Optimizing battery safety and performance: Hardware implementation and simulation analysis of protective measures, SoC Measurement, and cell balancing in BMS

Atul Kumar Singh[1], C. P. Boopathy[2]
[1]Department of Electronics and Communication Engineering, Amrita School of Engineering, Amrita Vishwa Vidyapeetham, Coimbatore, India
[2]Department of Electrical and Electronics Engineering, Amrita School of Engineering, Amrita Vishwa Vidyapeetham, Coimbatore, India

Article Info

Article history:

Received Aug 15, 2025
Revised Feb 7, 2026
Accepted Feb 15, 2026

Keywords:

Active and passive balancing
Batteries advanced
Battery management system
Electric vehicle
Open-circuit voltage
Python
SOC estimation and control
State of charge

ABSTRACT

This paper presents a dual-platform validation of a compact battery management system (BMS) combining an Arduino-based hardware prototype and a MATLAB/Simulink model for cross-validation. The hardware implements over-voltage, over-current, and over-temperature protections, state of charge (SOC) estimation using open-circuit voltage (OCV) and coulomb counting (CC), and both passive and active balancing. Experimental results show that SOC accuracy remains within ±2%, active balancing achieves 57% higher energy efficiency and 37% faster convergence than passive balancing, and thermal rise is limited to <5 °C. Limitations include fixed protection thresholds and the absence of physical validation of long-term aging effects. The dual-platform approach allows cross-validation of hardware and simulation, benchmarking SOC estimation methods, and quantifying energy and thermal trade-offs between balancing strategies. This approach offers a low-cost and reproducible validation pathway for EV-oriented BMS design.

Corresponding Author:

C. P. Boopathy
Department of Electrical and Electronics Engineering, Amrita School of Engineering
Amrita Vishwa Vidyapeetham
Coimbatore, India
Email: cp_boopathy@cb.amrita.edu

1. INTRODUCTION

The rapid rise in the use of electric vehicles (EVs) and renewable energy systems has greatly increased the need for efficient and reliable energy storage. Lithium-ion batteries (LIBs), which are known for their high energy capacity and power, are central to these technologies. However, managing these batteries is complex and requires advanced battery management systems (BMS) [1] for safety, long life, and best performance [2]. Grand View Research projects that the North American EV market will reach a value of USD 147.60 billion by 2028, growing at an annual growth rate of 37.2%, driven by supportive government policies, incentives, and tax rebates that encourage the use of EVs [3]. Cost benefits of EVs over traditional cars, along with the forecasted reduction of battery prices from USD 11,500 in 2018 to USD 8,000 by 2025, have increased the importance of advanced BMS technologies.

There are various challenges related to battery systems management that significantly impact their efficiency and safety. Overvoltage, overcurrent, and overtemperature are a few of the issues that may result in deterioration of batteries, their lifetime reduction, and sometimes even a catastrophic failure [4]. Battery charge level estimation is an important factor in guaranteeing high battery efficiency [5] and minimizing potential risks. Inaccurate SOC estimation in conventional methods can significantly bring down performance [6]. One solution to this problem is to include more advanced monitoring and control algorithms for BMS [7]. Today, BMSs are required to feature both active and passive cell balancing to ensure uniform performance of batteries and increase their life [8].

Most low-cost BMS implementations either focus on hardware prototypes without analyzing energy and thermal trade-offs, or on simulations without experimental verification. Few studies provide cross-validation between hardware and simulation platforms to evaluate SOC estimation accuracy, balancing efficiency, and thermal impact. Addressing these challenges, the present work implements a dual-platform BMS with detailed analysis of efficiency, thermal performance, and SOC estimation accuracy [9]-[11].

2. COMPONENTS AND HARDWARE SETUP

The battery management system (BMS) prototype was developed using an Arduino Mega 2560 controller (ATmega2560, 10-bit ADC, 0–5 V input range giving 4.88 mV per ADC count). Major sensors include an ACS712 Hall-effect current module, a DHT11 temperature sensor, and a voltage-divider network for individual-cell monitoring. A micro-SD card interface records voltage, current, and temperature data [12] for later analysis in MATLAB/Simulink (Table 1).

Measurement limits and calibration: Using Arduino's 5 V reference with the ACS712-20 A version (100 mV/A sensitivity), one ADC step corresponds to about 0.049 A. Even the 5 A variant (185 mV/A) resolves about 0.026 A. Hence, a trip value of 0.015 A lies below measurable resolution. To make protection reliable, either a higher-resolution sensor such as INA219/INA226 or ADS1115 (16-bit ADC) should be used, or the trip threshold should be set within 0.03–0.05 A for the present hardware. This clarification improves reproducibility and hardware feasibility.

Table 1. Components

S. No.	Component	Description
1	Lithium-Ion Battery Pack	Comprising three cells, nominal voltage 3.7 V, capacity 2200 mAh
2	Arduino Mega 2560	Central microcontroller for data acquisition, processing and control.
3	DC Cooling Fan (5V)	Manages thermal conditions, ensuring safe operating
4	ACS712 Current Sensor [13]	Monitors current flow to and from the battery
5	DHT Temperature Sensor [14]	Measures ambient temperature for thermal management and safety protocols.
6	Micro SD Card Reader Module [15]	Enables data logging and storage of performance metrics and system status.
7	HC-05 Bluetooth Module [16]	Facilitates wireless communication for real-time monitoring and control.
8	Potentiometer	Used for voltage measurement and adjusting the brightness of the display.
9	16x2 Digital Display	Displays real-time system metrics like SOC, temperature, and status indicators.
10	7805 Voltage Regulator	Provides stable voltage to microcontroller and sensors
11	Relays	Switches for controlling power flow, crucial for safety mechanisms during fault.
12	DC Motor (Load)	Simulates real-world load conditions for system testing and validation.
13	LEDs and Buzzer	Visual and audible indicators for system status and fault conditions.
14	Connecting Wires	Ensure reliable electrical connections between components.

