Practical application of lithium-ion battery management systems: heating system

Brahim Zraibi, Mohamed Mansouri, Abdelghani Ezzahi
Laboratory LAMSAD, National School of Applied Sciences of Berrechid, Hassan First University of Settat, Settat, Morocco

Article Info

Article history:

Received Aug 22, 2024
Revised Mar 10, 2025
Accepted Mar 29, 2025

Keywords:

Arduino
Battery management system
Lithium-ion batteries
Microcontroller
Prototype

ABSTRACT

This paper presents a lithium-ion battery management system (BMS) aimed at improving battery longevity through hardware and software optimization. The system targets enhancing energy efficiency in heating devices like burners, commonly used in industrial and domestic applications. A key innovation is the modification of the Arduino Pro Mini 8 MHz 3.3 V microcontroller to reduce power consumption during sleep mode. The study evaluates two iterations of the system: an initial manually soldered prototype using the Arduino board and a second iteration with a robust printed circuit board assembly (PCBA). The transition to the PCBA improved system efficiency and eliminated connection issues. The development integrates conventional circuitry and modern software strategies for efficient battery charge/discharge management. Results from both prototypes demonstrate significant improvements in battery life, offering a sustainable solution for energy-efficient applications.

Corresponding Author:

Brahim Zraibi
Laboratory LAMSAD, National School of Applied Sciences of Berrechid, Hassan First University of Settat
Settat, Morocco
Email: b.zraibi@uhp.ac.ma

1. INTRODUCTION

The rapid advancement of energy storage technologies is essential for addressing the multifaceted challenges of the modern energy landscape [1], [2]. As the global demand for efficient, safe, and cost-effective energy management solutions continues to rise [3], optimizing energy storage systems has become a critical priority [4], [5]. Batteries, as the cornerstone of these systems, are integral to a variety of applications, from portable consumer electronics to large-scale industrial systems and renewable energy storage [6], [7]. Despite their importance, batteries often present limitations in energy systems, including constraints on autonomy, energy capacity, and high storage costs [8], [9]. A major challenge in battery technology is balancing the need for maximum energy output with the goal of extending battery lifespan [10], [11]. Monitoring charge levels is a key component of any battery management system (BMS), as it directly impacts the efficiency and longevity of the battery [12], [13]. This is especially important in the context of global energy challenges, where optimizing battery performance can help reduce waste and improve the sustainability of energy systems [14], [15].

This paper explores a lithium-ion BMS designed to optimize battery life by integrating hardware and software enhancements. The focus is on energy-intensive applications such as burners, commonly used in boilers, water heaters, industrial furnaces, and domestic heating systems [16]-[18]. The integration of advanced energy management systems in these burners is not only crucial for improving their operational efficiency but also for enhancing the sustainability of energy use in these systems [19], [20]. To validate the proposed BMS, two prototypes were developed: an initial model using traditional soldered components and a refined version based on a printed circuit board assembly (PCBA). These prototypes demonstrate improvements in battery performance through intelligent energy management, addressing both economic and environmental concerns associated with energy storage. This study highlights the potential for significant advancements in battery management through the integration of advanced technologies [21]. By focusing on both hardware and software aspects of BMS, this paper seeks to find solutions that extend the operational life of batteries in energy-intensive applications while addressing both economic and environmental concerns related to energy storage [22]. The subsequent sections are organized as: i) Section 2 outlines the hardware and software integration within the BMS framework; and ii) Section 3 presents the results of energy optimization techniques and battery life estimation; and the conclusion summarizes key findings and their implications for improving the sustainability and efficiency of energy storage systems.

2. METHOD

2.1. Prototype description

We employed low-power electronic components to effectively extend the battery's lifespan and achieve practical and logical results. This study enables us to analyze the impact of these optimization methods on the battery's longevity. As shown in Figure 1, the prototype of our system is presented.

This prototype comprises several key components, including a modified Arduino Pro Mini board operating at 3.3 V and 8 MHz, a pump, a high-voltage generator, a liquid crystal display (LCD) and/or organic light-emitting diode (OLED) display, a potentiometer for adjusting the startup temperature, a temperature sensor, and a metal-oxide-semiconductor field-effect transistor (MOSFET) transistor. Before proceeding further with our study, it is crucial to outline the criteria that guided the selection of the Arduino Pro Mini board, specifically the version operating at 3.3 V and 8 MHz [23].

