

Article

Experimental Approach to Intelligent Estimation of the State-of-Charge (SoC) of Batteries: Case of Electric Vehicles

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Abstract

The development of the electric vehicle sector increasingly requires optimal intelligent and embedded energy management. Electric vehicles are now positioning themselves as a strategic alternative to traditional fuel vehicles. This article therefore highlights the design of an embedded system capable of evaluating and transmitting in real time the state-of-charge (SoC) of an electric vehicle battery to a cloud platform, while optimizing energy consumption and data reliability. The methodological approach proposes an experimental study involving the development of two deep learning models, LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit), in the MATLAB 2024.b environment, associated with the design of an embedded prototype for data collection and transmission via Arduino IoT Cloud. Then, a comparative analysis of the models' performances is also carried out. The results obtained show that the GRU model offers the best performance, with an accuracy of 83.6%, an MSE of 0.0715, and an RMSE of 0.2589, thus validating the relevance of the proposed approach for the intelligent estimation of the state-of-charge in a real application context.

Keywords: state-of-charge (SoC); lithium-ion battery; intelligent embedded system; deep learning LSTM and GRU; statistical indicators MSE and RMSE; experimental prototype

1. Introduction

The electric vehicle (EV) sector has experienced exponential growth worldwide, with gradual adoption in various countries, including on the African continent [1]. This development is part of a global context of energy transition and the fight against climate change. However, one of the major limitations to the widespread adoption of EVs remains the optimal management of energy stored in their batteries, particularly the assessment of their state-of-charge (SoC) [2]. Several researchers have already addressed this issue, proposing various approaches such as Kalman filtering, empirical models, and machine learning. However, most of these studies are applied in standard environments, often poorly representative of African climatic realities, highlighting the need to adapt methods to tropical contexts and local constraints [3].

1.1. Context and Background

Several algorithms for estimating battery state-of-charge have been used, such as Kalman filtering, which is a method that assesses the state-of-charge by combining real-



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world measurements with predictions from a dynamic battery model [4–6]. It generally relies on observational techniques, such as Kalman filters, to correct in real time the discrepancies between measured values and those simulated by the model [7–9]. There are also heuristic or combinatorial methods that rely on algorithms capable of simultaneously integrating several measured parameters, such as voltage, current, and temperature, to examine the state-of-charge more accurately and robustly. This combination of data improves the reliability of the estimation, particularly under varying operating conditions [10]. Each method has specific advantages, but also some limitations, particularly in terms of accuracy, implementation cost, algorithmic complexity, and sensitivity to environmental conditions and battery aging. This is why, in practice, battery management systems (BMSs) integrated into electric vehicles often use a combination of several estimation techniques. This hybrid approach improves the reliability and accuracy of the state-of-charge assessment.

1.2. Motivations of the Study

The increasing adoption of electric vehicles presents a series of challenges and opportunities for industry, research, and technological innovation. Effective battery management is central to these challenges, being essential for ensuring the proper functioning and longevity of electric vehicles [11–13]. The main objective of our study is to highlight the importance of accurate estimation of the state-of-charge (SoC) of batteries, as this is crucial not only for avoiding the risks of overcharging and over-discharging, but also for extending their lifespan and ensuring optimal range management [14]. One of the main challenges of this study lies in estimating the state-of-charge (SoC), which is complicated by the nonlinear nature and specific characteristics of battery behavior. This behavior is influenced by several factors, such as temperature variations, current fluctuations, and aging, highlighting the need to refine estimation methods to ensure optimal battery management [15] and premature battery wear [16]. In the context of this research, it should be emphasized that the state-of-charge of a battery cannot be measured directly and must be measured by taking into account several factors, such as capacity, voltage, current, and temperature. Furthermore, battery aging and driving conditions, including fluctuations in temperature and humidity, significantly affect these parameters [17].

1.3. Previous Works

The study [17] proposed a state-of-charge estimation technique for battery electric vehicles utilizing deep learning combined with cloud-connected IoT. Its specific objectives were to prevent batteries from overcharging and discharging, increase battery lifespan, and determine battery range. Strengths of this work included accuracy, as it captures complex relationships, providing more precise estimates, and fast processing time. However, limitations included data storage, real-time monitoring, early detection of abnormal operation, and complexity, which impacts computational efficiency and memory consumption. The work [18] focused on estimating the state-of-charge of electric vehicles using random forests. Its specific objectives were to improve real-time estimation accuracy, extend battery lifespan, and optimize electric vehicle performance. The advantages of these studies [19–21] were accuracy, offering more precise estimates, robustness, being less sensitive to noise, and ensuring stable predictions and handling of missing data. Limitations included computation time, requiring longer training, which can be problematic for real-time applications, and data requirements, necessitating a sufficient amount of data for good performance. This determines the remaining range of electric vehicles by calculating the operating time of the battery-powered equipment. This offers advantages such as minimal errors, significantly improved accuracy in state-of-charge estimation, and enhanced prediction robustness. The study [22] developed battery state-of-charge estimation for electric vehicles using

