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Internet of Everything (IoE) - Input Based Research Framework: Machine Learning Model for Battery Module Longevity Optimization and Failure Prediction

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Abstract: Battery storage plays a vital role in smoothing out the fluctuations in energy demand and generation from distributed renewable sources. Batteries are susceptible to various factors such as a change in temperature, charging cycles, etc. Power storage batteries are expensive, therefore various measures should be taken to make sure it is working in the optimal conditions, these batteries also fail during operations thus affecting the power demands. The research will investigate various machine learning approaches to optimize battery operations in domestic applications (Modules Longevity and failure predictions). Machine learning can help predict battery failure and optimize battery life by using reinforced learning, it is possible to make optimal battery charging and discharging decisions. It involves two methods: supervised learning, which trains a model with previously known input and output data so it can predict future outputs, while unsupervised learning, which finds hidden patterns and intrinsic structures within the input and output data (Temperature, Charging cycles, Voltage and Current). The research will involve extensive simulations and building machine learning models. The machine learning models are trained to capture a battery's state of health and to predict its remaining lifetime. These two concepts help to know when to recharge its battery as well as when to schedule battery module replacements. The outcome of the research will be reflected in the application of a smart power storage system for ideal self battery monitoring and optimization.

Keywords: *Machine Learning; Battery Optimization; Failure Prediction*

1. INTRODUCTION

The traditional off-grid power sources in remote areas in Malaysia are using gasoline-electric generators. They pollute the environment by producing noise and add up a substantial carbon footprint. These generators need periodic maintenance which is messy & oily. Its efficiency would wear off significantly throughout their service, they consume a significant amount of gasoline/petrol where the overall efficiency of a typical electric gasoline generator is about (10%-18%). This low efficiency is due to various mechanical working parts involved. At the same time as an alternative, for decades lead-acid batteries have been the dominant choice for electrical energy storage. They are bulky, heavy and sometimes release fumes. Lead-acid batteries cost ranges from medium to high depending on the quality, power density and output amperage. All lead-acid batteries have low energy density to weight ratio while having shallow discharge and low charging cycles, making them less ideal to be a practical portable electric generator. The conventional portable power generation system mostly depends on carbon-based fuel, leading to a higher carbon footprint and ecological pollution effect.

Moving towards a progressive and green nation, power storage is becoming prominently used to take advantage of renewable energy strategies, the demand of battery based power storage is not limited to only store stationary energy, it is also increasingly being used in the transportation segment such as Electric Vehicles (EV). As an example, major advancements in lithium-ion battery technology have been a game-changer where lithium-ions are now taking over the battery market.

Currently, in Malaysia battery power storage information monitoring systems were only used to monitor the power and battery voltage current stage throughout its service. Batteries' health are merely predicted by using only the voltage level. No substantial data showing the battery real life performance other than the specs sheet provided by the manufacturer. It is known that power storage batteries are expensive and difficult to maintain once they are fabricated. Battery cells do fail throughout their service without notice; this could lead to unwanted downtime and replacement cost. By identifying the cell which would fail can eliminate downtime by introducing preventive maintenance (replacing affected cells/modules).

This research will focus on how machine learning could assist to process huge pool of data to predict battery cell failure and furthermore optimize its lifespan.

2. OBJECTIVE(S) OF THE RESEARCH

1. Establish IOE database input for data collection during partial charge cycles to estimate battery capacity fade and monitor the real time state of health (SOH) of battery modules.

2. Develop the machine learning models through supervised ML algorithms which leverage the current and past SOH to predict battery modules failure and the module's Remaining Useful Life (RUL).

3. Optimization and real-time SOH monitoring of the battery modules using a reinforced machine learning model.

3. LITERATURE REVIEWS

In the early 1990s, lithium-ion battery technology was invented and allowed the revolution in portable electronics. The technology is now being developed for use in electric vehicles (EVs) and grid storage applications. Compared to traditional flooded lead-acid battery technology, lithium-ion battery technology is costly and thus has been intended for premium applications so far. (Marom et al., 2011) .

Nominal cell voltage is also an important factor as it determines the number of cells in series required to get the desired battery voltage and thus affects the cost of the battery (Kizilel et al., 2009). Because the application is for low charge/discharge rates for stationary energy storage, energy density and rate capacity are secondary factors for consideration.

