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Real-Time Monitoring of a Lithium-Ion Battery Module to Enhance Safe Operation and Lifespan †

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Abstract: Lithium batteries are characterized as the heart of every electronic device introducing a plethora of benefits like high energy density and durability without the need for maintenance However, lithium cells suffer from increased temperatures caused by high voltage and peak loads. These operating conditions lead to lithium deposition and partial electrolyte decomposition, limiting the total capacity (State of Health) or even causing a possible breakdown. Hence, consistent monitoring is essential to ensure maximum lifespan without risking safety. In this paper a compact module consisting of three batteries is introduced to gather values like temperature, voltage and current, all transferred to an online server and monitored through the Grafana application. Tests indicate that temperature is very high after power output increased stress to the battery components. To further project this pattern, two distinct sets of batteries were applied for testing with the use of different power states, like 2.5 increased power output with voltage drops. Results show that high power output, on the second set limited state of health, is increased by an additional 5%, while the battery was highly stressed within the manufacturer safety zone.

Keywords: Battery; Monitoring; Safety; Temperature; Power;Mmodule

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1. Introduction

Since the invention of the first accumulator, battery technology has progressed rapidly throughout the years. From alkaline nickel-cadmium (Ni-Cd) cells to rechargeable lead acid and Lithium-ion Batteries, each type provided specific advancements to power any electronic device [1]. Lithium batteries are now widely adopted as they inherit a plethora of advantages including high energy density, low self-discharge rate, without the need of maintenance. Therefore, they are the perfect choice for modern electronics like laptops, smartphones, drones and electric vehicles [2]. They consist of a positive (anode) and negative (cathode) electrodes with an electrolyte for ion transfer and a separator layer to avoid short-circuit and total breakdown. Hence lithium cells are easy to manufacture, with limited weight for applications that must be compact and robust like electric vehicles or monitoring tools.

Unfortunately, lithium battery technology has its limitations. Increased temperature caused by high current due to peak loads and the need for fast charging, is considered a great flaw. Lithium dendrites are formed inside the cell causing the maximum capacity or state of health (SoH) of the battery to decrease [3]. In addition, constant operation above the operational limits can lead to partial electrolyte decomposition or even a possible breakdown. Hence, battery values like voltage, current, capacity and temperature, inside and out of the cell, must be monitored regularly, to ensure safe operation and escalated life cycles, a parameter that determines the lifespan of the battery [4]. These parameters may be used to calculate valuable values like [5–7]:

- State of Voltage (SoV), to be merged with state of charge
- State of Health (SoH), and
- Depth of Discharge (DoD)

SoV can be used as an alternative to state of charge to indicate the current capacity of the battery while State of Health reflects the maximum capacity of the cells at any given time [7]. Depth of discharge shows the percentage exploited after each use, for example if the battery was charged at 80% and discharged to 20%, the DoD rate is 60%. High DoD can lead to excess stress of the cells which has to be avoided to enhance battery lifetime [8]. Since voltage is constantly monitored, capacity can be easily calculated by utilizing the state of voltage value and then the other two values are computed to determine the battery state to maximize longevity as a diagnostic tool.

Monitoring of these criteria is crucial, as it provides an easy and adequate scheme to diagnose battery status. Low state of charge enhances battery stress as the operation below 20% charge can lead to increased temperatures through operation causing lithium deposition limiting State of Health [9]. On the other hand, operation at high SoC limits, induces stress to the electrolyte and separator that may cause additional damage or breakdown. This effect is also connected with high DoD where, as stated by literature and previous works, has to be retained within 20–80% limit for maximum efficiency and lifespan [7,10]. In previous work a compact module was introduced, based on Arduino that monitored a single cell through a 10 s time rate [11]. Results showed that low DoD and current output lead to SoH preservation after 50 cycles with limited losses and operation at temperatures way below the maximum limit of 40 °C.