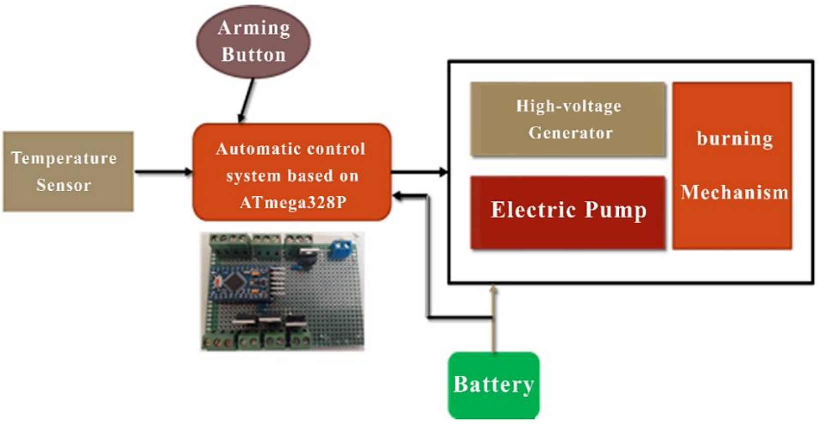

Figure 1. The prototype of the system was used

2.2. Comparison between Arduino (ATMEGA) and STM32 microcontrollers

In this study, the Arduino Pro Mini 8 MHz 3.3 V microcontroller, based on the ATMEGA328P architecture, was initially considered for its simplicity, low power consumption [24], and the large community support it offers for rapid prototyping. However, to expand the range of potential microcontroller solutions, a comparison was made between the Arduino/ATMEGA and the STM32 microcontroller. While the ATMEGA328P offers an adequate balance of performance and energy efficiency for small-scale applications, it lacks some of the advanced features provided by the STM32. The STM32 microcontroller is a more powerful option, offering superior low-power modes, advanced processing capabilities, and better optimization for complex tasks, making it suitable for more demanding battery management applications. Despite the advanced features of the STM32, the Arduino/ATMEGA was selected for this study due to its simplicity, ease of use, low cost, and its ability to meet the specific needs of the prototype. Future research may consider implementing the STM32 microcontroller for more complex systems to fully leverage its energy efficiency and processing power in energy-constrained applications.

2.3. Selection of processing board

The selection of the processing board prioritized two operational modes to minimize power consumption:

i) Active mode: The microcontroller operates fully, executing code, managing inputs/outputs, and utilizing peripherals such as timers and serial communication. This mode has the highest power consumption.
ii) Sleep mode: Components are selectively disabled to conserve energy. Key modes include:
  - Idle mode: Central processing unit (CPU) is halted while peripherals remain active.
  - Analog-to-digital converter (ADC) noise reduction mode: Keeps the ADC active for efficient analog-to-digital conversions.
  - Power-down mode: Essential functions like timers or interrupts remain active while most components are off.
  - Standby mode: Combines low power consumption with rapid wake-up capabilities.

The evaluation of boards led to the selection of an optimized Arduino model, detailed in the next section.

2.4. Comparison of Arduino boards

Various Arduino models were evaluated for their power consumption in both active and sleep modes, as summarized in Table 1 [22]. Key findings include:
i) Power variance: Pro mini models exhibit superior energy efficiency, with modified Pro Mini 8 MHz achieving only 1.5 µA in sleep mode.
ii) Voltage regulator and light-emitting diode (LED) impact: Voltage regulators and LED diodes significantly increase power draw. For example, LEDs add 180–380 µA, depending on the resistor.
iii) Optimizations: Removing the voltage regulator and LEDs drastically reduces consumption, making the modified Pro Mini 8 MHz an ideal choice for energy-sensitive applications.

Table 1. Power consumption of Arduino boards

Power supply type	Card type									
	UNO		NANO		Pro Mini 16 MHz (5 V)		Pro Mini 8 MHz (3.3 V)		Pro Mini 8 MHz modified (3.3 V)	
	Awake	Sleep	Awake	Sleep	Awake	Sleep	Awake	Sleep	Awake	Sleep
USB	38 mA	20 mA	29 mA	13 mA						
Pin 5 V or 3.3 V (for Pro Mini 8 MHz)	25 mA	6 mA	27 mA	7.5 mA	24 mA	3.2 mA	5.6 mA	1.4 mA	--	1.5 µA
JACK or VIN Pin (7 V) or RAW in 7.5 V	30 mA	11 mA	32 mA	12.5 mA	28 mA	3.22 mA	5.7 mA	1.5 mA	--	--

2.5. Comparison with existing BMS designs

This study employed a classical BMS as a baseline for exploring the energy efficiency impact on battery lifespan in industrial settings. The system demonstrates the feasibility of optimizing battery longevity using low-power electronic components. Future work will integrate advanced machine learning techniques, including a hybrid approach combining convolutional neural networks (CNN), long short-term memory (LSTM) networks, and deep neural networks (DNN) [2]. These algorithms aim to enhance battery health predictions and adapt charge-discharge cycles in real time, offering significant performance improvements over the classical method. While this study does not directly compete with advanced BMS designs, it provides a foundational step toward energy-efficient solutions. Subsequent research will incorporate machine learning strategies to further optimize battery performance and longevity in industrial applications.

