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Design and Validation of Battery Management Subsystems for High-Performance EV Batteries: A Tesla Model S Case Study

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***Abstract*—This article presents the creation of a simulation environment for a Battery Management System (*BMS*) using SIMULINK. The environment is then paired with a Tesla Model S battery, and the *BMS* is simulated under different conditions to test the *BMS* algorithms. The simulation covers core *BMS* functions such as State of Charge (*SOC*), charging control, thermal management, State of Health (*SOH*), and Controller Area Network (*CAN*) communication, while prioritising battery safety and minimising user risk. The system was tested under various conditions, and the results confirmed the ability of the system to respond as expected, meeting the design objectives.**

Keywords*—*battery management systems, electric vehicles, lithium-ion batteries, Simulink, state estimation, passive balancing, thermal management

I. Introduction

In Electric Vehicles (*EVs*), batteries serve as the primary energy source powering the vehicle. Numerous battery technologies have been developed; however, the core battery schematic remains unchanged despite technological advancements. A battery is an electrochemical cell in which voltage is generated between its terminals due to the potential difference between the cathode and anode. Ongoing research continually aims to achieve higher power density, extended longevity, and reduced failure rates [1].

The most widely used battery technology in *EVs* is lithium-ion. Lithium-ion batteries offer high energy density, storing energy at a much lower volume compared to other types-up to 3800mAh per gram of lithium. They also exhibit the longest lifecycle among battery technologies. This high energy density and extended service life makes lithium-ion batteries the standard for *EVs*, as greater range and lower maintenance are advantageous for both consumers and manufacturers.

Battery performance and efficiency are influenced by several variables, including charging current and voltage, charging duration, self-discharge rate, cell temperature, discharge rates, and the frequency of charge-discharge cycles. To manage these factors, battery cells are integrated with a Battery Management System (*BMS*). The *BMS* ensures optimal battery operation by monitoring and managing cell performance through multiple subsystems, each with a defined role.

BMS is essential for battery safety, longevity, and user protection via fault management and thermal regulation. It operates by sampling battery and environmental data, processing it, and generating appropriate control signals. The most common *BMS* subsystems include state estimation, cell balancing, charging control, communication, and thermal management [2].

II. Battery Management Systems

A. Battery Modelling

Battery modelling refers to building an equivalent battery cell for use in simulation environments. Accurate modelling is crucial for reliability of *BMS* simulation since all sampled inputs by the *BMS* are provided through the battery model. Various battery modelling methods have been developed such as the equivalent circuit model, electrochemical model, neural network model, and the data driven models. The most popular model is the Thevenin model circuit, shown in Figure 1. The model considers the capacitive and resistive properties of the battery cell. Uocv represents the open-circuit voltage of the cell, RΩ is the battery cell resistance, Rp and Cp are connected in parallel to describe the cell's overpotential. All the mentioned parameters are a function of the state of charge and cell temperature. The model has high adaptability as more RC branches can be added to increase accuracy [3].

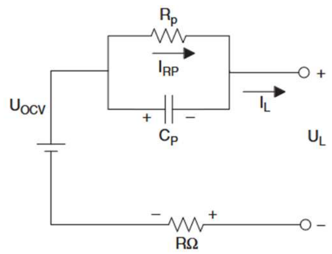

Fig. 1 – Thevenin Circuit Model [4]

B. Battery State of Charge and Health Estimation

1) State of Charge Estimation:

State of Charge (*SOC*) is the remaining capacity of the battery as a percentage of the total capacity available. It is also an indicator of when to charge the battery. It is measured in Ampere hours (Ah) or percentage. Coulomb counting and Kalman filters are popular methods for *SOC* estimation. Coulomb counting states that the current *SOC* is a function of the initial *SOC* and the charge difference between specific time intervals. An accurate calculation of the initial *SOC* is vital for accuracy. Accurate current measurement is also vital for accurate *SOC* estimation. A downside to this method is the dependence on the initial *SOC* which can have a high error percentage [4]. Kalman Filters are a set of algorithms that utilise measurements-such as voltage, current, temperature, and internal resistance-obtained over time, including measurement noise, to estimate the state of charge (*SOC*). The algorithm operates in two main phases: a prediction phase and an update phase. During the prediction phase, the Kalman Filter generates estimates of the current state variables. Once the next measurement is obtained, the estimates of the state variables (*SOC*) are updated using a weighted average. This process continues iteratively in real time. Due to the non-linearity of battery cells, a linearization step is required for the Kalman Filter to maintain accurate estimations.