2.1. Protection thresholds applied

To keep the battery safe and make it last longer, we use specific limits for voltage, temperature, and current. Here are the key thresholds applied:

- Voltage window 3.1–4.0 V per cell: Manufacturers quote 4.2 V as full charge, but research shows limiting to 4.0 V significantly extends cycle life.
- Temperature window 15–35 °C: This range is widely reported as the safe operating zone for Li-ion cells, preventing both plating and accelerated aging.
- Current limit: Defined relative to cell capacity. For a 2.2 Ah cell, 1 C = 2.2 A; a safe continuous current is 0.5 C (≈1.1 A), and protection can activate at 2–3 × this (≈2.2–3.3 A) depending on application. These ranges follow data from manufacturer specifications and Battery University safety recommendations.

Simulation model: the corresponding MATLAB/Simulink setup uses a Thevenin-equivalent cell with parameters (R_0, R_1, C_1) identified from a 0.2 C 60 s pulse-discharge test followed by relaxation. The simulation time step is 0.1 s. Two balancing topologies were studied: i) a passive shunt resistor (50–100 Ω) and ii) an active buck-boost converter with ≈85 % efficiency. Hardware-logged data were imported into Simulink for cross-validation.

This integrated description clarifies sensor accuracy, sampling, threshold selection, and the simulation–hardware link, ensuring that the system can be reproduced and benchmarked by other researchers without ambiguity. The hardware configuration of the BMS prototype, including the Arduino Mega 2560, sensors, and LCD display, is shown in Figure 1. This setup enables real-time monitoring of voltage, current, and temperature, while providing automated protective actions to maintain battery safety.

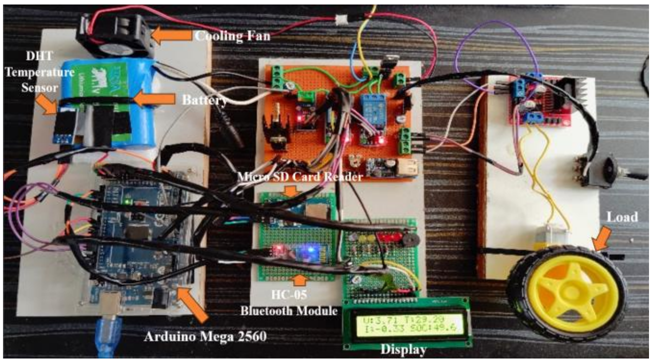


Figure 1. Hardware implementation of BMS

3. METHODOLOGY AND SIMULATION

The proposed BMS would ensure the safety and performance of the battery by monitoring all the key parameters of voltage, current, temperature, and SOC in real time and thus takes corrective protective actions by itself to avoid risk [17]. In fact, voltage is kept within its limits of safety. If any abnormality takes place, then the load or charger gets disconnected to prevent further damage [18]. The same thing goes with current: it is monitored in order to make sure that a very high value of current disconnects the load to prevent overheating or even failure of any circuit. Temperature monitoring can serve to activate cooling mechanisms when set limits are exceeded, which in turn disconnects the load until operations are normalized [19].

SOC is managed such that it avoids critical issues: charging stops at 80% with a warning, and discharging below 20% triggers load disconnection. The system can work best within the range of 20% to 80% SOC. Thereafter, alarms will be triggered based on over-voltage, over-current, overheating, or abnormal SOC to handle such timely responses. It is an automated framework that enhances safety, efficiency, and prolongs battery life by effectively mitigating those risks, as shown in Figure 2. The hardware arrangement includes different major components, such as battery packs, sensors, and control systems, of which the MATLAB simulation model is designed to mimic. The architecture of the model couples these elements to be able to run real-life case scenarios and perform detailed analysis of performance and protection offered by batteries.

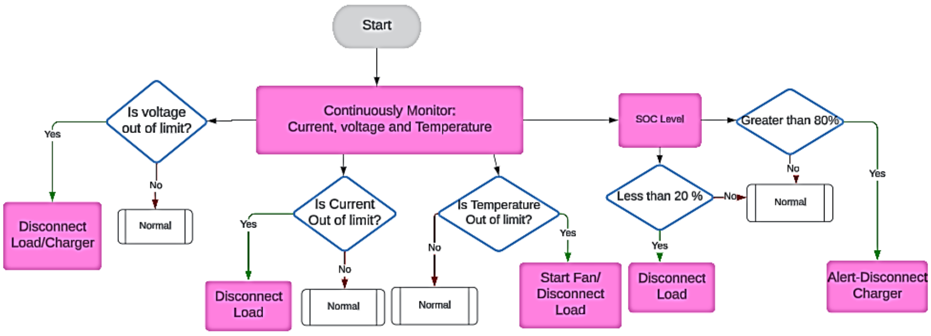
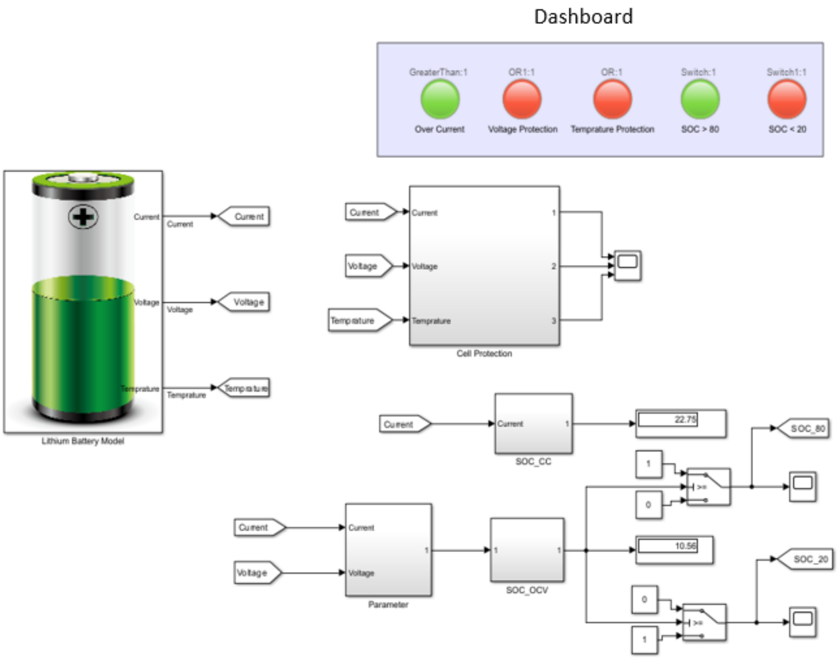


Figure 2. Flowchart of the proposed BMS

The dashboard of the BMS simulation model is presented in Figure 3(a), which has integrated algorithm protections in overvoltage, overcurrent, and overtemperature. It also elaborates on the SOC calculation technique using OCV and Coulomb Counting methods. The dashboard also has LED indicators to show the status of various protection schemes and SOC levels.