This paper is the next step of the project presented at Design and Development of a Low-Cost and Compact Real-Time Monitoring Tool for Battery Life Calculation [11]. Its aim is to establish a larger module based on Arduino Platform. Three lithium batteries are equipped, with a voltage and temperature sensor and a common current sensor each. Cells array are connected in series, to provide a typical value of 12 Volts which is widely applicable at mobile applications. Output temperature and load voltage-power are also introduced in the assembly, while a five second frame is selected for faster and precise diagnosis through the Arduino device with additional automations. All values are transferred through Wi-Fi to an application server for real-time monitoring. Hence the connection between SoV and depth of discharge parameters to battery aging will be investigated.

2. Materials and Methods

2.1. Experimental Layout

For the experiment to be held, it was necessary to implement a board to enclose all components involved in the measurements. The heart of the system is the microcontroller ESP32 Devkit v4 while the CPU is the Xtensa dual-core 32-bit LX6 microprocessor, operating at 240 MHz [12]. It was selected as it well sized unit with a very high processing power plus a plethora of ports (16 analog with 12-bit analog to digital converter and 30 digital ports). Additionally, communication protocols such as SPI, UART, I2S, I2C are supported. The microcontroller includes transmission, wireless networking (Wi-Fi) and Bluetooth protocols, programmed using the user-friendly Arduino IDE programming environment. In low-cost microcontrollers, energy efficiency is feasible according to the work [13], which constitute an important factor in mobile applications.

A simple 3S Battery Management System (BMS) with a 25 Amps Li-ion Battery Protection Board is exploited as shown in Figure 1, to manage the power energy of three 18650 batteries [14]. Samsung INR18650-30Q batteries are selected with a capacity of 3000 mAh and a nominal voltage of 3.7 volts, connected in series for a total of 12 V. From the BMS the voltage of each battery is obtained by using a resistor network and a trimmer to micro-adjust the voltage divider. The voltages of the batteries are sent to the analog ports of the microcontroller.

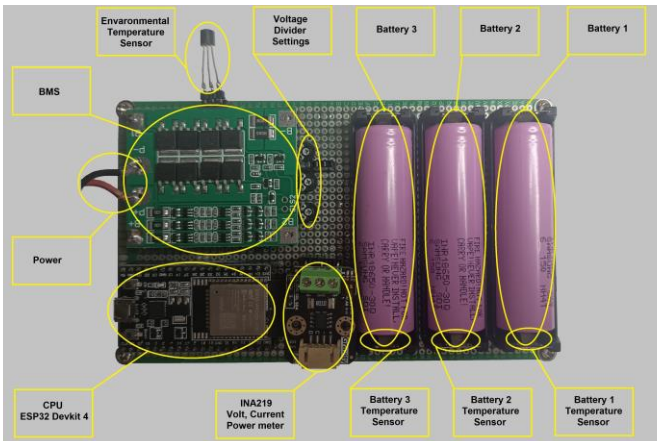
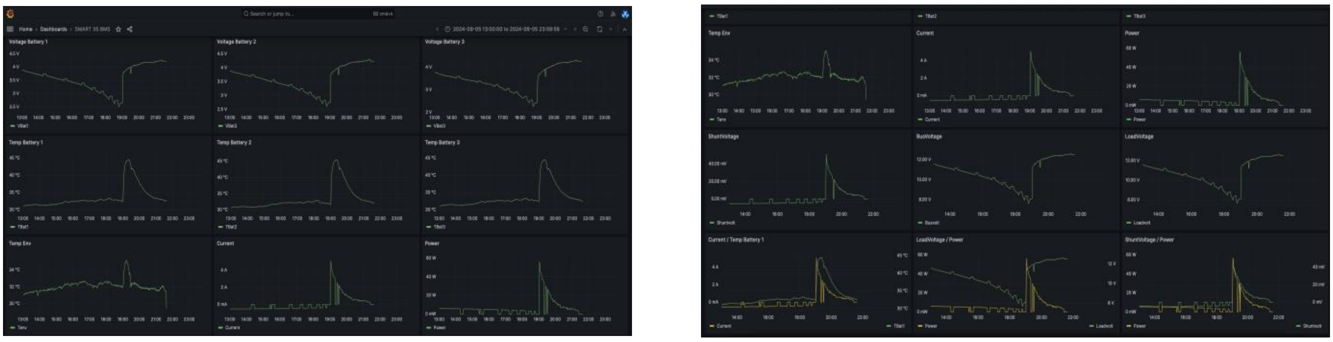


Figure 1. Layout consisting of the battery board, current and voltage collectors, NTCs and the Arduino device.