2.6. Results

The study identified several measures to optimize power efficiency:
i) Hardware modifications:
  - Desoldering the Power light-emitting diode (PWR LED) and voltage regulator on Arduino Nano reduced standby consumption to 90 µA.
  - Replacing Nano with a modified Pro Mini 8 MHz (3.3V) reduced standby current to 1.5 µA.
  - Switching to low-dropout regulators (LDOs) further minimized energy consumption.
ii) Software optimizations:
  - Implementing sleep modes during idle periods and specific operations (e.g., temperature readings).
iii) Battery improvements:
  - Using high-performance batteries optimized for low-temperature operations.
  - Properly sizing batteries to the system’s requirements.
iv) Charging circuit integration:
  - Including a TP405 charging circuit for efficient battery management.

In conclusion, the modified Arduino Pro Mini achieved a minimal standby current of 1.5 µA, significantly extending battery life. Subsequent chapters present theoretical and practical validations of these results.

3. EXPERIMENTAL RESULTS

3.1. Power consumption assessment: theoretical study

In this study, we analyzed the power consumption of the Arduino-based system when powered by a battery or a cell. Power consumption plays a critical role in determining the system's efficiency and autonomy. The system is designed to activate the burner automatically based on temperature conditions. Table 2 presents the hardware components of the system along with their power consumption in both active and standby modes.

To achieve autonomous operation for 3 months with 10 activations triggered by critical temperature days, the following conditions were considered:
- Active mode duration: 17 seconds per activation (8 seconds for the pump and 9 seconds for the high voltage generator), and 27 seconds for the microcontroller.
- Total active time: 10 activations over 3 months.
- Sleep mode duration: The remaining time of the period (~2160 hours).

Table 2. Power consumption of system components in active and sleep modes

Component	Active mode	Sleep mode
High voltage generator	3 A	Not Active
Pump	200 mA	Not Active
LCD 16×2	2.5 mA	1 µA
LM2596s	300 µA	250 µA
DS18B20	4 mA	1 µA
Arduino Nano (5 V, 16 MHz)	23 mA	9 mA
Arduino Pro Mini (3.3 V, 8 MHz)	5.7 mA	1.5 mA
Modified Arduino Pro Mini (3.3 V, 8 MHz)	5.7 mA	1.5 µA
Total	3.2125 A	253.5 µA

We analyzed the total power consumption of various Arduino models over 3 months to determine their battery requirements. The calculations were based on a standard battery capacity of 2,600 mAh, ensuring consistency across all models. The findings are presented in Table 3, which summarizes the power demands and corresponding battery needs for each Arduino variant.

This analysis provides valuable insights into the energy efficiency of different Arduino boards. By comparing their power consumption, users can select the most suitable model for long-term projects. Additionally, the results highlight the importance of choosing the right battery capacity to ensure uninterrupted operation.

The study highlights that using a modified Arduino Pro Mini (3.3 V, 8 MHz) dramatically reduces total power consumption to 628.5 mAh over 3 months. This reduction means the system can operate with just one 2,600 mAh battery, significantly improving efficiency and autonomy. While theoretical calculations provide an initial understanding of power requirements, practical experimentation offers deeper insights into real-world performance. The following section presents experimental results.

Table 3. Summary of power consumption and battery requirements

Case	Arduino model	Total energy consumption (3 months)	Battery requirement (2,600 mAh each)
1	Arduino Nano (5 V, 16 MHz)	19520.94 mAh	8 batteries
2	Arduino Pro Mini (3.3 V, 8 MHz)	3865.26 mAh	2 batteries
3	Modified Arduino Pro Mini (3.3 V, 8 MHz)	628.5 mAh	1 battery

3.2. Power consumption assessment: practical study

To validate the theoretical findings, practical measurements were carried out using a multimeter and a DC power supply. The results showed that the power consumption of both the high-voltage generator and the pump varied proportionally with the input voltage, confirming the expected relationship. These measurements are documented in Table 4 for reference. Additionally, the system components were configured to operate at 5 V to assess their power requirements under standard conditions. The corresponding consumption data, including detailed readings for each component, are summarized in Table 5.