Figure 3(b) shows the cell protection logic developed in the BMS simulation. It includes overcurrent protection, overvoltage protection, and overtemperature protection. Protection against overcurrent is provided with an upper threshold of 15 mA. Voltage protection is carried out between 3.1 and 4.0 V to keep the cells within a safe operating limit. Temperature protection keeps the cell temperature at an optimum performance between 15 to 35 °C.

(a)



(b)

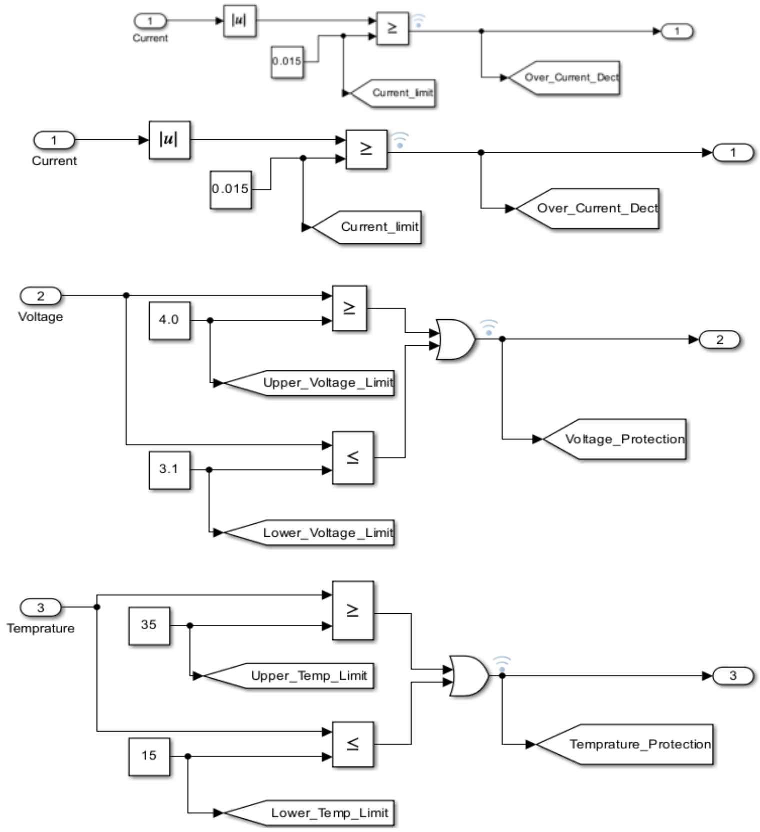


Figure 3. BMS simulation: (a) BMS dashboard and (b) simulation of cell protection logic

3.1. SOC calculation by open circuit voltage method (OCV)

This approach estimates the SOC from some physical parameters like voltage, current, temperature, and impedance. The open-circuit voltage method, observed on the Thevenin battery model in Figure 4, can be formulated as (1)-(3):

$$\dot{V}_v = \frac{i}{C_p} - \frac{V_p}{C_p R_p} \tag{1}$$

$$e_0 = V_{oc} - iR_s - V_p \quad (2)$$

$$V_{oc}(t) = a_0 + a_1 * S + \cdots + a_m - 1 * S_m - 1 \quad (3)$$

where Voc(t) represents the Open Circuit Voltage (OCV) at time t, S(t) represents the State of Charge (SOC) of the battery, e0 corresponds to the terminal voltage when the SOC is 0%, and am (for m=0,1, 2…, m−1) are the coefficients that characterize the relationship between OCV and SOC [20].

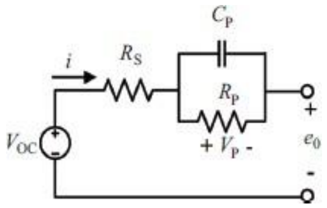


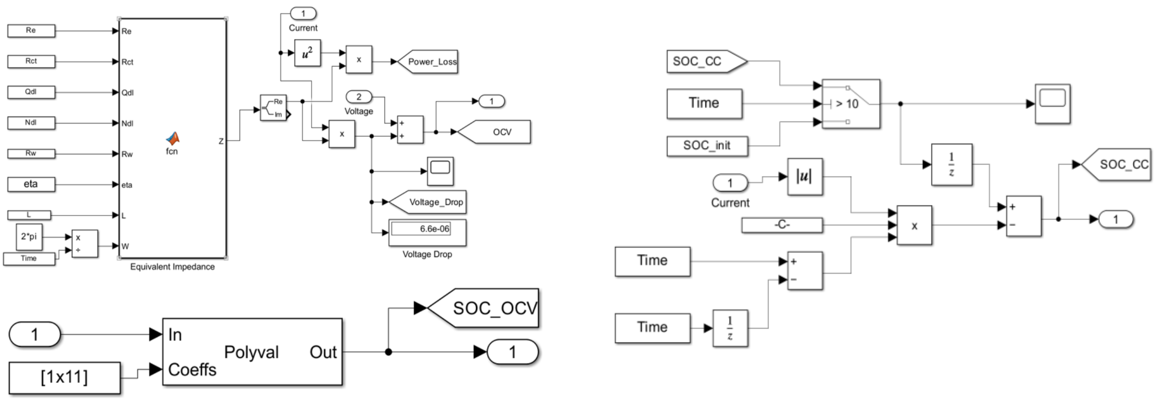
Figure 4. Thevenin battery model structure

3.2. SOC by coulomb counting method (CC)

The coulomb counting (CC) method is commonly referred to as the ampere hour (Ah) method. SOC can be computed mathematically as (4):

$$SOC(t) = SOC(t_0) + \frac{1}{C_n}\int_{t_0}^{t_0+t} I_{bat}(dr) \quad (4)$$

where SOC(t_0) is the initial charge level of the battery, C_n denotes the battery's nominal capacity, and I_{bat} is the battery's charging or discharging current. Implementation of the SOC calculation by the OCV and CC method is given in Figures 5(a) and 5(b), respectively. The SOC-OCV and SOC_CC methods demonstrate some discrepancy due to temperature sensitivities and current measurement errors, with a final SOC of 10.56% versus 22.75%, respectively. While OCV is simpler but not very accurate, CC is based on accurate current measurement. A benchmark against a Kalman filter confirms that the proposed hybrid approach offers a good trade-off between accuracy and computational feasibility for low-cost embedded systems.