2) State of Health Estimation

State of Health (*SOH*) is an estimation of the total capacity available in a battery with reference to its total capacity when manufactured. It is used as a measure of battery degradation. *SOH* can be estimated through the changes in cell internal resistance, and data driven methods.

C. Charging Control

Controlling the charging process protects the battery and the user from hazards such as fire. It is also crucial for ensuring an efficient and prolonged battery life. Charging control regulates the charging current to prevent overcharging, delivers appropriate voltage and current level, and implements specific charging profiles based on battery type and use case [5].

The most popular charging methods are constant current (*CC*), constant voltage (*CV*), and the constant current-constant voltage (*CC-CV*). In *CC* charging, the battery is charged with a low constant current. A limitation of using *CC* is finding the correct charging current that optimises speed and capacity utilisation. In *CV* charging, the battery is charged by applying a constant voltage, however this method can cause over-voltage at the cell terminals resulting in undesirable effects. Additionally, *CV* requires high current to maintain a constant terminal voltage when charging the battery at low *SOC*. *CC-CV* is a hybrid approach that utilizes both approaches to gain their benefits. An algorithm is produced such that the battery is charged using constant current at the start until a certain terminal voltage is reached, then the battery continues charging using constant voltage until a minimum current is reached. The total charging time is based upon battery capacity, and the value of charging current. Figure 2 shows *CC-CV* charging with respect to time.

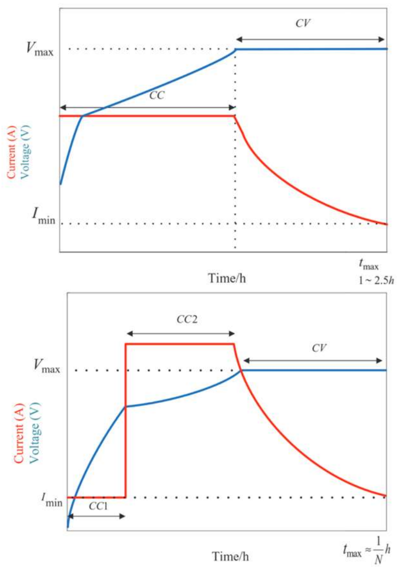

Fig. 2 – CC-CV Charging Graphs [6]

D. Cell Balancing

In a battery pack, cells are connected in series, parallel or a combination of both. Each cell has its own characteristics due to manufacturing differences, or operational environments that cause different rates of degradation [4]. Cell inconsistencies cause degraded charging and discharging where fully charged cells limit charging capacity for the less charged cells, and similarly this occurs during discharging as well. Limited output power is also a consequence since the maximum available current is limited by the cells with minimum *SOC*. Additionally, different state of charges within a pack causes *SOC* estimation to be more error prone. To overcome the inconsistencies and equalize cell SOCs and voltages, cell balancing is implemented. There are two types of balancing: Active and Passive Balancing.

Active Balancing equalizes *SOC*'s across the battery cells in a battery pack by using the higher *SOC* cells to charge the lower *SOC* cells. This is achieved by using capacitors, inductors, or power electronics with control algorithms. Figure 3 shows two different circuit schematics for active balancing using capacitors and inductors, respectively. The designs are scalable to accommodate larger packs. Capacitor-based topology offers easier control but requires long balancing time. Inductor-based topology has the highest efficiency but requires complex control algorithms. Active balancing is the more complex method with higher cost and component count, but offers much better efficiency than passive balancing, and is ideal for high power applications [7].

