ARDUINO UNO DIGITAL DISPLAY SYSTEM FOR AUTOMOBILE BATTERY VOLTAGE AND CURRENT MONITORING

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ABSTRACT
Automobile batteries require practical monitoring of voltage and current to support early identification of abnormal operating conditions. This study aimed to design and implement an Arduino Uno-based digital display system for monitoring a nominal 12 V automobile battery. The prototype integrates a resistor-divider voltage sensor, an ACS712-20A current sensor, an LM2596 DC-DC converter, a 16×2 I2C liquid-crystal display, and a buzzer. A Research and Development approach organized as an engineering design cycle was used, covering system design, prototype assembly, functional testing, and evaluation. Voltage readings were compared with a digital multimeter at five test points and produced a mean absolute percentage error of 0.38%. Current readings were examined under five charging and discharging conditions and produced a mean absolute percentage error of 3.61%; the largest relative deviation occurred at the lowest-magnitude discharge point. The buzzer remained off at 11.50 V and activated below 11.50 V, confirming the programmed comparator logic. The findings support the prototype as a simple continuous voltage-current and status monitoring device under the tested conditions. The study does not establish direct ampere-hour capacity or validated state-of-charge estimation; further validation with calibrated reference instruments, repeated measurements, multiple batteries, environmental variation, and dynamic automotive loads is required.

Keywords: Arduino Uno, battery condition monitoring, current monitoring, lead-acid battery, voltage monitoring

INTRODUCTION

Automobile electrical systems depend on the battery as a low-voltage energy source for engine starting and for supplying auxiliary electrical loads. In a conventional 12 V vehicle architecture, changes in terminal voltage and current provide direct operational evidence of charging, discharging, load demand, and potential abnormal conditions (Firdaus et al., 2021). Modern battery management literature consistently treats voltage and current acquisition as foundational monitoring functions because they support state estimation, protection, diagnostics, and control decisions (Gabbar et al., 2021; Habib et al., 2023; Hossain Lipu et al., 2021; Uzair et al., 2021). Although advanced electric-vehicle battery management systems may include cell balancing, thermal management, fault diagnosis, communication, and state estimation, the quality of these higher-level functions still depends on reliable electrical measurements and clearly defined operating thresholds.

Lead-acid batteries remain especially relevant to low-voltage automotive applications. Their terminal behavior reflects electrochemical processes, operating load, charge condition, temperature, and aging, which makes interpretation more complex than reading a single voltage value. Research on automotive lead-acid batteries therefore distinguishes routine electrical monitoring from deeper estimates of state of charge (SOC), state of health (SOH), cranking capability, and usable capacity. Model-based work on 12 V lead-acid batteries has shown that capacity and health estimation require dedicated equivalent-circuit parameters and validation against controlled aging or vehicle-like operating data rather than simple instantaneous measurements (Khodadadi Sadabadi et al., 2021). Similarly, real-time lead-acid SOC estimation has been developed using open-circuit-voltage relationships and recursive state-estimation methods (Loukil et al., 2021), while data-driven approaches have been proposed to improve SOC prediction under complex nonlinear behavior (Sun et al., 2022). These studies demonstrate why the terms voltage, current, battery condition, SOC, and capacity should not be used interchangeably.

The distinction is important for low-cost embedded prototypes. SOC is a latent quantity rather than a directly measured electrical variable, and contemporary battery research commonly derives it from an explicit model, observer, filter, or learned mapping. Examples include adaptive observers (Wang, Jiang, Gao, & Ren, 2022), neural-network model banks for joint SOC/SOH estimation (Lee & Lee, 2022), residual convolutional neural networks (Wang, Shao, Chen, Hsu, & Wu, 2022), bidirectional long short-term memory models (Yang et al., 2022), and Kalman-filter variants evaluated across different temperature and drive-cycle conditions (Hu et al., 2022; Wadi et al., 2022). A lead-acid SOC study using neural-network methods likewise emphasizes the need for an explicit estimation framework and empirical validation (Widjaja et al., 2023). Consequently, a prototype that directly validates voltage and current measurements should be presented primarily as a battery-condition monitoring system unless an SOC or capacity algorithm is fully documented and independently validated.