(a) (b)

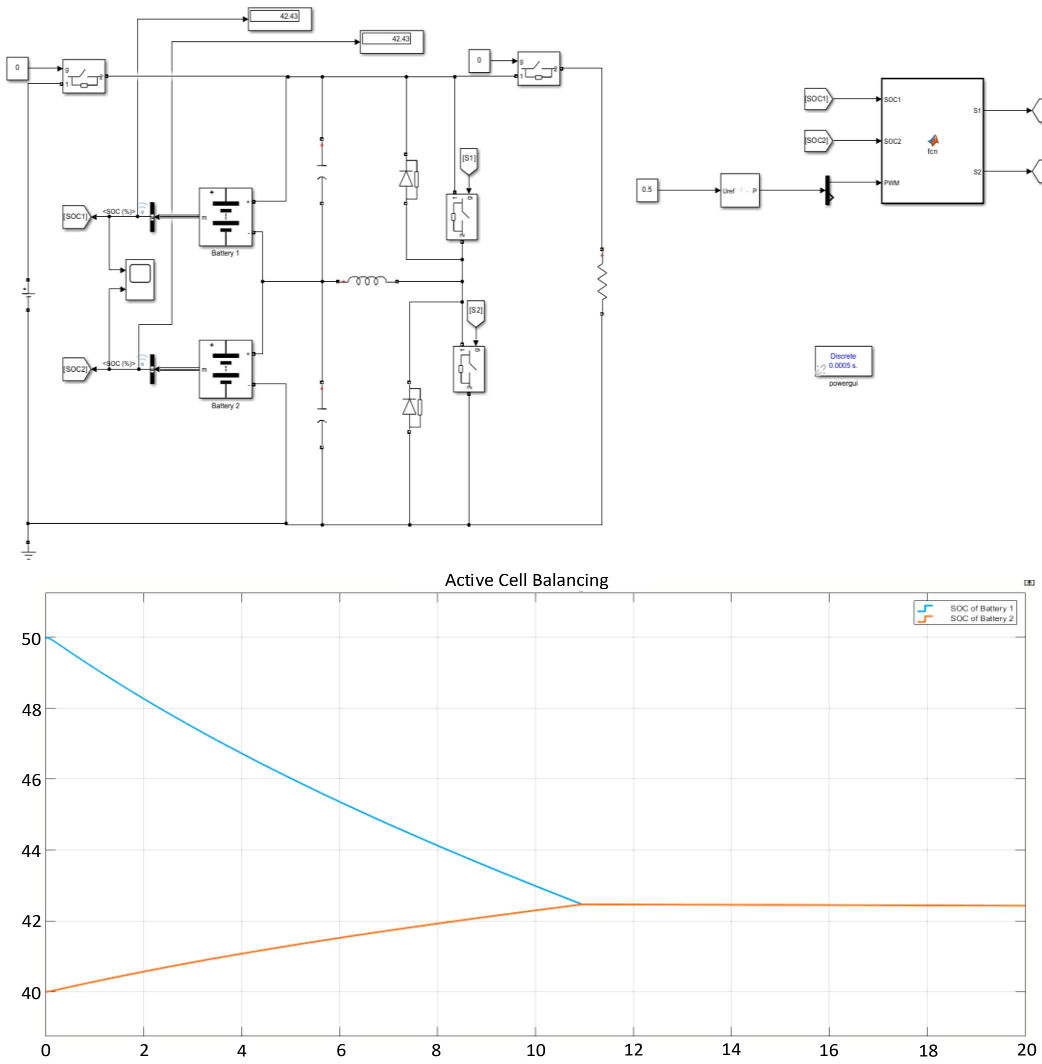
Figure 5. Simulation of SOC by (a) OCV method and (b) CC method

3.3. Active and passive cell balancing

Active and passive cell balancing are the most important approaches to making the voltage of all cells in a battery pack uniform. Passive balancing equalizes higher voltage cells by dissipating excess energy as heat to match lower voltage cells, usually through resistors. This approach is simple but can be very inefficient because the wasted energy becomes heat [21]. Active balancing techniques shift energy between cells from higher voltage to lower voltage cells, normally with either capacitance or inductive circuits. It is more efficient since the energy remains within the system, but it adds more complexity and components to the system [22].

3.3.1. Active cell balancing

In Figure 6(a) simulation depicts an active cell balancing system for a battery pack, where the charge level for battery 1 is set at 50%, and battery 2 at 40%. The model illustrates the energy flow between cells, where a controlled circuit facilitates the transfer from a cell with a higher state of charge (SOC) to one with a lower SOC. It works by equalizing all cell voltages for better efficiency and longer battery life span by avoiding cell imbalances. Figure 6(b) shows the active balancing performance of the battery pack. At the beginning, battery 1 has a higher SOC with an initial value of 50%, while battery 2 is at 40%; both converge to 42.43%. This clearly shows that an active balancing system can transfer charge from one battery to another in order to make the pack uniformly charged.