Table 4. Power consumption of high voltage generator and pump at various voltages

Voltage	High-voltage generator	Pump
3 V	0.87 A	70 mA
3.3 V	0.98 A	90 mA
3.7 V	1.17 A	100 mA
4 V	1.25 A	100 mA
4.5 V	1.42 A	100 mA
5 V	1.63 A	100 mA
5.5 V	1.82 A	110 mA
6 V	~2 A	110 mA
6.2 V	2.10 A	110 mA

Table 5. Power consumption of system components at 5 V

Component	Active mode	Sleep mode
High voltage generator	1.63 A	Not active
Pump	100 mA	Not active
LCD 16×2	2.5 mA	1 µA
LM2596s	300 µA	250 µA
DS18B20	4 mA	1 µA
Arduino Nano (5V, 16 MHz)	23 mA	9 mA
Arduino Pro Mini (3.3V, 8 MHz)	5.7 mA	1.5 mA
Modified Arduino Pro Mini (3.3V, 8 MHz)	5.7 mA	1.5 µA
Total	1.7425 A	253.5 µA

During system startup, the power consumption is calculated as follows:
- Pump operation (8 seconds): (8/3600) × (0.1+0.0125) A = 0.25 mAh
- High voltage generator operation (9 seconds): (9/3600) × (1.63+0.0125)A = 4.10 mAh
- Arduino Pro Mini operation (27 seconds, without pump and high voltage generator):

(27/3600) × 0.0125A = 0.09375 mAh

Based on these operational parameters, the power consumption over a 3-month period, assuming 10 system startups for the modified Arduino Pro Mini, is calculated as follows:
- Energy consumption in standby mode = (total time (3 months) - total active time) × current consumption = 547.56 mAh
- Energy consumption in active mode: 44.4375 mAh
- Total energy consumption over 3 Months: 592 mAh

This total energy consumption of 592 mAh over 3 months is equivalent to using one rechargeable 18650 battery (2600 mAh capacity) or one alkaline battery (2800 mAh capacity). This assessment confirms that the modified system can operate efficiently with minimal battery requirements.

3.3. Validation and quantifiable metrics

To substantiate the claims made in this study, we introduce quantifiable validation metrics to assess the system's performance in real-world conditions. These metrics include energy consumption (measured in watts over time), temperature accuracy (comparison with a calibrated reference sensor with an acceptable error margin of ± 0.5 °C), burner activation frequency (number of activations over 3 months), and overall system efficiency (measured as the ratio of useful energy output to total energy consumed). Specifically, energy consumption will be tracked over a defined period to measure the system's ability to optimize power usage. Temperature accuracy will be evaluated by comparing the system’s readings with calibrated sensors under varying conditions. Burner activation frequency will be logged over a 3-month period to assess the system's long-term responsiveness to temperature variations. Data collected from these metrics will be analyzed to validate the system’s operational efficiency and performance, ensuring that the design meets the expected goals before proceeding to the battery life estimation.

3.4. Estimation of battery life for a real system (printed circuit board assembly)

This section evaluates the system’s current consumption based on the power requirements of its functional blocks [25]:
- Input filter: Stabilizes power supply.
- Microcontroller: Core processing and decision-making.
- Communication interfaces: Data exchange between components.
- Power outputs: Controls the pump and high-voltage generator.
- LED Indicators: Displays battery status.
- Battery life estimation: Predicts system longevity based on power consumption.

3.4.1. Power consumption estimation

The system manages burner activation using a flowchart as shown in Figure 2. It calculates the correct measured temperature (CMT) by adjusting the measured temperature (MT) with a tolerance factor and compares the temperature difference (DeltaTemp) to a threshold (THT). The burner activates when DeltaTemp ≤ 0 or enters sleep mode, otherwise, optimizing energy use.

a) Two battery packs are proposed:
- Duracell DL2032: Powers the microcontroller.
- Duracell AA Alkaline Batteries: Power high-power components.

b) Microcontroller power assumptions
- Operating conditions: Consistent ambient temperature of 25 °C.
- Low-power configuration: Deep sleep mode activates after tasks, leaving critical functions active (e.g., GPIO, ADC, INT0, LEDs).
- Operational schedule: 70% of the time: 60 minutes of deep sleep
  15%: 30 minutes of deep sleep.
  7.5%: 10 minutes of deep sleep.
  7.5%: 5 minutes of deep sleep.
- Total active time: The system activates eight times over 3 months.

This configuration prioritizes energy efficiency, ensuring reliable operation over the expected period.

c) Current consumption calculation

Based on these considerations, the total current consumption (Icc_total) for the microcontroller is calculated as:

$$Icc\_total = 9mA * (1 + 0.15 + 0.09) + 0.3mA = 0.0115\,A \tag{1}$$

$$Total\_Load = 3.3V / Icc\_total = 287.96\,\Omega \tag{2}$$

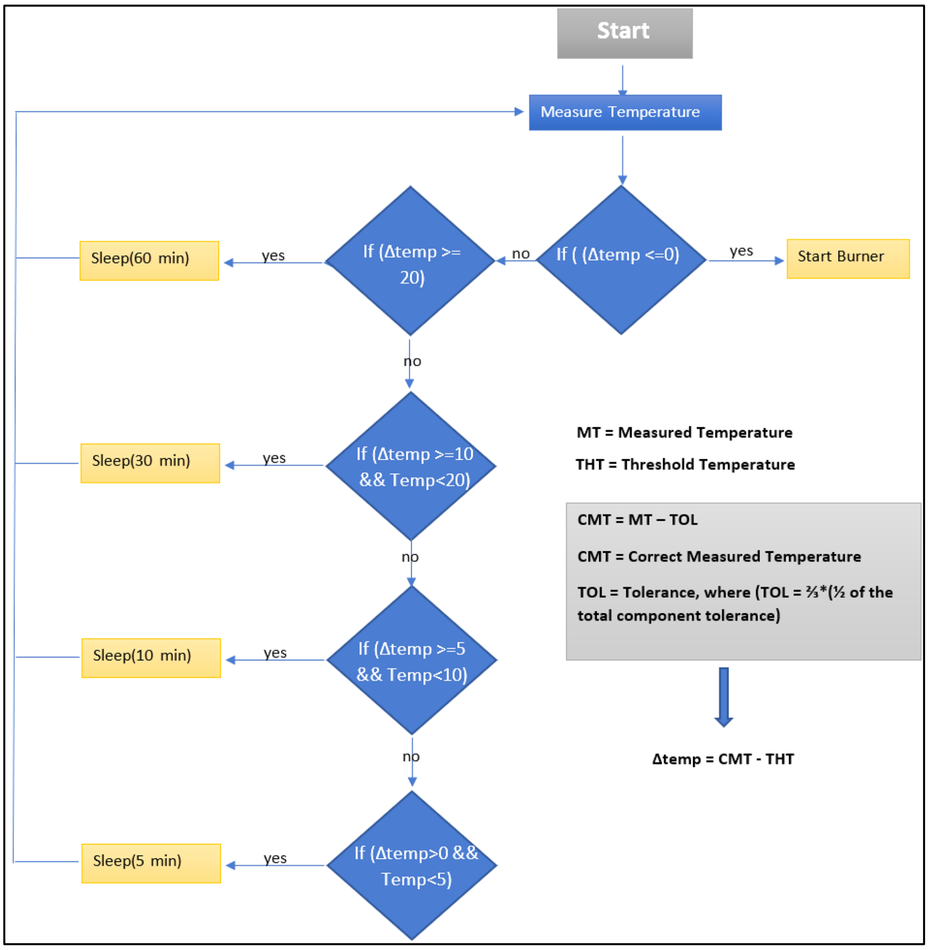

Figure 2. Flowchart of the power consumption estimation process

The system operates in a specific mode where both the pump and the high-voltage generator are active when the system is in the 'ON' state. Since there are two connected loads, their conditions are combined during system activation, as illustrated in Figure 3. In the next section, the operational modes of the ATMEGA328p microcontroller [11] will be further explored, with an emphasis on the practical application of these power-saving strategies in the real-world system.

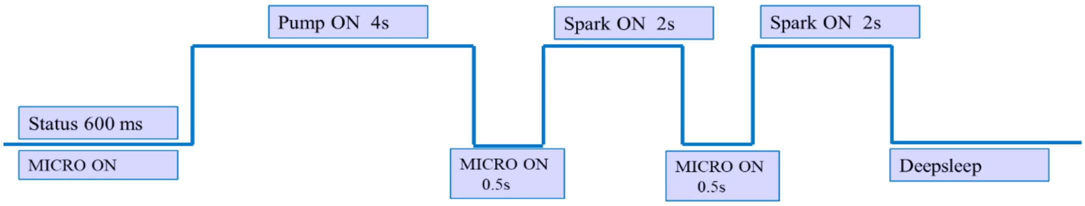

Figure 3. Automatic operating mode for Atmega328p

3.5. Estimation with system OFF (only the microcontroller is operational)

When the system is OFF and only the microcontroller (µC) is operational, the parameters and conditions considered in this state are summarized in Table 6. The estimated battery autonomy is calculated as (3).

$$Autonomy_{Auto} = \frac{Batt_{Alkaline}}{T_{Auto_{Load}}} = \frac{2800\,mAh}{927.23\,mAh} = 3.02 \quad (3)$$

With the system primarily in deep sleep mode and only the microcontroller active, the estimated battery life is approximately 3 years, assuming ideal battery conditions and that the batteries are replaced every 3 years.