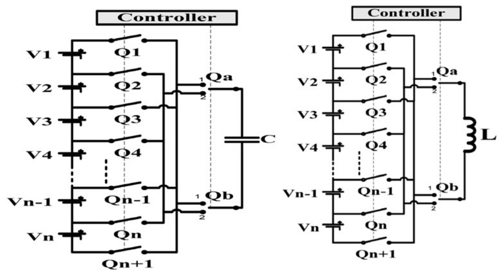

Fig. 3 – Active Balancing Schematics [7]

Passive Balancing uses resistors to equalize the *SOC* across all cells by dissipating energy from higher *SOC* cells through resistors. Shown in Figure 4 is the circuit schematic utilizing switched shunt resistors and MOSFETs to control which cells are to dissipate through which resistor for the required balance. This method is easy to implement and allows for simple control algorithms based on *SOC* and voltage, however there are various losses as well as a bulkier circuit due to MOSFETs and control circuitry. Passive balancing is deployed in low power applications which will result in a lower current environment hence low overall loss [7].

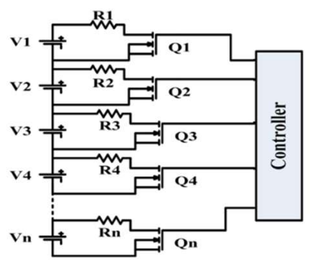

Fig. 4 – Passive Balancing Schematic [7]

E. Data Communication

The *BMS* data must be communicated to a vehicles' Electronic Control Unit *(ECU)* which enables monitoring, system diagnostics, and optimization management. The communication allows for commands such as limiting current, start cooling process, and more. There are various communication protocols that are used. The choice depends on the required data rate, physical distance, cost, reliability, and power consumption. Controller Area Network (*CAN)* Communication is the most popular protocol. *CAN* is a multi-master serial bus protocol. Multiple nodes transmit data on the same bus without a master node, which makes the system stable and still function when a node fails. It also supports multi-drop where it can support multiple devices on the line. *CAN* offers high reliability, advanced error detection, robustness against Electromagnetic Interference which is vital in *EV*, and high data rates [8].

F. BMS Implementations

As battery systems grow, *BMS* implementations vary. The implementation method depends on the system requirements, battery cell count, and future system scalability. There are three types of implementations: Distributed, Centralized, and Modular.

Distributed *BMS* implementation integrates *BMS* functionality directly at the cell level, where each cell or a group of cells have their own *BMS* module. The individual *BMS* modules are referred to as nodes. Each node monitors and balances its own cells that are connected to it. The nodes are then all connected to a central bus through *CAN* communication. Each nodes operates individually but the communication is necessary to communicate the overall system performance and state. This method is used in large high voltage batteries used in energy storage systems.

Centralized *BMS* implementation has one *BMS* module that controls all the battery cells of a system. This singular module is responsible for monitoring and managing all the cells in the system and providing all the functions mentioned earlier. This implementation method is widely used on small battery cell count commercial products [9] [10].

Modular *BMS* partitions the battery cells into multiple identical modules. (A 36-cell system would be split into 3 modules where each module contains 12 battery cells. Each module would get its own *BMS* sub-module). Each *BMS* sub-module is connected to a central master *BMS* module with the main controller which controls the functions of the sub-modules. The sub-modules are responsible for voltage, current, and temperature monitoring as well as executing functions sent from the main controller. The main controller focuses on higher level functions such as isolating faults, calculating overall *SOC* and *SOH*, charging control, and communication. Modular *BMS* is used in medium to large sized battery systems.

III. MATLAB SIMULINK SIMULATION

A. Battery Modelling

The chosen Tesla Vehicle is the Tesla Model S. The Model S was chosen as it uses the Panasonic 18650 cells for its battery, which MATLAB has all its cell characteristics and data parameters built in, so the simulation data is to be of high accuracy [11].

The Model S pack is modelled using the built-in MATLAB battery builder app. Figure 5 shows battery creation workflow. The app exports a Simulink battery model that outputs *SOC*, cell current, discharge cycle count, cell temperature, and cell voltage. Alongside the electrical connections are thermal related connection ports such as "Fluid In" for liquid cooling to the battery pack. The battery pack is shown in Figure 6. Exporting the battery pack also exports a ".m" file where battery initial conditions and parameters can be manually tuned and controlled.