Arduino-based platforms provide a practical route for prototyping such monitoring functions because they combine analog-to-digital acquisition, embedded processing, digital output control, and straightforward display integration. Previous battery-oriented prototypes have demonstrated Arduino-based voltage monitoring, local or remote status reporting, and current sensing. Setiawan and Puriyanto (2020) implemented Arduino-based battery-voltage monitoring with communication capability; Roslan and Wan Muda (2020) integrated voltage and current sensing with an Arduino Uno and display interface; and Ratnawati and Sunardi (2020) examined ACS712 current detection in an Arduino environment. These studies establish the feasibility of low-complexity embedded battery instrumentation but also indicate that prototype claims should be aligned with the parameters actually measured and with the precision of the reference instruments used for validation.

Battery monitoring also has a broader systems context. Reviews of battery management architectures identify continuous electrical monitoring, protection logic, data communication, and safety functions as interdependent elements rather than isolated features (Gabbar et al., 2021; See et al., 2022). Wireless battery management research further shows how sensing architecture and data communication become increasingly important as systems scale beyond simple local prototypes (Samanta & Williamson, 2021). The present work does not attempt to reproduce a full automotive BMS; instead, it focuses on a compact local monitor that makes voltage, current direction, operating status, and a low-voltage warning directly visible to the user. The engineering value of such a prototype lies in transparent integration and testable functional behavior, not in equivalence to a production-grade BMS.

A second context concerns laboratory and engineering education. Low-cost microcontroller platforms are widely used to create physical experiments in which students can connect sensor behavior, data acquisition, embedded programming, and system response. Arduino-based hardware has been used as a benchmark platform for process dynamics and control (Park et al., 2020), as a portable kit for introducing digital control concepts (de Moura Oliveira et al., 2020), and as a low-cost data-acquisition platform in introductory laboratory work (Vallejo et al., 2020). More generally, engineering-laboratory research shows that physical, remote, and simulated laboratory environments require clear learning objectives and evidence if educational effectiveness is to be claimed (Nikolic et al., 2021), while empirical studies of laboratory pedagogy demonstrate the value of structured preparation and active engagement for student performance (Gómez-Tejedor et al., 2020). For this reason, the prototype developed here may be relevant as an instructional demonstrator, but the present study evaluates technical function only and does not claim measured learning outcomes.

Against this background, the research gap addressed by the study is not the invention of a new voltage or current sensing principle. Rather, it is the need for a clearly documented, low-complexity prototype that integrates safe voltage sensing, bidirectional current sensing, microcontroller processing, local display, and a low-voltage alarm, while reporting its functional measurement agreement without overstating battery-capacity or SOC capability. The study therefore aims to design and implement an Arduino Uno-based automobile battery monitor and to evaluate four outputs: voltage measurement agreement, current-measurement agreement and direction, display functionality, and buzzer activation behavior. The contribution is a transparent prototype-level implementation and an evidence-bounded interpretation of its performance, with a secondary potential application as a laboratory demonstrator in automotive or electronics education.

METHOD

This study used a Research and Development approach structured as an engineering design cycle. The sequence included identification of the monitoring need, formulation of functional requirements, review of relevant sensing and microcontroller literature, hardware and software design, component selection, prototype assembly, Arduino programming, sensor integration, functional testing, analysis of recorded measurements, and refinement of the prototype. Figure 1 summarizes the process. The design cycle was selected because the research objective concerned the development and functional verification of an integrated hardware-software product rather than testing a behavioral intervention or estimating population parameters.

