validated against a multimeter as no government body or private entity available for checking. Since the study is a pioneer in the battery industry, its reference or standards being followed are basically from a multimeter.

6.Conclusion and future work

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 showed in the data that DOD doesn't affect the battery life since the discharged current was 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. SOH still decrease no matter how efficient the battery was used. If the battery was discharged with a high current, the decrease in SOH is great and evident. The data showed that battery aging doesn't affect the decrease in SOH. The battery gets consumed easily as the SOH decreases continuously. In addition, the increase in the charge-discharge cycle of the battery contributed 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. It was confirmed that battery life was prolonged when the e-trike kept constant speed than speeding up then stopped and vice versa. It was observed that e-trike with varying speed consumes high current which greatly degrades the battery life. Also, overloading an e-trike experience is the same. The battery life was also prolonged when the difference between the ambient (external) and internal temperature was kept at 10 degrees Celsius. Not completely exhausting the battery and recharging it when 20% charge remains added to prolonging the battery life.

For further research related to this study, here are some of the recommendations from the proponents:

● Estimation of Remaining Useful Distance. The study only developed BattMan capable of predicting the Remaining Useful Life in terms of time and not what's left to travel.
● More sample data acquisition per second. The group had a hard time gathering data because of the pandemic.
● Testing of different battery capacities. Manufacturers have produced e-trikes of higher battery capacity for larger accommodation.
● Real-time data acquisition to the database using IoT. This study requires human force to ensure the security of data from the SD Card till it makes it to the database on the shop owner's personal computer.
● Coordinate trackers for e-trike.

Conflicts of interest
The authors have no conflicts of interest to declare.

References
[1] http://boi.gov.ph/wp-content/uploads/2018/03/Electric-Vehicle-Industry-Roadmap.pdf? fbclid=IwAR0y1Q-UnwulEIySuyKszxtV3uRhCoe_dDTYAQJhgu23CT05pM-zYiCGbhU. Accessed 30 January 2019.
[2] Buchmann I. Batteries in a portable world: a handbook on rechargeable batteries for non-engineers, Fourth Edition. U.S. Department of Energy Office of Scientific and Technical Information 2002:1-292.
[3] Lipschultz A. Batteries in a portable world. Biomedical Instrumentation & Technology. 2015; 49(2).
[4] Azzollini IA, Di Felice V, Fraboni F, Cavallucci L, Breschi M, Dalla Rosa A, et al. Lead-acid battery modeling over full state of charge and discharge range. IEEE Transactions on Power Systems. 2018; 33(6):6422-9.
[5] Burgos C, Saez D, Orchard ME, Cárdenas R. Fuzzy modelling for the state-of-charge estimation of lead-acid batteries. Journal of Power Sources. 2015; 274:355-66.
[6] Polis MP, Yin GG, Chen W, Fu Y, Mi CC. Battery cell identification and SOC estimation using string terminal voltage measurements. IEEE Transactions on Vehicular Technology. 2012; 61(7):2925-35.
[7] Diao W, Jiang J, Zhang C, Liang H, Pecht M. Energy state of health estimation for battery packs based on the degradation and inconsistency. Energy Procedia. 2017; 142:3578-83.
[8] Liu D, Xie W, Liao H, Peng Y. An integrated probabilistic approach to lithium-ion battery remaining useful life estimation. IEEE Transactions on Instrumentation and Measurement. 2014; 64(3):660-70.
[9] Hou ZY, Lou PY, Wang CC. State of charge, state of health, and state of function monitoring for EV BMS. In international conference on consumer electronics 2017 (pp. 310-1). IEEE.
[10] You GW, Park S, Oh D. Diagnosis of electric vehicle batteries using recurrent neural networks. IEEE Transactions on Industrial Electronics. 2017; 64(6):4885-93.
[11] Yang A, Wang Y, Tsui KL, Zi Y. Lithium-ion battery SOH estimation and fault diagnosis with missing data. In international instrumentation and measurement technology conference 2019 (pp. 1-6). IEEE.
[12] Dong G, Chen Z, Wei J, Ling Q. Battery health prognosis using Brownian motion modeling and particle filtering. IEEE Transactions on Industrial Electronics. 2018; 65(11):8646-55.

[13] Qu J, Liu F, Ma Y, Fan J. A neural-network-based method for RUL prediction and SOH monitoring of lithium-ion battery. IEEE Access. 2019; 7:87178-91.

[14] Stroe DI, Schaltz E. SOH estimation of LMO/NMC-based electric vehicle lithium-ion batteries using the incremental capacity analysis technique. In energy conversion congress and exposition 2018 (pp. 2720-5). IEEE.

[15] Topan PA, Ramadan MN, Fathoni G, Cahyadi AI, Wahyunggoro O. State of Charge (SOC) and State of Health (SOH) estimation on lithium polymer battery via Kalman filter. In international conference on science and technology-computer 2016 (pp. 93-6). IEEE.

[16] Dung LR, Wu SH, Yuan HF. An SOH estimation system based on time-constant-ratio measurement. In 23rd international symposium on industrial electronics 2014 (pp. 1784-7). IEEE.

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