A power-meter device based on the INA219 integrated circuit, measures the total voltage and current of the DC Bus transferring the information to the controller via the I2C protocol [15]. A DS18B20 temperature sensor is installed at each battery negative pole to record the temperature variations during charging–discharging. In addition, a similar temperature sensor is placed opposite the batteries to measure the ambient temperature. The temperature sensors transmit the measurement data by means of a 1-Wire protocol while the microcontroller sends the measurement data to the database every 60 s, using an HTTP POST message, via Wifi [11].

The microcontroller is connected to all the devices on the board, as its function is to take readings from all of them and send them to a central server for collection and data logging. The information system is based on a Linux operating system, while the applications run through the open source influxDB database and Grafana visualization software, with constant access and csv file export is selected [16]. Figures 2 and 3 show the visualized data at the Grafana User Interface.



(**a**) (**b**)

Figure 2. All fifteen parameters monitored and visualized through the Grafana Interface. Specifically, the following values are available: (**a**) Battery Voltages and temperatures (**b**) Ambient temperature, Bus Current, Voltage and Power and various juxtapositions.

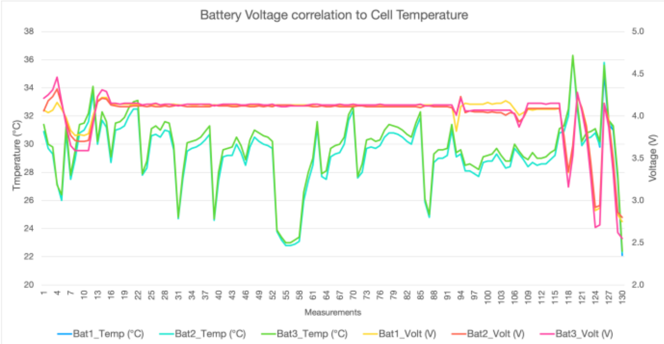


Figure 3. Battery fluctuations for the 3 battery cells in correlation to internal temperature.

2.2. *Battery Parameters Calculation*

Temperature and current values are used separately to observe the stress applied to each cell. Also, all values collected, are exploited to calculate the battery operation parameters like State of Voltage, state of health and Depth of discharge. As these parameters are typically hard to calculate due to the requirements of complex strategies like neural networks, certain rules are applied in this work for simplification [17,18]:

- SoV equals to the ratio of monitored voltage divided by the nominal value;
- SoH defines as the battery maximum voltage as manufactured, divided by nominal;
- DoD is manually computed, as the SoV difference before and after each use.

The following equations are utilized to calculate all three parameters:
For State of Voltage:

$$\text{SoC} = \frac{V}{V_{RATED}} \quad (1)$$

For State of Health:

$$\text{SoH} = \frac{V_{MAX}}{V_{RATED}} \quad (2)$$

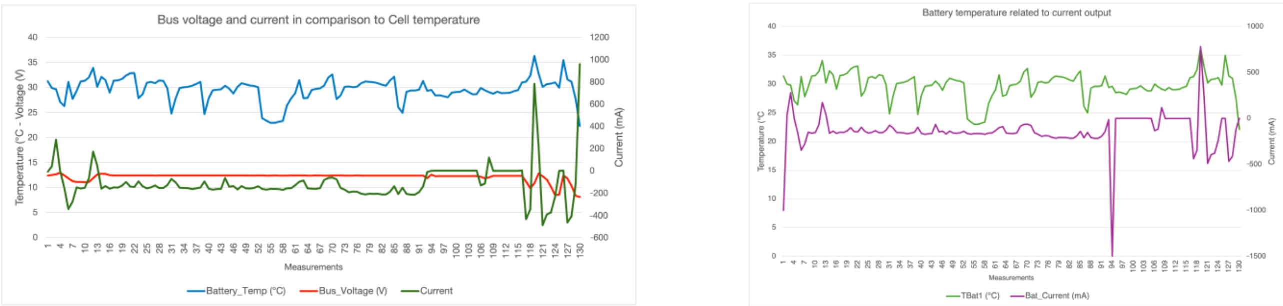
For Depth of Discharge:

$$\text{DoD} = \text{SoV}_{\text{END}} - \text{SoV}_{\text{START}} \quad (3)$$

3. Results and Discussion

Over 20,000 measurements were collected over a monthly period, with testing taking place in the province of Agia Paraskevi in Athens, Greece. To validate the performance and accuracy of the BMS, each battery temperature and voltage was recorded so that proper charging is ensured as shown in Figure 3 above.