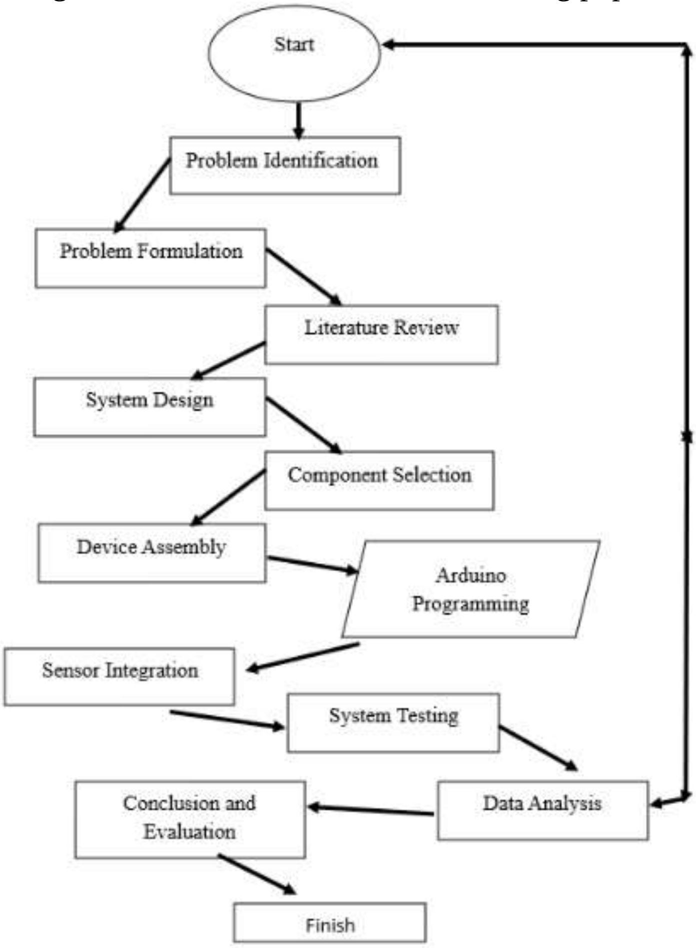

Figure 1. Engineering Design and Testing Flow of the Arduino Uno-Based Battery Monitoring Prototype

The developed system consisted of five functional blocks. The first was a resistor-divider voltage-sensing stage using R1 = 30 kΩ and R2 = 7.5 kΩ. The divider reduces the nominal battery voltage before it reaches the Arduino analog input; for an ideal divider, the output is Vout = Vin × R2/(R1 + R2). The second block was an ACS712-20A Hall-effect current sensor for observing current magnitude and direction. Positive values in the recorded test set represented charging and negative values represented discharging. The third block was the Arduino Uno, based on the ATmega328P microcontroller, which acquired the sensor signals and executed the display and warning logic. The fourth block was a 16×2 I2C liquid-crystal display for local presentation of voltage, current, and operating status. The fifth block was a buzzer controlled as a low-voltage warning output. An LM2596 DC-DC converter was used in the prototype power path to provide a regulated 5 V supply for the low-voltage electronics.

The embedded software followed a simple acquisition-decision-display sequence. Analog inputs were read from the voltage and current channels, converted into engineering-unit values according to the prototype scaling, and then used to update the LCD fields. The current sign determined whether the operating status was reported as charging or discharging. The alarm branch compared the measured voltage with the programmed threshold and energized the buzzer only when the voltage was below 11.5 V. This logic is intentionally less complex than the multi-state estimators used in advanced BMS research, where model parameters, noise statistics, temperature, and historical data may be processed recursively (Hossain Lipu et al., 2021; Wadi et al., 2022). The simplicity of the present algorithm makes the relationship between the measured signal and output action transparent, which is advantageous for prototype verification and laboratory demonstration. At the same time, it means that the device should be understood as a direct monitoring and warning system rather than an estimator of hidden electrochemical states.

The research subject was the prototype itself and its recorded bench-test outputs. The available source record does not specify the battery manufacturer, battery model, ampere-hour rating, age, or detailed electrochemical condition; therefore, those characteristics cannot be reconstructed and are not inferred in this revision. Likewise, the reference instrument used during voltage testing is described only as a digital multimeter, while the current table reports reference-current values without documenting the model, accuracy class, calibration certificate, or uncertainty of the reference instrument. These omissions are treated as limitations of the evidence rather than filled with assumed specifications.

Functional data collection used direct comparison between reference values and prototype readings. Voltage performance was evaluated at five reference points: 12.80, 12.50, 12.10, 11.80, and 11.40 V. Current performance was evaluated at five conditions: +1.50, +3.20, +5.00, -1.20, and -2.50 A. The recorded system values at these points were 12.75, 12.45, 12.06, 11.75, and 11.36 V for voltage, and +1.45, +3.15, +4.92, -1.10, and -2.42 A for current. Buzzer behavior was checked at 12.60, 12.20, 11.80, 11.50, 11.40, and 11.20 V. The display was inspected to confirm that it presented voltage, current, charging/discharging status, and the interface fields produced by the Arduino program.