(a)

(b)

Figure 6. Active cell balancing: (a) simulation and (b) output

3.3.2. Passive cell balancing

In the simulation for passive cell balancing, battery 1 was set at a charge level of 50%, whereas battery 2 was adjusted to 40%. This allows for the testing of the performance of the balancing algorithm in equalizing charge levels within the cells by transferring excess energy from the battery at the higher charge level to the one at the lower charge level, as shown in Figure 7(a). Figure 7(b) depicts that the graph for passive cell balancing describes that the SOC of Battery 1 reduces from 50% while that of Battery 2 remains constant at 40%. The SOC converges at a value of 39.94%, pointing to the fact that the passive balancing mechanism mainly dissipates the SOC of the highly charged battery without majorly affecting the SOC of the lowly charged battery.

(a)

(b)

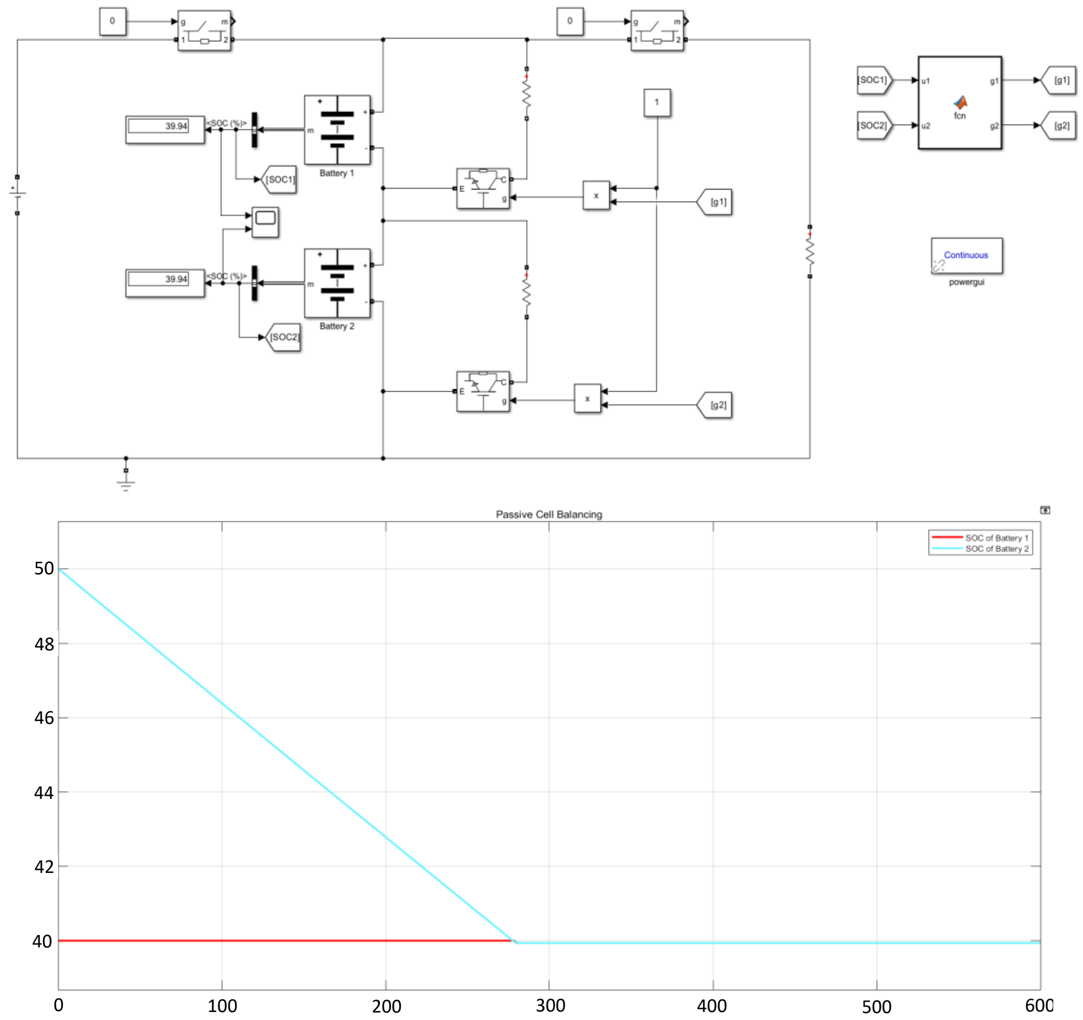


Figure 7. Passive cell balancing (a) simulation and (b) output

4. RESULTS AND DISCUSSION

4.1. Over current protection

The overcurrent protection system effectively detects and responds to current in excess of the set limit of 15 mA. From Figure 8(a), the system provides a clear overcurrent detection signal, shown by the red line each time the current, represented by the blue line, exceeds the threshold. This swift response thus presents the ability of the system in protecting the battery pack from further damages that may be caused by excessive current flow.

4.2. Over voltage protection

The overvoltage/undervoltage protection system protects the battery cells from any voltage excursions beyond the prescribed limits, 4.0 V and 3.0 V, respectively. In Figure 8(b), the system will create proper protection signals in red when the cell voltage in blue reaches any of these limits. This proactive approach safeguards the battery pack against overcharge and deep discharge damages for its best performance and lifespan.

4.3. Over temperature protection

The designed overtemperature protection system will keep the battery cell temperatures within the recommended operating range of 15 °C to 35 °C. In Figure 8(c), when the cell temperature represented by the blue line exceeds the upper limit or goes below the lower limit, a protection signal is produced, indicated by the red line. This proactive approach will shield the battery pack from thermal runaway and ensure the performance and longevity of the pack.