Table 6. Parameter definitions for the microcontroller (operational mode only)

Parameter	Value	Description
Batt_Alkaline	2800 mAh	Capacity of the alkaline battery.
Current_Spark	2.6 A	Current consumed by the spark generator.
Current_Pump	0.23 A	Current consumed by the pump.
Deep_sleep	0.422 mA	Current in deep sleep mode.
Total_Current_ON	2.84 A	Total current in active mode (ON).
T_OP	2160 hours	Total operation time over 90 days (3 months).
T_OP_60min	1512 hours	Operation time during 60 minutes (70% of total time).
T_OP_30min	324 hours	Operation time during 30 minutes (15% of total time).
T_OP_10min	162 hours	Operation time during 10 minutes (7.5% of total time).
T_OP_5min	162 hours	Operation time during 5 minutes (7.5% of total time).
Status_time	1 second = 0.000278 hour	Duration during which the microcontroller is operational with the burner off.
Times_ON_Loop1	1512 cycles	Number of cycles during 60 minutes of operation.
Sec_ON_Loop1	0.42 hour	Total time in active mode during 60 minutes of operation.
Sec_OFF_Loop1	1511.58 hours	Total time in sleep mode during 60 minutes of operation.
Times_ON_Loop2	648 cycles	Number of cycles during 30 minutes of operation.
Sec_ON_Loop2	0.18 hour	Total time in active mode during 30 minutes of operation.
Sec_OFF_Loop2	323.82 hours	Total time in sleep mode during 30 minutes of operation.
Times_ON_Loop3	1012.5 cycles	Number of cycles during 10 minutes of operation.
Sec_ON_Loop3	0.28 hour	Total time in active mode during 10 minutes of operation.
Sec_OFF_Loop3	161.72 hours	Total time in sleep mode during 10 minutes of operation.
Times_ON_Loop4	1951.81 cycles	Number of cycles during 5 minutes of operation.
Sec_ON_Loop4	0.54 hour	Total time in active mode during 5 minutes of operation.
Sec_OFF_Loop4	161.46 hours	Total time in sleep mode during 5 minutes of operation.
Total_Auto_Load_ON	16.31 mAh	Total power consumption in active mode.
Total_Auto_Load_OFF	910.92 mAh	Total power consumption in sleep mode.
Total_Auto_Load	927.23 mAh	Total power consumption (sleep + active).

3.6. Estimation with system ON (normal operation)

The estimation assumes that each part of the system activates up to 8 times within a 3-month period. During these activations, the components draw power to perform their functions, contributing to the overall energy usage. The system remains in sleep mode for the remaining time, significantly reducing power consumption when not in operation.

Table 7 provides the corresponding power consumption estimates for this operational pattern. These calculations account for both the active and sleep phases, ensuring an accurate representation of energy use. By analyzing these figures, stakeholders can better understand the system's efficiency and optimize its performance.

The estimated battery autonomy is calculated as (4).

$$Autonomy_{FULL} = \frac{Batt\_Alkaline}{Total\_System\_Load} = \frac{2800\,\text{mAh}}{3737.63\text{mAh}} = 0.75 \tag{4}$$

With the system in normal operation mode, including up to 8 activation cycles within 3 months, the estimated battery life is approximately 9 months. This estimation assumes ideal battery conditions, with the batteries needing to be replaced every nine months. The results from both prototypes clearly show the advantages of the printed circuit board assembly, confirming its potential for improving battery life in energy-constrained applications.

Table 7. Parameter definitions for normal operation

Parameter	Value	Description
Time_Pump_ON	4 s = 1.11 * 10^{-3} hours	Duration for which the pump is active.
Time_Spark_ON	4 s = 1.11 * 10^{-3} hours	Duration for which the spark is active.
Total_time_OFF	6600 hours	Total time the system remains off.
Time_Wait_Spark	0.5 s	Wait time before the spark ignites.
Time_µC_ON	1.5 s	Duration for which the microcontroller is on, including status and wait time.
Total_Pump_Load	2.05 mAh	Total power consumption by the pump during the 8 cycles.
Total_Spark_Load	23.11 mAh	Total power consumption by the spark generator during the 8 cycles.
Total_µC_Load	0.04 mAh	Total power consumption by the microcontroller during the 8 cycles.
Total_µCsleep_Load	2785.2 mAh	Total power consumption in sleep mode while the system is off.
Total_System_Load	3737.63 mAh	Total power consumption of the system, including all loads.

4. CONCLUSION

This paper successfully demonstrates the development of an innovative lithium-ion battery management system that significantly enhances battery longevity by reducing power consumption through hardware modifications and software optimizations. The experimental results validate the effectiveness of the proposed system, highlighting its potential for energy-constrained applications. The findings contribute to the broader field of energy efficiency, providing a practical solution for extending battery life in real-world applications. Looking ahead, the research paves the way for further advancements in battery management, particularly in enhancing system adaptability and exploring renewable energy integration. In the next steps, we will implement a more advanced BMS incorporating machine learning techniques. Specifically, we plan to apply a remaining useful life (RUL) assessment method for lithium-ion batteries using a CNN-LSTM-DNN hybrid approach, which aims to improve the accuracy of battery life predictions and optimize battery usage.

FUNDING INFORMATION

The authors affirm no grants or financial assistance supported this research.

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
Brahim Zraibi	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓	
Mohamed Mansouri		✓				✓				✓	✓	✓	✓	
Abdelghani Ezzahi	✓		✓	✓		✓	✓			✓	✓		✓	

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

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [BZ], upon reasonable request.