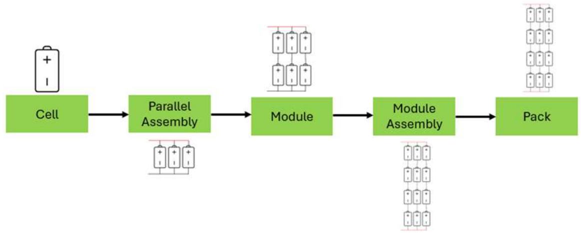

Fig. 5 – Battery Pack Creation Workflow

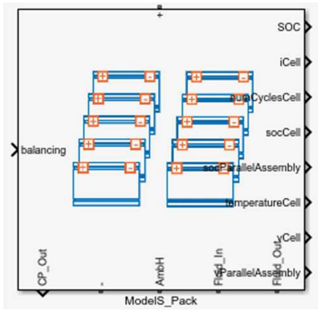

Fig. 6 – Exported SIMULINK Battery Model

B. BMS Electrical Components

Firstly, the battery charging control module and algorithms are designed. Data has been compiled from the real vehicle based upon user testing regarding the vehicle's reaction to different currents and voltages at different temperatures and SOCs. Overall, charging current has been made to be a function of the charger voltage, cell temperature, and cell *SOC*. Cell *SOC* has the highest priority in determining the charging current, then cell temperature, and then charger voltage. The algorithm has also been designed to support multistage *CC-CV* to save on battery life and promote longevity. Multistage *CC-CV* is normal *CC-CV* with n stages where current slightly increases after 1/n *SOC* level. *MCC-CV* brings benefits such as reduced charge time, reduced cell stress, and an efficient charging process.

For *SOC* estimation, the built-in Simulink coulomb counter block is used. The Kalman filter would have been used, however it requires inputs of battery parameters such as internal resistance which the created Simulink battery model does not provide.

For *SOH* estimation, SIMULINK has an *SOH* estimator block that calculates the *SOH* based on the terminal resistance changes as the battery ages, however the block cannot be used with the model since the battery model does not report terminal resistance changes. A formula and curve fitting method will be used to estimate the *SOH* based upon the discharge cycles. The graph has been compiled from user data and public surveys for the Tesla Model S. The trendline of the user data graph will be used to estimate the *SOH*. The trendline is a second order formula

Whilst building the battery pack, the option to incorporate passive cell balancing was turned on, adding a shunt resistor with a control signal to each module. When high, the modules discharge themselves through the shunt resistor. Within the passive balancing block, a threshold for the voltage differences has been set as 0.002V. The balancing output command is connected directly to the battery pack. Finally, the shunt resistance value can be set within the battery parameters .m file. By default, it is set to 50 Ω, but it has been changed to 2 Ω to speed up the balancing in simulation.

C. *BMS Thermal Management System*

BMS is also responsible for the thermal management of the battery to maximize safety, efficiency, and longevity. The Tesla Model S cooling system will be modelled, adding a radiator, reservoir, and a pump. Algorithms will be created as required to link the flow rate and coolant temperature to the battery pack temperature. Figure 7 shows the Tesla Model S Thermal Management System (TMS) in a simplified manner focusing on the battery loop only. A heater has been added to the simple model that will be required to heat up the battery in instances where the vehicle has been parked in a subzero weather and needs to be warmed up to allow battery discharge.

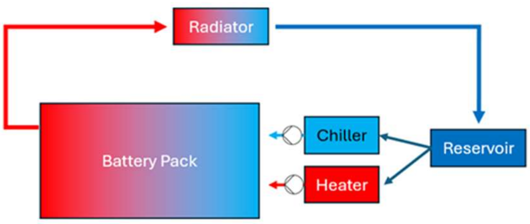

Fig. 7 – Tesla Model S Simplified *TMS*

The radiator is simulated using Heat Exchanger (TL-MA) block. The liquid cooling pipes are input on one side, and on the other side is cold moist air that simulates cold air falling on the radiator from a condenser fan. The reservoir is Modelled using a Controlled Volume Chamber block, with an 18L volume to match the Tesla Model S. The Heater/Chiller part is modelled using the "H" port of the "reservoir" where the reservoir temperature can be modified, which is a simple effective way of modelling the radiator effect. The temperature is controlled using a MATLAB function heating and cooling the reservoir when the battery temperature is below 5° C and above 40° C, respectively. Figure 8 shows the full MATLAB *TMS*.