The next step is the correlation between cell temperature with bus voltage and current. Both voltage and current are connected to cell temperature but unrelated to each other. Only as current increases, a voltage drop is noticeable, however its variation is directly associated with fluctuations on cell temperature, as noticed in previous work [11]. Depth of discharge on each test varied between 20% and 60%. This is until the control module shuts off due to low voltage. Both at the DC bus and each battery separately results were similar. So, to avoid high stress on the battery, temperature must be balanced as it can be seen in Figure 4 below.



(**a**) (**b**)

Figure 4. Correlation between cell temperature with battery voltage and current variations on two separate Measurements: (**a**) DC Bus; (**b**) Battery cell No.1. The negative values signify that the batteries are being discharged show the INA219 detects a loss of power at the energy storage.

Lastly, the need to control battery temperature is seen at Figure 5 below. Despite the fluctuations of power and voltage, cells operate within their optimum temperature (20–30 °C). Batteries were fully charged and a step of 0.5 V was exploited with a small break to see the differences of battery state when the electrolyte becomes stable again after several seconds. Power output reaches 12 W leading to a 10 °C battery temperature increase, with adequate voltage drop. Afterwards it drops steadily, and cell internal temperature is normalized. This pattern continues until DC Bus reaches 9 V, where it is shut off by the microcontroller. All small power spikes are controlled, and the battery is protected not to get too warm, avoiding high stress. However, in situations like EVs where high power is required, cooling is essential, otherwise lifespan can be massively reduced.

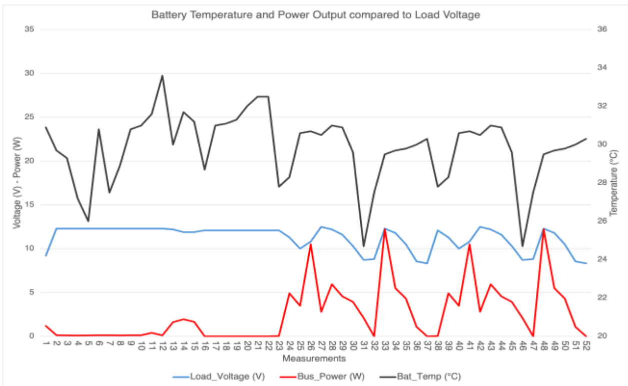


Figure 5. Battery temperature is highly affected by power spikes leading to voltage drops.

Two different sets of batteries were utilized to test different operating conditions. Different depth of discharge and power output scenarios were applied to measure the battery stress via State of Health parameter. Battery set No.2 showed a 6% drop in state of health with the same DoD range but with 2.5 times the power applied. All results are summarized at Table 1.

Table 1. Battery parameters for the two different set of batteries tested.

Parameter	Bat_Set No.1	Bat_Set No.2
Maximum Power	12 W	30 W
State of Health_Before	100%	100%
State of Health_After	99%	94%
Depth of Discharge [1]	20–60%	20–60%

[1] Typical DoD range achievable due to layout limitations.

4. Conclusions

In this work, a compact and affordable module has been introduced for lithium battery monitoring through a web app platform. Different values like cell temperatures, voltages and current were gathered to calculate various parameters like State of Health. As stated in previous work [11], stress on the battery is mainly applied by high currents during charging or discharging leading to increased temperatures hence lithium plating and capacity loss. Two sets of batteries were tested with different power outputs. Results reveal that high power on the second set of cells led to 5% bigger drop in state of health and high voltage variations hence stress was increased, but still inside the safety zone. Further work is based on a more advanced monitoring system focused on a rule-based strategy, that will allow the battery to operate in the safe zone. Thus, safety conditions are always satisfied, and battery longevity can be increased for maximum performance towards the goal for minimum waste.

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