In addition, tiny solar PV solutions such as the solar home lighting system (SHLS) are ideal for household and small business self-ownership (Mulder et al., 2010). Financial support from rural banks and microcredit organizations to handle SHLS's high upfront costs has been successful in implementing small solar PV solutions by clients from the bottom of the pyramid (BoP). Compared with kerosene burners, SHLS is cheaper to run, offers much better light quality and does not emit harmful gases. (Tsai et al., 2018).

As a means of transmitting energy, technological advances focused on electricity are central to our understanding of various forms of complex energy sources. ,On the one side, the concept of electricity developed by humans for electricity storage (the electric battery), has evolved. Since the beginning of this millennium, an energy transition has been underway, consisting mainly of a movement to replace big, fossil-fuel plants with renewable and distributed generation (IRENA, 2017). Increased volatility and ambiguity both in business transactions and in physical energy flows in the smart grid result from this ongoing transition. On the other hand, the first artificial (brain-like) network could be developed by one part of the scientific community based on the certain principle of electricity (Lin et al., 2013). While controversial, one part of this group believes that we are all electrical machines. Artificial intelligence, still under development, has now reported remarkable success using increasingly complex neural networks. To date, several interconnected layers are composed of all types of networks (e.g. electrical batteries and neural networks) (Dong et al., 2015). From a theoretical viewpoint, for their mutual benefit, we tried to bring the future electric battery and artificial intelligence closer (Ocran et al., 2005).

Energy is a limited resource which, due to recent efficiency and de-carbonization goals worldwide, faces additional challenges. More and more complex approaches are required to turn the electricity grid into a reliable, effective and scalable electricity network (Garcia-Valle & Lopes, 2013). Moreover, developments in urbanization and electrification show that the overall demand for energy will rise in the future, while the world's total electricity consumption is growing and renewable energy penetration is also increasing (Keiner et al., 2019). Therefore, the analysis of potential smart battery capabilities from literature in order to provide a device that can track, forecast, plan, learn and make decisions on local battery energy consumption and real-time output (Buennemeyer et al., 2008; Kim et al., 2013a, 2013b). These difficult battery problems were restricted to more basic research problems, such as: (1) how to obtain a more precise prediction method; (2) how to find an optimum schedule when an online learning task is performed; and (3) how to learn more automatically from multiple tasks.

Machine learning is a data analysis technique in which computers are taught to make decisions based on experience (Amari, 2016). This learning process uses calculation methods to ‘learn’. The algorithms adaptively boost their efficiency as the number of samples available increases (Silva & Zhao, 2016). Machine learning has become a critical strategy for solving problems with the rise in the quantity of big data. It includes two techniques: supervised learning, which trains a model with previously established input and output data so that it can predict future outputs and unsupervised learning, which seeks hidden patterns and intrinsic structures within the input data (Kotsiantis, 2007).

Supervised energy prediction — Different sub-fields were developed as prediction progressed. Depending on several complex factors, the problem of electrical demand forecasting can be called a nonlinear time series prediction problem as it is needed at different aggregation levels and at high resolution (Ahmad et al., 2018). Deep learning techniques are expected to improve prediction accuracy by being stochastic and enabling bi-directional connections between neurons as an evolution of neural network-based prediction methods.

Unsupervised energy prediction/ Optimization — The potential benefits of strategic optimization at the battery and aggregate level are developed in the second section, which does not include historical data from previous data (Chon et al., 2011). In addition, it is anticipated that a cost minimization issue could be resolved to cause real-time price responsiveness actions.

This research has the potential to enable the predictive control/maintenance of Li-ion batteries applications. Employing a machine learning approach with IOE application will be used to build predictive models for battery modules failure prediction. The approaches and tools will provide greater transparency into the current and future health of an operating battery cell, more cost-effective maintenance/control (M/C) strategies and improved safety, and opportunities for life extensions. The platform, if successfully implemented, will potentially lead to the development of a cost-effective, and highly reliable and safe energy storage solution.

4. FRAMEWORK AND RESEARCH METHODOLOGY

The study's framework is broken down into 3 parts, data logging, IoE linkage to cloud ML processing platform and Battery management optimization as shown in Figure 1.