Measurement agreement was summarized using absolute percentage error, calculated as Error (%) = |Reference value - System value| / |Reference value| × 100. The mean absolute percentage error (MAPE) was then calculated as the arithmetic mean of the absolute percentage errors across the available test points. Using the recorded values, voltage MAPE was 0.38% and current MAPE was 3.61%. The sign of current was also evaluated because correct sign preservation is necessary for distinguishing charging from discharging. Buzzer validation was categorical: the observed on/off output was compared with the programmed low-voltage comparator rule.

The study record does not document repeated measurements at each point, sensor zero-offset calibration, temperature compensation, sampling interval, display refresh rate, response-time measurement, vibration exposure, road testing, or long-duration operation. Accordingly, the analysis is limited to descriptive prototype-level functional agreement. It does not constitute metrological calibration, repeatability or reproducibility validation, uncertainty estimation, or quantified real-time performance testing. The interface also contains a battery-level percentage, but the source record does not provide a validated voltage-to-SOC lookup table, coulomb-counting method, equivalent-circuit estimator, or data-driven SOC model. Consistent with battery-estimation literature (Loukil et al., 2021; Sun et al., 2022; Wadi et al., 2022), that percentage is therefore treated only as an undocumented interface indicator and is excluded from the validated outcomes.

The procedures involved hardware and prototype measurements only. No human participants, student participants, personal data, medical information, or personally identifiable data were involved in the reported testing. Consequently, participant consent and human-subject data protection procedures were not applicable to the available study record.

RESULTS AND DISCUSSION

System Architecture and Functional Outputs

The completed prototype integrated the voltage divider, ACS712-20A sensor, Arduino Uno, LM2596 converter, 16×2 I2C LCD, and buzzer into a single monitoring arrangement. Figure 2 presents the system architecture in English and emphasizes the signal path rather than reproducing every wiring detail. The voltage-divider output was directed to an Arduino analog input, the ACS712 current signal was directed to a second analog input, and the Arduino generated display and alarm outputs. This arrangement is consistent with the modular logic used in embedded monitoring systems: sensing and signal conditioning are separated from processing, user interface, and protection outputs (Gabbar et al., 2021; Uzair et al., 2021).

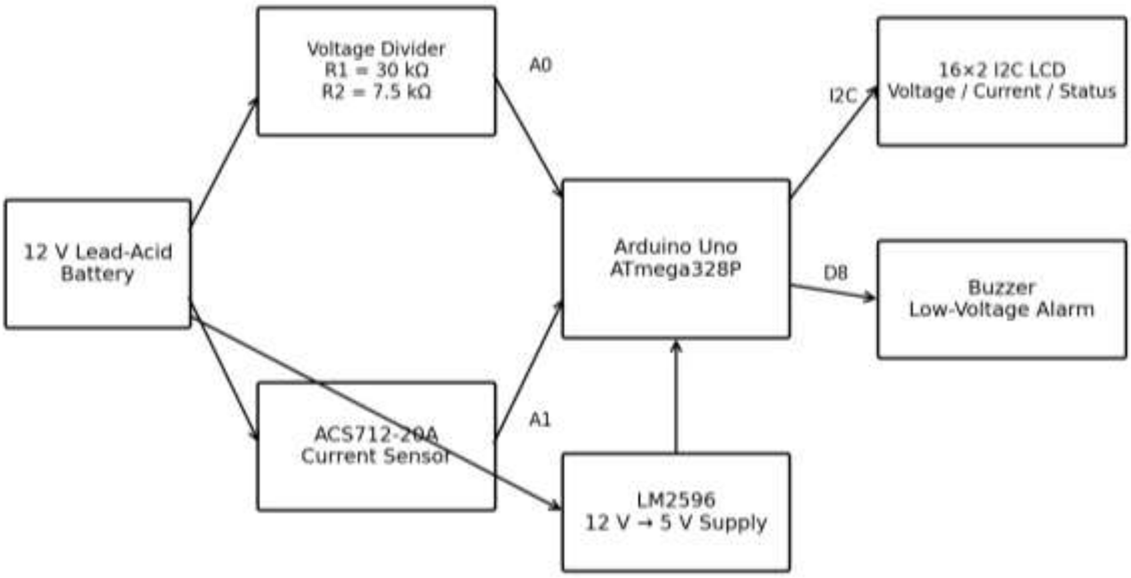

Figure 2. Electronic Circuit Architecture of the Arduino Uno-Based Battery Monitoring Prototype