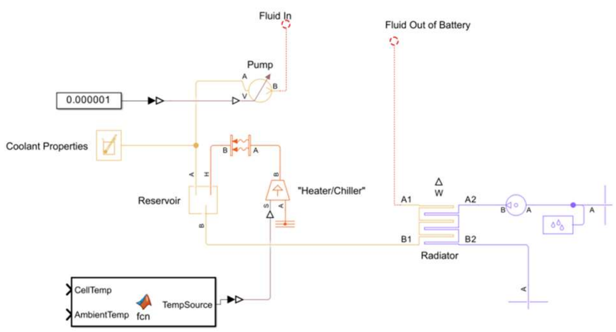

Fig. 8 – Tesla Model S Simulink *TMS*

IV. Results and Discussion

As the simulation environment has been finalised, two tests will be conducted to determine the designed *BMS* effectiveness.

The first test is conducted where the cells temperatures are set at 40°C and an ambient temperature of 45°C. The battery pack is charged at 480V mimicking charging the car in a station on a very hot summer day. Figure 9 shows the results where it took the vehicle 3.5 hours to fully charge, which is longer than typical but expected due to hot weather. Figure 9 shows the temperature (top graph) and charging current (bottom graph) with respect to time. As expected, due to the hot weather, the charging current is lower than expected, where it was not sustained at 200A. The Multistage CC-CV charging can also be noticed where the different stages linked to *SOC* can be noticed.

These results show the effectiveness of the *BMS* to keep the battery operating in a safe region at the harsh environmental conditions the battery is put at.

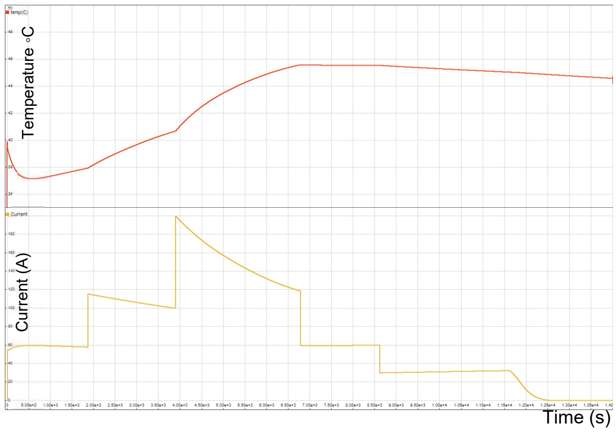

Fig. 9 – Test Run 1 Results

In the second test, the SOCs of the modules are randomized between 95% and 100%. The cells are set at 7°C wintry weather and are discharged then charged multiple times. The balancing, charging, and the heating are assessed in this test.

Figure 10 shows the current, *SOC*, temperature, and balancing graphs with respect to time. Initially for the first 2 hours, the pack was at standby as evidenced by the 0 A current and 100% *SOC*. During that time, balancing was in action as well as the heater as evidenced by the rising cell temperature graph. The pack is then discharged at a constant -120A current, then charged. The cycle is repeated four times. The cooling effectiveness and Multistage *CC-CV* charging is evidenced and clear where the current curve is linked to *SOC* and temperature. The temperature of the packs does not exceed 37° C during charging. The cooling is more effective during discharging.

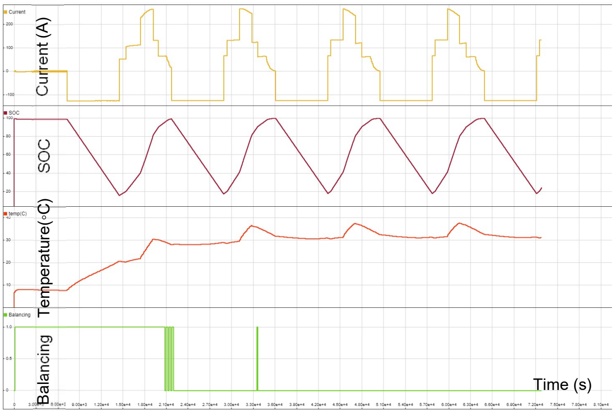

Fig. 10 – Test Run 2

The two test runs demonstrate how the different *BMS* sub-systems come together protecting the user and the battery. It is emphasized how much the thermals affect the battery performance where the battery had to be heated up in test run 2 and cooled in test run 1 with limited current. Test run 2 also demonstrated the passive balancing that equalized the cells state of charge to maximize the output power.