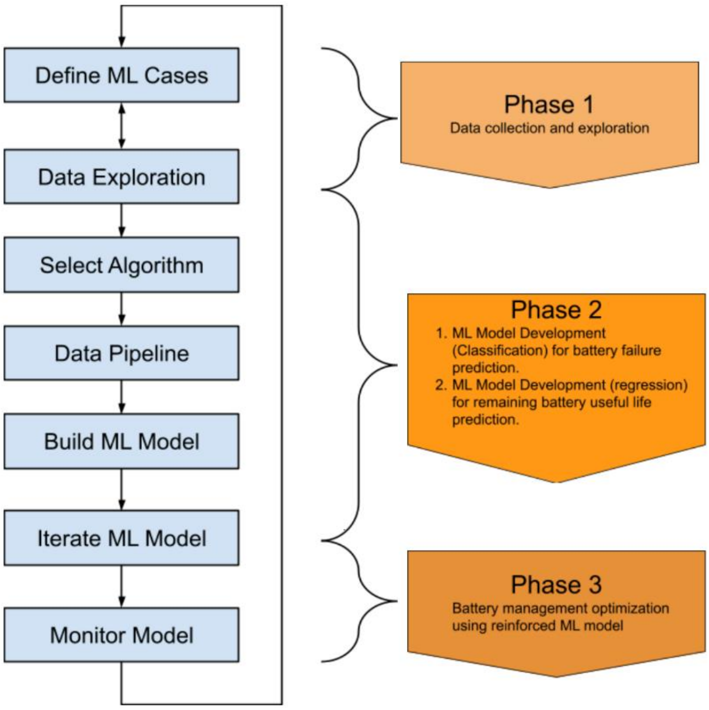

Figure 1: Phase 1 to Phase 3 of the research

Phase 1 : Data collection and exploration.

Data collected from IoE signal from sensors (continuously). Data gathered are (voltage, capacity, current, temperature) as shown in figure 2. This is time series data collected from sensors through a data pipeline (bigdata). The data obtained is in good fit, data cleaning would probably be required. Cleaned data will then be used to build the algorithm model.

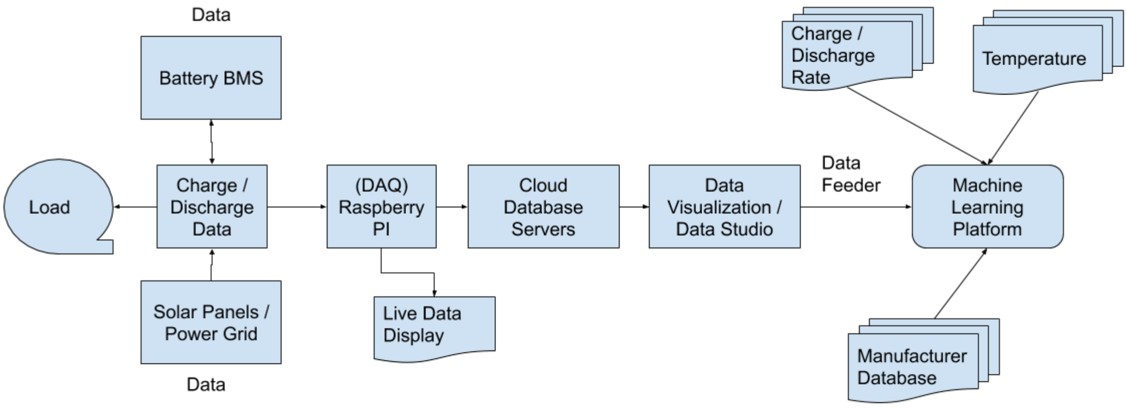

Figure 2 : Framework of IoE battery ML monitoring system.