The validated outputs of the study are battery voltage, measured current, charging/discharging direction, display functionality, and low-voltage buzzer behavior. The distinction between validated and displayed variables is important. The LCD example included a percentage level in addition to voltage, current, and status, but the underlying percentage algorithm was not documented. Because SOC is not a directly measurable variable and modern estimation approaches require explicit models or data-driven mappings (Hu et al., 2022; Lee & Lee, 2022; Wang, Jiang, Gao, & Ren, 2022; Wang, Shao, Chen, Hsu, & Wu, 2022; Yang et al., 2022), the percentage field cannot be interpreted as validated capacity or SOC from the available evidence.

Voltage Measurement Performance

Voltage measurement was evaluated by comparing the prototype output with the digital-multimeter reference at five points across the recorded 11.40-12.80 V range. The values and calculated errors are reported in Table 1. The absolute percentage error ranged from 0.33% to 0.42%, with a mean of 0.38%. The largest reported voltage error occurred at the 11.80 V reference point. Within this limited bench-test range, the close numerical agreement supports the basic voltage-monitoring function of the prototype.

Table 1. Battery Voltage Measurement Results

No.	Multimeter Voltage (V)	System Voltage (V)	Error (%)
1	12.80	12.75	0.39
2	12.50	12.45	0.40
3	12.10	12.06	0.33
4	11.80	11.75	0.42
5	11.40	11.36	0.35

The observed agreement is compatible with the feasibility reported in other Arduino-based battery-monitoring prototypes (Roslan & Wan Muda, 2020; Setiawan & Puriyanto, 2020). However, the numerical result should be interpreted narrowly. The reference multimeter model and calibration status are unknown, repeated readings were not reported, and the available record does not quantify analog-reference stability, resistor tolerance, ADC uncertainty, or temperature effects. Therefore, 0.38% is best described as the mean disagreement between the reported reference values and prototype readings at the five test points, not as a certified accuracy specification. This distinction reflects good measurement practice and prevents prototype-level comparison data from being presented as instrument calibration.

Current Measurement Performance

Current-sensor testing covered three charging and two discharging conditions. Table 2 reports the reference current, system current, and calculated absolute percentage error. The current sign was preserved at every test point, meaning that the prototype correctly distinguished the recorded charging conditions from the recorded discharging conditions. The mean absolute percentage error was 3.61%. The largest relative deviation, 8.33%, occurred at -1.20 A, the smallest-magnitude discharge test point, whereas the remaining errors ranged from 1.56% to 3.33%.

Table 2. Current Measurement Results Using ACS712

No.	Condition	Reference Current (A)	System Current (A)	Error (%)
1	Light charging	+1.50	+1.45	3.33
2	Moderate charging	+3.20	+3.15	1.56
3	High charging	+5.00	+4.92	1.60
4	Light discharging	-1.20	-1.10	8.33
5	Moderate discharging	-2.50	-2.42	3.20

The ACS712 result is consistent with the general use of Hall-effect current sensing in Arduino-based measurement systems (Ratnawati & Sunardi, 2020). The higher relative error at the lower-magnitude discharge point should not be overinterpreted because only one observation is available for each condition and the reference-current instrumentation is not described. In Hall-effect sensing, zero offset, noise, supply stability, and analog-to-digital conversion can become proportionally more influential when the measured signal approaches the lower end of the tested range. The current table therefore supports functional magnitude tracking and direction detection, but it does not establish a full sensor linearity curve, repeatability, or uncertainty budget.

Display and Alarm Behavior

Table 3. Buzzer Alarm Test Results

No.	Battery Voltage (V)	Buzzer Status
1	12.60	Off
2	12.20	Off
3	11.80	Off
4	11.50	Off
5	11.40	On
6	11.20	On

The 16×2 I2C LCD displayed the monitored values and operating status locally. For consistency with the English manuscript, the interface can be represented as VOLT: 12.45 V; CURRENT: -2.35 A; STATUS: DISCHARGING; LEVEL: 75%. The first three fields correspond to variables or status logic directly represented in the test record. The LEVEL field is retained only as evidence that the program displayed a percentage; it is not interpreted as validated capacity or SOC because no estimation rule is available. The local interface eliminates the need for a separate computer during basic observation, although the study did not assess usability, display latency, readability under vehicle lighting conditions, or user response to warnings.