The simulation model strengths lie in it being a comprehensive and conclusive model covering all aspects of *BMS*. The accuracy of the battery model makes the obtained results more robust. Each subsystem has been thoroughly tested during design until the required outcomes were achieved.

Limitations in the simulation model include the unavailability of Active Balancing due to SIMULINK limitations. Additionally, the Thermal Management System was simplified where in the EVs, the system is much more complex than what has been developed.

V. Conclusions

In conclusions, the required outcomes discussed in the introduction have been successfully addressed. Battery Management Systems (*BMS*) were thoroughly examined, providing in-depth theoretical understanding into each sub-system. The theoretical findings allowed the development of a comprehensive and accurate *BMS* simulation in SIMULINK, using the Tesla Model S as a basis for it for a more realistic approach.

Once the simulation environment has been set up, it was used in two test runs. The test runs strengthened the understanding of the need for *BMS*, and how it affects battery safety. The test runs also outlined the competence of the created simulation and how conclusive it is, covering all aspects of traditional *EV BMS*.

References

[1] Dhammika Widanalage, “Battery Cell Modelling - Battery Design,” Battery Design, Dec. 24, 2022. https://www.batterydesign.net/battery-cell-modelling/ (accessed Jul. 05, 2025).

[2] A. M. Ralls et al., “The Role of Lithium-Ion Batteries in the Growing Trend of Electric Vehicles,” Materials, vol. 16, no. 17, p. 6063, Jan. 2023, doi: https://doi.org/10.3390/ma16176063.

[3] “Lithium-ion Battery Modeling for the Automotive Engineer,” Gamma Technologies, Dec. 8, 2021. https://www.gtisoft.com/blog-post/lithium-ion-battery-modeling-for-the-automotive-engineer/ (accessed Jul. 05, 2025).

[4] Jiuchun Jiang and Caiping Zhang, (Chemist, Fundamentals and applications of lithium-ion batteries in electric drive vehicles. Singapore: Wiley, 2015.

[5] “Battery Management Systems vs. Charge Controllers: What’s the Difference?,” TDT, Jul. 29, 2023. https://www.tdtbms.com/news/battery-management-systems-vs-charge-controllers-whats-the-difference.html (accessed Jul. 05, 2025). I. S. Jacobs and C. P. Bean, “Fine particles, thin films and exchange anisotropy,” in Magnetism, vol. III, G. T. Rado and H. Suhl, Eds. New York: Academic, 1963, pp. 271–350.

[6] N. Ghaeminezhad and M. Monfared, “Charging control strategies for lithium‐ion battery packs: Review and recent developments,” IET Power Electronics, Nov. 2021, doi: https://doi.org/10.1049/pel2.12219R. Nicole, “Title of paper with only first word capitalized,” J. Name Stand. Abbrev., in press.

[7] S. Hemavathi, “Overview of Cell Balancing Methods for Li‐ion Battery Technology,” Energy Storage, Aug. 2020, doi: https://doi.org/10.1002/est2.203.M. Young, The Technical Writer’s Handbook. Mill Valley, CA: University Science, 1989.

[8] J. Liu, “A Guide to *BMS* Communication Protocols - MokoEnergy - Your New Energy Solution Provider,” MokoEnergy - Your New Energy Solution Provider, May 14, 2024. https://www.mokoenergy.com/a-guide-to-*BMS*-communication-protocols/

[9] Ivor.p, “Centralized *BMS* - Battery Design,” Battery Design, Apr. 14, 2023. https://www.batterydesign.net/centralized-bus (accessed Jul. 05, 2025)

[10] “Types of *BMS*,” Monolithicpower.com, 2025. https://www.monolithicpower.com/en/learning/mpscholar/battery-management-systems/*BMS*-basics/types-of-*BMS* (accessed Jul. 05, 2025).

[11] S. Bhowmick, “Tesla Model S Battery System: An Engineer’s Perspective,” Circuit Digest, Dec. 16, 2021. https://circuitdigest.com/article/tesla-model-s-battery-system-an-engineers-perspective