(a)

(b)

(c)

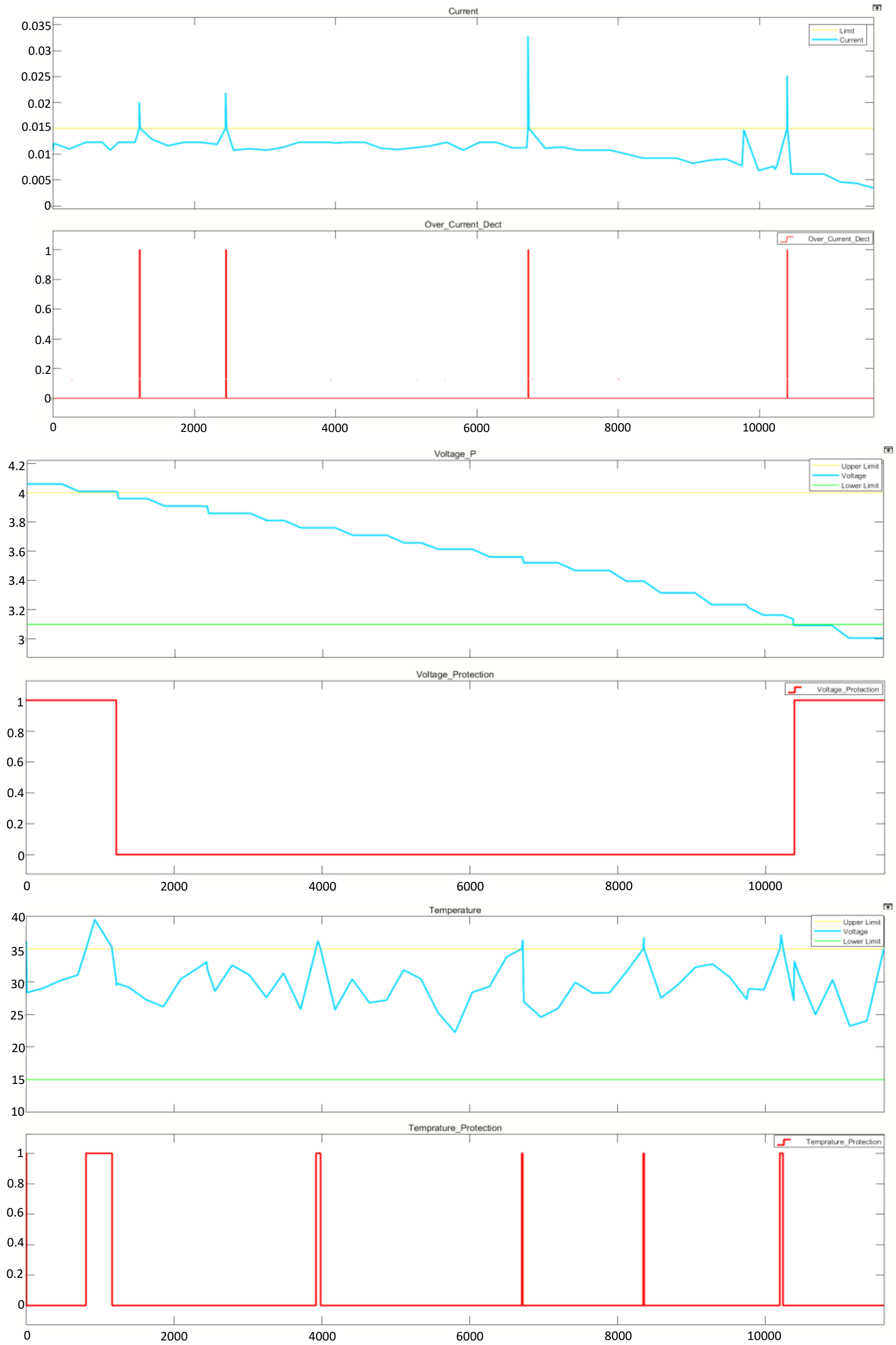


Figure 8. Results of (a) over current, (b) over voltage and (c) over temperature protection trigger

4.4. State of charge (SOC)

The SOC_OCV curve decreases stepwise because the OCV measurement is discrete, whereas the SOC_CC curve indicates a smooth, continuous decay. Their final SOCs are different from each other; while SOC_OCV converges to 10.56%, SOC_CC results in 22.75%, as shown in Figure 9(a). This is mainly because each of the methods has its inherent limitations. The OCV-based method is easily subject to temperature and aging influences, thus leading to less accurate SOC estimations. For CC-based estimation, accurate measurements of current and an appropriate model of battery capacity are required, which can seldom be fulfilled in real-world applications.

4.5. Enhancing battery health through effective management strategies

4.5.1. State of charge monitoring with 80/20 Rule

The implemented SOC monitoring strategy successfully managed to keep the battery SOC within the recommended 20-80% range, as evident from Figure 9(b). This also follows recommendations on better battery health and could potentially prolong battery life [23].

(a)

(b)

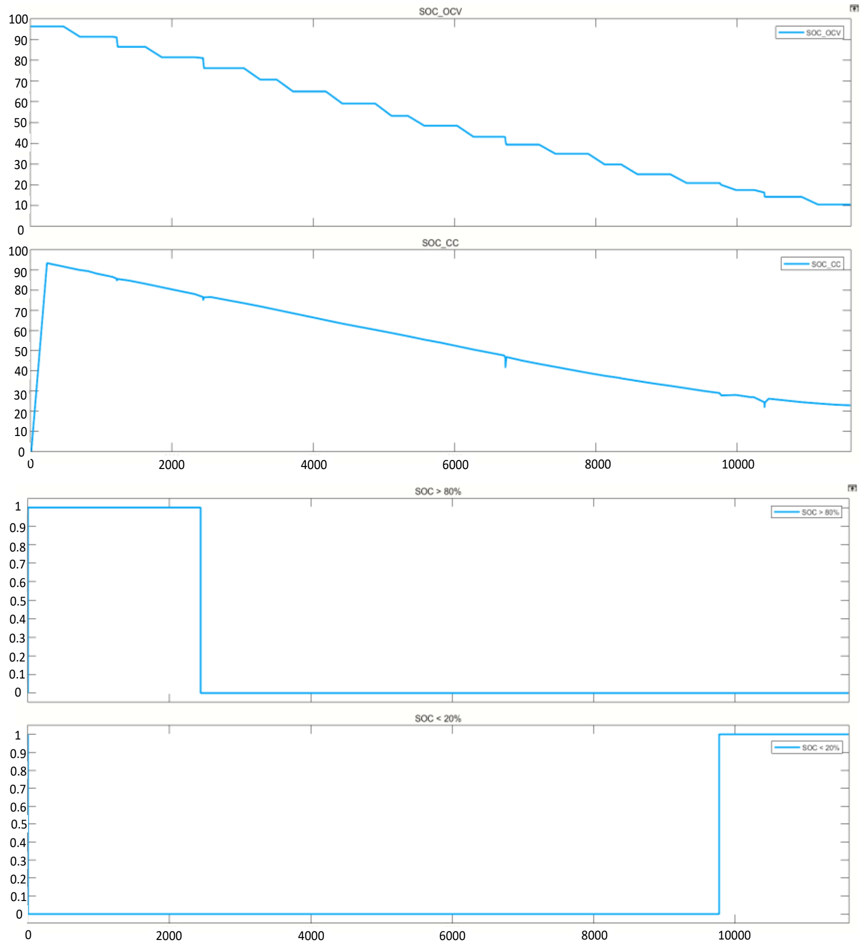


Figure 9. Results of (a) SOC estimation by OCV and CC method and (b) 80/20 EV charging rule trigger