The buzzer was tested across six voltage points, as shown in Table 3. It remained off at 11.50 V and switched on at 11.40 V and 11.20 V. The implemented logic can therefore be stated precisely as activation when $V < 11.5$ V for the reported program and test sequence. This is preferable to describing 11.5 V as a universal battery-damage threshold. Appropriate warning limits depend on battery chemistry, load, temperature, battery age, and manufacturer recommendations. Reviews of battery management safety emphasize that monitoring and protection thresholds should be tied to the relevant operating context and validated system behavior (Habib et al., 2023; Hossain Lipu et al., 2021; See et al., 2022).

Continuous Monitoring and the Meaning of Real-Time Performance

The prototype continuously updates its display during operation, but the available test record does not quantify the sampling interval, analog-conversion cadence, software loop period, display refresh rate, or alarm latency. For that reason, continuous monitoring is a more precise description of the demonstrated functionality than a validated real-time performance claim. In embedded systems, real-time performance is not established merely because values appear without manual intervention; it normally requires a defined timing requirement and evidence that sensing, processing, and actuation meet that requirement under relevant operating conditions. Hardware-benchmark research with microcontrollers demonstrates the importance of discrete sampling intervals, communication overhead, and physical process timing when real hardware is evaluated (Park et al., 2020). A future version of the present study should therefore report the Arduino sampling frequency, LCD refresh interval, and measured buzzer response time under controlled voltage transitions. These metrics would convert the current qualitative observation of continuous updating into a reproducible timing specification.

Positioning Against Related Monitoring and State-Estimation Research

Table 4. Positioning of the Present Prototype Against Representative Related Research

Study	Primary Focus	Key Relevance to Present Study
Setiawan & Puriyanto (2020)	Arduino battery-voltage monitoring and communication	Supports feasibility of microcontroller-based voltage monitoring
Roslan & Wan Muda (2020)	Arduino voltage/current sensing with display	Closest functional precedent for local electrical monitoring
Khodadadi Sadabadi et al. (2021)	Model-based SOH estimation for 12 V lead-acid batteries	Shows that battery health/capacity claim require validated models and aging data
Loukil et al. (2021)	Online model/SOC estimation for lead-acid batteries	Demonstrates explicit estimation methoc beyond raw voltage/current sensing
Sun et al. (2022)	Data-driven lead-acid SOC prediction	Reinforces distinction between monitore variables and predicted SOC
Present study	Voltage/current display, direction status, and low-voltage warning	Integrates simple sensing and warning functions; does not validate SOC or capa

The contribution of the prototype becomes clearer when it is positioned against related work rather than described as a new sensing principle. Table 4 summarizes representative strands of prior research. Earlier Arduino prototypes demonstrate that voltage, current, display, and communication functions can be implemented with inexpensive microcontrollers, while advanced battery studies focus on state estimation, health estimation, safety, or distributed management. The present system occupies the first category: it is an integrated measurement-and-warning demonstrator. Its novelty is therefore architectural and instructional at the prototype level, not algorithmic novelty in battery electrochemistry or state estimation.

The comparison also clarifies why the present study should not claim superiority over advanced SOC approaches. Adaptive observers, Kalman-filter methods, neural networks, and recurrent architectures are designed to infer a latent battery state from dynamic measurements and models (Hu et al., 2022; Lee & Lee, 2022; Wadi et al., 2022; Wang, Jiang, Gao, & Ren, 2022; Wang, Shao, Chen, Hsu, & Wu, 2022; Yang et al., 2022). Those studies typically use controlled datasets, repeated drive cycles, temperature variation, or structured training and validation. In contrast, the current prototype offers transparent local measurement and warning behavior with very low computational complexity. That narrower contribution is still useful when stated accurately, particularly for introductory prototyping, basic automotive-electrical diagnostics, or as a foundation for future SOC algorithms.

Battery-management reviews further indicate that a production-oriented system would normally incorporate additional protections and validation layers. These can include temperature sensing, cell-level monitoring, balancing, fault detection, robust communication, data logging, and compliance with relevant safety standards (Gabbar et al., 2021; Samanta & Williamson, 2021; Uzair et al., 2021). The present prototype is not designed to replace such systems. Rather, it demonstrates the sensing-processing-display-warning chain in a form that is easy to inspect and extend. This distinction is particularly important for publication because it preserves practical value without implying automotive qualification, certification, or equivalence to commercial BMS hardware.