REFERENCES

[1] M. Uzair, G. Abbas, and S. Hosain, “Characteristics of battery management systems of electric vehicles with consideration of the active and passive cell balancing process,” *World Electric Vehicle Journal*, vol. 12, no. 3, p. 120, Aug. 2021, doi: 10.3390/wevj12030120.

[2] B. Zraibi, C. Okar, H. Chaoui, and M. Mansouri, “Remaining useful life assessment for lithium-ion batteries using CNN-LSTM-DNN hybrid method,” *IEEE Transactions on Vehicular Technology*, vol. 70, no. 5, pp. 4252–4261, May 2021, doi: 10.1109/TVT.2021.3071622.

[3] B. Zraibi, M. Mansouri, and S. E. Loukili, “Comparing deep learning methods to predict the remaining useful life of lithium-ion batteries,” *Materials Today: Proceedings*, vol. 62, pp. 6298–6304, 2022, doi: 10.1016/j.matpr.2022.04.082.

[4] J. Li *et al.*, “The state-of-charge predication of lithium-ion battery energy storage system using data-driven machine learning,” *Sustainable Energy, Grids and Networks*, vol. 34, p. 101020, Jun. 2023, doi: 10.1016/j.segan.2023.101020.

[5] S. Ansari, A. Ayob, M. S. Hossain Lipu, A. Hussain, and M. H. M. Saad, “Remaining useful life prediction for lithium-ion battery storage system: A comprehensive review of methods, key factors, issues and future outlook,” *Energy Reports*, vol. 8, pp. 12153–12185, Nov. 2022, doi: 10.1016/j.egyr.2022.09.043.

[6] J. Schaeffer *et al.*, “Cycle life prediction for lithium-ion batteries: machine learning and more,” *arXiv*, doi: 10.48550/arXiv.2404.04049.

[7] A. Samanta and S. Williamson, “Machine learning-based remaining useful life prediction techniques for lithium-ion battery management systems: a comprehensive review,” *IEEJ Journal of Industry Applications*, vol. 12, no. 4, p. 22004793, Jul. 2023, doi: 10.1541/ieejjia.22004793.

[8] V. C. Srikantappa and S. Devarakonda, “Dimensionality reduced deep learning-based state of health estimation of Lithium-Ion batteries using standard dataset,” *International Journal of Power Electronics and Drive Systems (IJPEDS)*, vol. 15, no. 3, p. 1942, Sep. 2024, doi: 10.11591/ijpeds.v15.i3.pp1942-1950.

[9] V. T. Ha, V. Q. Vinh, and L. N. Truc, “Machine learning-based lithium-ion battery life prediction for electric vehicle applications,” *International Journal of Power Electronics and Drive Systems (IJPEDS)*, vol. 15, no. 3, p. 1934, Sep. 2024, doi: 10.11591/ijpeds.v15.i3.pp1934-1941.

[10] S. R. Hashemi, A. Bahadoran Baghbadorani, R. Esmaeeli, A. Mahajan, and S. Farhad, “Machine learning-based model for lithium-ion batteries in BMS of electric/hybrid electric aircraft,” *International Journal of Energy Research*, vol. 45, no. 4, pp. 5747–5765, Mar. 2021, doi: 10.1002/er.6197.

[11] M. Nizam, H. Maghfiroh, R. A. Rosadi, and K. D. U. Kusumaputri, “Battery management system design (BMS) for lithium ion batteries,” in *AIP Conference Proceedings*, vol. 2217, No. 1, 2020. doi: 10.1063/5.0000649.

[12] H. Gabbar, A. Othman, and M. Abdussami, “Review of battery management systems (BMS) development and industrial standards,” *Technologies*, vol. 9, no. 2, p. 28, Apr. 2021, doi: 10.3390/technologies9020028.

[13] P. M. W. Salehen, M. S. Su’ait, H. Razali, and K. Sopian, “Development of battery management systems (BMS) for electric vehicles (EVs) in Malaysia,” *MATEC Web of Conferences*, vol. 90, p. 01001, Dec. 2017, doi: 10.1051/matecconf/20179001001.

[14] X. Hu, L. Xu, X. Lin, and M. Pecht, “Battery Lifetime Prognostics,” *Joule*, vol. 4, no. 2, pp. 310–346, Feb. 2020, doi: 10.1016/j.joule.2019.11.018.

[15] J. Hemdani, L. Degaa, M. Soltani, N. Rizoug, A. J. Telmoudi, and A. Chaari, “Battery lifetime prediction via neural networks with discharge capacity and state of health,” *Energies*, vol. 15, no. 22, p. 8558, Nov. 2022, doi: 10.3390/en15228558.

[16] K. A. Severson *et al.*, “Data-driven prediction of battery cycle life before capacity degradation,” *Nature Energy*, vol. 4, no. 5, pp. 383–391, Mar. 2019, doi: 10.1038/s41560-019-0356-8.