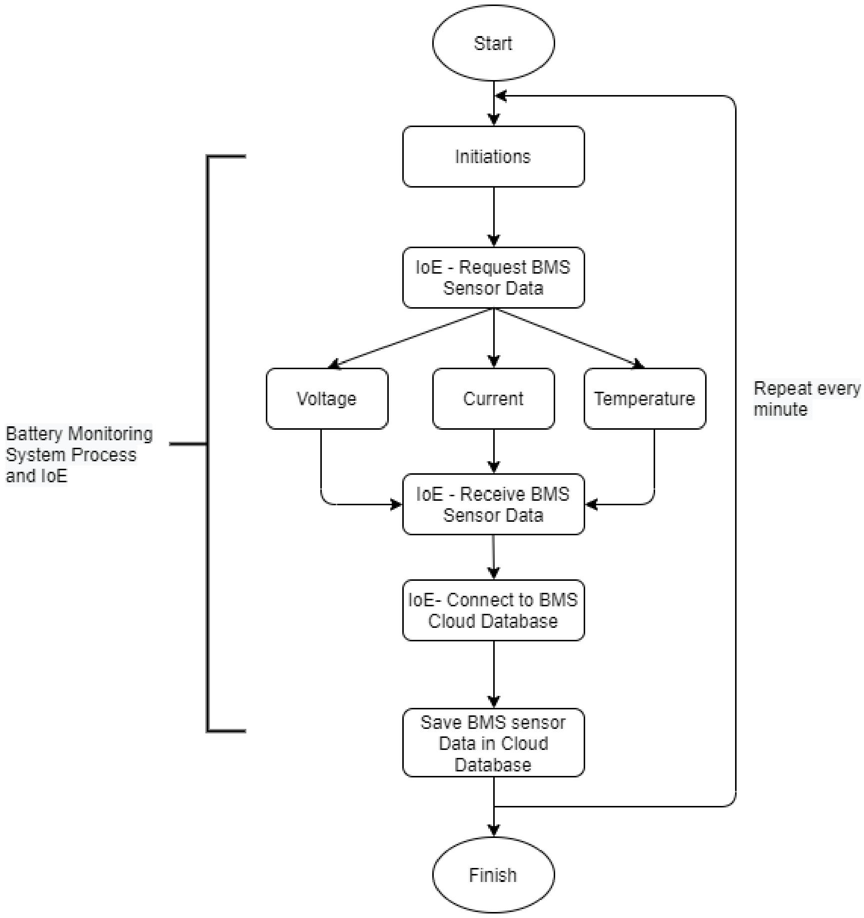

Fig 3 : Data Acquisition algorithm of battery monitoring system in IoE

A Raspberry Pi, where its primary role is to perform data acquisition, and as an Internet gateway to the cloud server, is the embedded system used as an IoE in this job. In the embedded voltage, current and temperature battery device shown in Fig.3, the data acquisition algorithm is implemented using a PHP server. The PHP executes a data acquisition program that uses Python to extract BMS battery calculation and store it in a cloud database and then upload it to send BMS-IoE data to the cloud server.

Phase 2 :

There are 2 possible ML techniques under supervised learning that could be used to evaluate, they are called Classification and Regression.

Classification ML converts failure signals into “label classification” to develop the ML model. This algorithm will predict which battery model would fail. It creates the right features from raw data for the ML task. We might be getting different hours every week. When a battery module actually fails, that is the final label. That is the failure data. So that is the positive label. And remaining data becomes the negative label, depending upon the use case, how far to predict the failure, it will tag the period before failure as the label. An algorithm will be selected, a data pipeline is built, and after applying the algorithm, we’ll have a model.

While Regression ML techniques convert degrade signals into unique labels. This algorithm will find/estimate the lifespan/longevity of the battery and predict what is the remaining life of the battery, it will develop a deep learning model where we have a final failure and the sensor data. Data at various places, like for example, how the signal was looking at 20% life, at 40% life, at 60% life, etc to get the accurate model.

Phase 3:

Optimization will use reinforced learning to apply iteration algorithms from either classification or regression models (or possibly combining both models). The algorithm will be deployed to optimize & real-time SOH monitoring.

5. CONCLUSION

This research has expected to enable the predictive control/maintenance of Li-ion batteries applications. Employing a machine learning approach with IoE application will be used to build predictive models for battery modules failure prediction. The approaches and tools will provide greater transparency into the current and future health of an operating battery cell, more cost-effective maintenance/control (M/C) strategies and improved safety, and opportunities for life extensions. The platform, if successfully implemented, will potentially lead to the development of a cost-effective, and highly reliable and safe energy storage solution.

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