Practical and Educational Implications

Practically, the prototype demonstrates that a small set of commonly available modules can be integrated to display battery voltage, current direction, and a programmed low-voltage warning. The numerical data show close voltage agreement and acceptable functional current tracking within the limited test set. For workshop or laboratory use, this architecture can help users observe how a voltage divider protects a microcontroller input, how a Hall-effect sensor represents bidirectional current, and how software logic converts sensor readings into a visible status and alarm. The system can also provide a starting point for more rigorous developments that add calibrated sensing, logging, temperature measurement, communication, or validated SOC estimation.

The potential educational relevance should be framed cautiously. Hardware benchmarks such as Arduino-based control kits have been used to expose students to real sampling, communication, sensor, and model-mismatch effects that are absent from ideal simulations (Park et al., 2020). Portable Arduino laboratory kits can also support hands-on exploration of embedded control concepts (de Moura Oliveira et al., 2020), and low-cost Arduino data-acquisition systems have been developed for introductory science laboratories (Vallejo et al., 2020). These precedents support the plausibility of using the battery monitor as an instructional demonstrator. However, educational effectiveness would require a separate study with stated learning outcomes, instructional procedures, participant data, and appropriate assessment. Reviews of engineering laboratories stress that the mere availability of a device does not itself demonstrate learning gains (Nikolic et al., 2021), while empirical laboratory research shows that instructional design and preparation can materially affect student performance (Gómez-Tejedor et al., 2020). The present article therefore identifies educational use as an implication, not an evaluated outcome.

Limitations and Future Validation

The study has several limitations that define the transferability of the findings. First, only five voltage points and five current conditions were available, with no repeated trials or dispersion statistics. Second, the battery manufacturer, rating, age, and detailed test condition were not reported. Third, the reference measurement equipment and calibration metadata were unavailable. Fourth, the study did not record sampling interval, display refresh rate, dynamic response time, temperature, vibration, electromagnetic disturbance, or long-duration drift. Fifth, the buzzer threshold was validated only as a program behavior around 11.5 V and should not be generalized as a universal automotive damage threshold. Sixth, no validated SOC or ampere-hour capacity estimator was documented. These limitations mean that the results demonstrate functional feasibility rather than production-grade accuracy, reliability, or safety certification.

Future work should therefore proceed in stages. A measurement-validation stage should use a traceable or calibrated reference multimeter/current instrument, repeated measurements, explicit sensor-zeroing procedures, resistor-tolerance documentation, temperature variation, and uncertainty reporting. A dynamic stage should test charge and discharge profiles representative of actual vehicle loads and should quantify sampling rate, display latency, alarm response time, and long-duration stability. A battery-state stage could then add and validate an SOC method appropriate to lead-acid chemistry, drawing on open-circuit-voltage/model-based approaches (Loukil et al., 2021), data-driven prediction (Sun et al., 2022; Widjaja et al., 2023), or other estimation frameworks with clearly defined training and validation procedures. Finally, if the device is positioned for education, a separate instructional study should measure learning outcomes, usability, and student interaction rather than inferring educational effectiveness from the hardware alone.

CONCLUSION

This study designed and functionally evaluated an Arduino Uno-based digital display system for automobile battery voltage and current monitoring. The prototype integrated a resistor-divider voltage sensor, an ACS712-20A current sensor, Arduino processing, a 16×2 I2C LCD, and a buzzer. Across five voltage test points, the mean absolute percentage error between the reported reference and system readings was 0.38%. Across five charging and discharging current conditions, the mean absolute percentage error was 3.61%, and the sign of current was preserved at every point. The buzzer remained off at 11.50 V and activated below 11.50 V, confirming the programmed alarm logic. These results support the system as a simple continuous monitoring and warning prototype under the reported bench-test conditions. The evidence does not establish direct ampere-hour capacity, validated state-of-charge estimation, metrological-grade accuracy, automotive qualification, or educational effectiveness. Future research should use calibrated reference instruments, repeated and dynamic tests, multiple batteries, environmental variation, a documented SOC algorithm if percentage level is retained, and a separate learning-outcome design if the prototype is used in engineering education.

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