[17] Y. Liu, Z. Ning, C. Sun, M. Lv, and Y. Wei, “Experimental and modeling study of full- condition combustion characteristics of exhaust gas burners for solid oxide fuel cells,” *Fuel*, vol. 365, p. 131321, Jun. 2024, doi: 10.1016/j.fuel.2024.131321.

[18] A. Pribadi, T. P. A. Setiyani, Tjendro, B. Setyahandana, and Martanto, “Utilization of used oil waste for boiler energy source,” *E3S Web of Conferences*, vol. 475, p. 05003, Jan. 2024, doi: 10.1051/e3sconf/202447505003.

[19] M. Bsiss, F. E. Nadir, and B. Amami, “Safety integrity level of shut-off valve in a burner management system,” *E3S Web of Conferences*, vol. 351, p. 01010, May 2022, doi: 10.1051/e3sconf/202235101010.

[20] M. Lelie *et al.*, “Battery management system hardware concepts: an overview,” *Applied Sciences*, vol. 8, no. 4, p. 534, Mar. 2018, doi: 10.3390/app8040534.

[21] A. F. Challoob, N. A. Bin Rahmat, V. K. A/L Ramachandaramurthy, and A. J. Humaidi, “Energy and battery management systems for electrical vehicles: A comprehensive review & recommendations,” *Energy Exploration & Exploitation*, vol. 42, no. 1, pp. 341–372, Jan. 2024, doi: 10.1177/01445987231211943.

[22] A. Sharma, A. Saxena, and G. Varshney, “Arduino - a brief review,” *International Journal of Scientific Research and Management Studies (IJSRMS)*, vol. 2, no. 11, pp. 445–451, 2016.

[23] R. Abdullah, Z. I. Rizman, N. N. S. N. Dzulkefli, S. Ismail, R. Shafie, and M. H. Jusoh, “Design an automatic temperature control system for smart tudung saji using Arduino microcontroller,” *ARPN Journal of Engineering and Applied Sciences*, vol. 11, no. 16, pp. 9578–9581, 2016.

[24] M. Samiullah and M. Z. Irfan, “Microcontrollers: a comprehensive overview and comparative analysis of diverse types,” *viXra.org*, [Online]. Available: https://vixra.org/pdf/2309.0075v1.pdf

[25] M. Khaery, A. A. N. Gunawan, and I. B. A. Paramarta, “Water flow control system by online based on ATmega328P microcontroller,” *Contemporary Engineering Sciences*, vol. 13, no. 1, pp. 303–314, 2020, doi: 10.12988/ces.2020.91603.

BIOGRAPHIES OF AUTHORS

Brahim Zraibi received the License's Degree in electronics and the Master's Degree in Electronics, Electrotechnics, Automatics, and Industrial Computing from the Faculty of Sciences Ain chock, Hassan II University, Casablanca, Morocco, in 2016 and 2019, respectively. He received the Ph.D. degree in Science and Technology exactly in Energy storage management and lifespan estimation of lithium-ion batteries by machine learning (with Hons.) from the National School of Applied Sciences in Berrechid, Hassan First University, Morocco, in 2023. His research interests focus on the lifetime estimation of lithium-ion batteries, machine learning, energy conversion, and energy storage systems. He can be contacted at email: b.zraibi@uhp.ac.ma.

Mohamed Mansouri received the Ph.D. degree in Mechanical Engineering and Engineering Sciences from the Faculty of Science and Technology, Hassan First University, Settat, Morocco, and from L'INSA, Rouen, France, in 2013. He is currently a professor and researcher at the National School of Applied Sciences in Berrechid, Department of Electrical Engineering and Renewable Energies, Research Laboratory of Analysis and Modeling of Systems and Decision Support, and head of the research team of Modeling and simulation of Multiphysics systems. His scholarly work has produced more than 30 journal and conference publications. His research interests include Mechano-reliability study, Industrial Engineering, Optimization of shape and reliability optimization of coupled fluid-structure systems, and energy storage systems. He can be contacted at email: mohamed.mansouri@uhp.ac.ma.

Abdelghani Ezzahi received his Engineering Degree in Telecommunications and Embedded Systems from the Faculty of Science and Technology, Hassan 1st University, Settat, Morocco, in 2018. He worked as a Mechatronics and Embedded Systems Engineer at Mohammed VI Polytechnic University for one year, and then as an Embedded Systems Engineer at MAVOR IMPORT (GHENT SUPPLY) for one year. He is currently working as a Hardware and Mechatronics Development Leader for ADAS Systems in Autonomous Vehicles at Capgemini Engineering. In addition, he is currently preparing his thesis on Electrical Vehicles. He can be contacted at email: abdelghani.ezzahi.doc@uhp.ac.ma.