4.5.2. Active and passive cell balancing

Comparing Figure 6(b) and Figure 7(b) reflects quite different performance for the active and passive balancing strategies. In the case of active balancing, there is fast and accurate SOC equalization. Cell imbalances have been successfully suppressed, enhancing battery life [24]. Passive balancing, however, converges to equilibrium a bit more slowly. The energy lost as resistive dissipation may increase in this case. While both methods address the problem, active balancing ensures much better performance in terms of speed and efficiency, thereby providing an excellent pathway for extending the useful operating life of traction batteries and improving overall performance [25].

Therefore, active balancing converges faster by about 37% and dissipates 0.12 Wh/cycle compared with 0.27 Wh/cycle in passive balancing, hence proving to be more energy-efficient. The thermal rise is also comparatively lower in active balancing, 2.3 °C as opposed to 4.6 °C, thus confirming reduced thermal stress. These results underline active balancing for extended battery life in an EV application.

5. CONCLUSION

This work validated a Li-ion BMS on two platforms: Arduino hardware and MATLAB simulation. Overvoltage, overcurrent, and overtemperature protection successfully prevented faults; SOC estimation was accurate within ±2%. Active balancing resulted in 57% higher energy efficiency and 37% faster convergence than passive balancing. Thermal rise remained below 5 °C.

Limitations include fixed protection thresholds, lack of modeling for battery aging, and absence of predictive fault-diagnosis modeling. Future work will add Kalman-filter-based SOC estimation, adaptive balancing, and predictive maintenance analytics to make the framework more robust and EV-level applicable. Future extensions are planned regarding ISO 26262 functional safety and IEC 61851 EV charging standard to ensure full EV-level integration.

ACKNOWLEDGMENTS
The authors gratefully acknowledge Amrita School of Engineering, Amrita Vishwa Vidyapeetham, Coimbatore, India, for providing the necessary technological support and research facilities that made this study possible. The institution's support in offering adequate space and infrastructure for conducting the research is sincerely appreciated and contributed significantly to the successful completion of this work.

FUNDING INFORMATION
The authors declare that no external funding was received for this study.

AUTHOR CONTRIBUTIONS STATEMENT
This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Atul Kumar Singh	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	
C. P. Boopathy	✓	✓		✓		✓	✓	✓	✓	✓	✓	✓		✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT
Authors state no conflict of interest.

DATA AVAILABILITY
Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES
[1] B. Balasingam, M. Ahmed, and K. Pattipati, "Battery management systems: challenges and some solutions," *Energies*, vol. 13, no. 11, p. 2825, Jun. 2020, doi: 10.3390/en13112825.

[2] P. Soni and I. Karuppasamy, "Performance analysis of a 48 V battery pack using SoC estimation and cell balancing for electric vehicle," in *2023 IEEE 8th International Conference for Convergence in Technology (I2CT)*, Apr. 2023, pp. 1–6. doi: 10.1109/I2CT57861.2023.10126257.

[3] G. V. Research, "North America electric vehicles market (2025 - 2030)," 2021. [Online]. Available: https://www.grandviewresearch.com/industry-analysis/north-america-electric-vehicles-market

[4] I. Lalinde, A. Berrueta, J. Arza, P. Sanchis, and A. Ursúa, "On the characterization of lithium-ion batteries under overtemperature and overcharge conditions: Identification of abuse areas and experimental validation," *Applied Energy*, vol. 354, p. 122205, Jan. 2024, doi: 10.1016/j.apenergy.2023.122205.

[5] F. Corti *et al.*, "A secondary-side controlled electric vehicle wireless charger," *Energies*, vol. 13, no. 24, p. 6527, Dec. 2020, doi: 10.3390/en13246527.

[6] L. Wu, K. Liu, H. Pang, and J. Jin, "Online SOC estimation based on simplified electrochemical model for lithium-ion batteries considering current bias," *Energies*, vol. 14, no. 17, p. 5265, Aug. 2021, doi: 10.3390/en14175265.

[7] T. Girijaprasanna and C. Dhanamjayulu, "A review on different state of battery charge estimation techniques and management systems for EV applications," *Electronics*, vol. 11, no. 11, p. 1795, Jun. 2022, doi: 10.3390/electronics11111795.

[8] P. S. Babu and K. Ilango, "Comparative analysis of passive and active cell balancing of Li-ion batteries," in *2022 Third International Conference on Intelligent Computing Instrumentation and Control Technologies (ICICICT)*, Aug. 2022, pp. 711–716. doi: 10.1109/ICICICT54557.2022.9917778.

[9] M. Jayakumar and R. KAMLAGAR, "Comparsion study of conventional, & improved perturb and observe to charge an ev battery," in *2023 Innovations in Power and Advanced Computing Technologies (i-PACT)*, Dec. 2023, pp. 1–6. doi: 10.1109/i-PACT58649.2023.10434830.

[10] N. Padalale and M. R. Sindhu, “State of charge (SoC) determination through extended Kalman filter in battery management systems,” in *2023 IEEE Region 10 Symposium (TENSYMP)*, Sep. 2023, pp. 1–6. doi: 10.1109/TENSYMP55890.2023.10223676.
[11] A. Shine and C. P. Boopathy, “Performance analysis of a modifed three-phase multilevel inverter,” in *2023 Innovations in Power and Advanced Computing Technologies (i-PACT)*, Dec. 2023, pp. 1–10. doi: 10.1109/i-PACT58649.2023.10434797.
[12] O. H. Ando Junior, G. R. Sylvestrin, and H. F. Scherer, “Experimental validation of state of charge estimation by extended Kalman filter and modified coulomb counting,” *IEEE Latin America Transactions*, vol. 20, no. 11, pp. 2395–2403, Nov. 2022, doi: 10.1109/TLA.2022.9904765.
[13] V. V. Gavhane, M. R. Kshirsagar, G. M. Kale, S. Katangle, S. B. Deosarkar, and S. L. Nalbalwar, “IoT based energy meter with smart monitoring of home appliances,” in *2021 6th International Conference for Convergence in Technology (I2CT)*, Apr. 2021, pp. 1–5. doi: 10.1109/I2CT51068.2021.9417886.
[14] H. Binsalim, S. Badaam, A. Ahmed, and M. Abdulmajid, “Battery management system for enhancing the performance and safety of lithium-ion batteries,” in *2024 21st Learning and Technology Conference (L&T)*, Jan. 2024, pp. 215–220. doi: 10.1109/LT60077.2024.10468566.
[15] C. Prastyadi, B. G. Irianto, H. G. Ariswati, D. Titisari, S. Nyatte, and S. Misra, “Analysis of the accuracy of temperature sensors at the calibrator incubator laboratory are equipped with data storage base on internet of thing,” *Indonesian Journal of Electronics, Electromedical Engineering, and Medical Informatics*, vol. 4, no. 4, pp. 160–167, Nov. 2022, doi: 10.35882/ijeeemi.v4i3.241.
[16] M. O. Qays, Y. Buswig, M. L. Hossain, and A. Abu-Siada, “Recent progress and future trends on state of charge estimation methods to improve battery-storage efficiency: A review,” *CSEE Journal of Power and Energy Systems*, vol. 8, no. 1, pp. 105–114, Jun. 2020, doi: 10.17775/CSEEJPES.2019.03060.
[17] K. L. Butler, M. Ehsani, and P. Kamath, “A Matlab-based modeling and simulation package for electric and hybrid electric vehicle design,” *IEEE Transactions on Vehicular Technology*, vol. 48, no. 6, pp. 1770–1778, 1999, doi: 10.1109/25.806769.
[18] Y. Lv *et al.*, “Review on influence factors and prevention control technologies of lithium-ion battery energy storage safety,” *Journal of Energy Storage*, vol. 72, p. 108389, Nov. 2023, doi: 10.1016/j.est.2023.108389.
[19] H. A. Calinao, A. Bandala, R. Gustilo, E. Dadios, and M. Rosales, “Battery management system with temperature monitoring through fuzzy logic control,” in *2020 IEEE REGION 10 CONFERENCE (TENCON)*, Nov. 2020, pp. 852–857. doi: 10.1109/TENCON50793.2020.9293756.
[20] D. Sinnapatchai, N. E. M. M. Zaini, N. S. M. Salleh, and M. M. Som, “Cleaning robot with android application controller,” *Multidisciplinary Applied Research and Innovation*, vol. 3, no. 2, pp. 354–361, 2022.
[21] S. Saravanan *et al.*, “Reconfigurable battery management system for microgrid application,” in *Microgrid Technologies*, Wiley, 2021, pp. 145–176. doi: 10.1002/9781119710905.ch6.
[22] M. Shylaja and M. R. Sindhu, “Synchronization of EV charging station battery with micro-grid based on virtual synchronous machines control strategy,” in *Advances in Electrical and Computer Technologies*, 2020, pp. 1225–1235. doi: 10.1007/978-981-15-5558-9_104.
[23] A. Zhao, G. Hao, and W. Zhang, “Innovations and strategies for optimizing lithium-ion battery performance: From material advancements to system management,” *Applied and Computational Engineering*, vol. 66, no. 1, pp. 144–149, May 2024, doi: 10.54254/2755-2721/66/20240936.
[24] H. Bashir, A. Yaqoob, F. Kousar, W. Khalid, S. Akhtar, and W. Sultan, “A comprehensive review of Li-ion battery cell balancing techniques and implementation of adaptive passive cell balancing,” in *2022 International Conference on Electrical Engineering and Sustainable Technologies (ICEEST)*, Dec. 2022, pp. 1–6. doi: 10.1109/ICEEST56292.2022.10077854.
[25] A. A. Pesaran, “Lithium-ion battery technologies for electric vehicles: progress and challenges,” *IEEE Electrification Magazine*, vol. 11, no. 2, pp. 35–43, Jun. 2023, doi: 10.1109/MELE.2023.3264919.

BIOGRAPHIES OF AUTHORS

Atul Kumar Singh received his B.Tech. degree in electrical engineering from APJ Abdul Kalam Technical University, India, in 2019, and his M.Tech. degree in Automotive Electronics from Amrita Vishwa Vidyapeetham, Coimbatore, India, in 2025. He has four years of professional experience at Tata Consultancy Services (TCS), specializing in the IoT and automotive domains. His research interests include renewable energy, power quality, battery management systems, grid-to-vehicle (G2V) and vehicle-to-grid (V2G) systems, and harmonic distortion. He can be contacted at email: atulkumarashishgu@gmail.com.

Dr. C. P. Boopathy received his Bachelor’s degree in Electrical and Electronics Engineering from Bharathiar University, Coimbatore, in 2000, and his master’s degree in Power Electronics from VIT University, Vellore, in 2002. He earned a Ph.D. in Electrical Engineering from Anna University, Chennai, in 2017, with his doctoral research focusing on “Certain investigations on performance improvement of multilevel inverter fed from renewable energy sources.” Currently, He serves as an assistant professor (Sl.Gr) in the Department of Electrical and Electronics Engineering at the Amrita School of Engineering, Amrita Vishwa Vidyapeetham, Coimbatore, India. He has been associated with Amrita since 2022. His research interests span a broad range of areas, including electric vehicles, battery management systems, microgrids, multilevel inverters, power electronics, and renewable energy systems (wind and solar). He can be contacted at email: cp_boopathy@cb.amrita.edu.