Kolmogorov–Arnold networks, with the ongoing objectives of ensuring efficient battery management, optimizing vehicle performance, and extending battery life. The study [23] introduced a machine learning method optimized with Bayesian techniques for precise estimation of the state-of-charge of lithium-ion batteries utilized in electric vehicle applications. This approach also aims to reduce battery costs and increase range by extending battery life. The work [24] proposed a battery state-of-charge estimation method using a time-domain convolutional network based on electric vehicle operating data. This method offers the advantages of a network execution time capable of handling a large number of parallel operations, and, importantly, avoids problems with gradient explosion or disappearance. The works [14,25] proposed a modified extended Kalman filtering algorithm for accurate voltage and state-of-charge estimations of rechargeable batteries. Their objectives are to improve the energy distribution performance of the battery system, enhance battery safety, prevent battery overcharging and over-discharging, extend battery life, and optimize energy distribution within the system.

1.4. Paper Contributions

The main contributions of this study are:

- (i) The development and deployment of two machine learning algorithms to estimate the state-of-charge of electric vehicle batteries.
- (ii) An experimental implementation with a prototype for validating the process of estimating the state-of-charge of EV batteries.
- (iii) A comparative study and classification of battery state-of-charge estimation methods in accordance with current literature.

1.5. Paper Organization

In the remainder of this study, Section 2 presents a battery model and a detailed overview of the learning algorithms used in the estimation process. Section 3 presents an experimental prototype designed to validate the process of estimating the state-of-charge of EV batteries. In Section 4, the results obtained are presented, along with a classification and positioning relative to the current literature, and in Section 5, the conclusion is presented along with future prospects of the work.

2. Equivalent Circuit Modeling of the Battery

When the battery discharges, the current is positive, and when it recharges, it becomes negative. The open-circuit voltage (U_{oc}) corresponds to the battery voltage when no current is flowing. It is also important to note that the internal resistance (R_{int}) is not fixed but depends on the state-of-charge (SoC) and the temperature. Although this model is simple to use and implement, it accurately represents the dynamic behavior of the battery. Indeed, it takes into account phenomena such as concentration and activation polarization [9]. Figure 1 presents the second-order Thévenin model.

This model is characterized by the following equations:

$$U_{pc} = \frac{dU_{pc}}{dt} = -\frac{U_{pc}}{(R_{pc}C_{pc})} + I_{bat} \frac{1}{(C_{pc})}; \quad (1)$$

$$U_{bat} = U_{co} - U_{pa} - U_{pc} - R_{int}I_{bat}. \quad (2)$$

The model above incorporates the transient response of the electrical double-layer (EDL) and dynamic biasing phenomena into the voltage evolution (U_{bat}). The two networks (R_{pa} , C_{pa} , R_{pc} , C_{pc}) cause the system to react at two different time constants. It consists of an ideal open-circuit voltage source (U_{oc}), an ohmic resistance (R_{int}), and

two biasing resistors, R_{pa} and R_{pc} , which respectively represent the electrochemical biasing resistance and the concentration biasing resistance. It also includes two capacitors, C_{pa} and C_{pc} , which respectively represent the electrochemical biasing capacitance and the concentration capacitance.

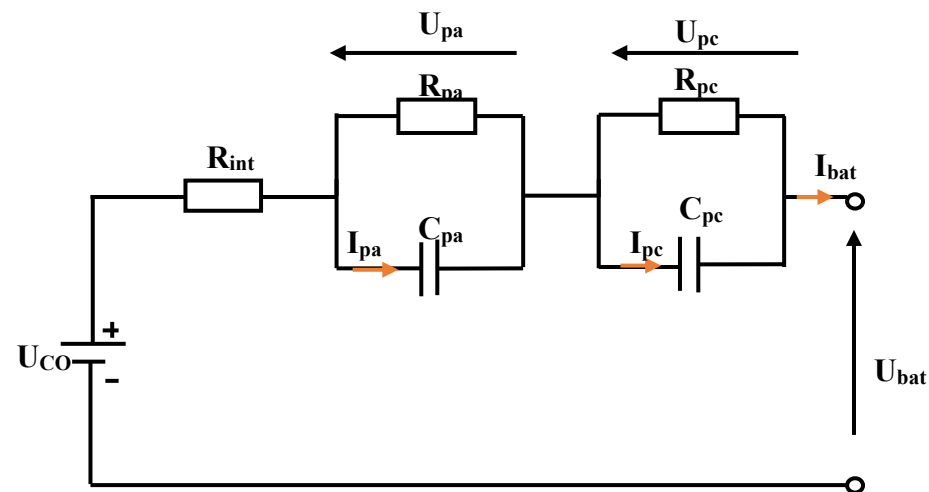


Figure 1. Second-order Thévenin model.

2.1. Proposed Methods

Figure 2 presents the general architecture proposed for its operating mode. For this task, the maximum number of epochs is set to 200, with early stopping after 50 epochs. The batch size is 32. The ADAM optimizer is used with a weight decay of 1×10^{-4} . The learning rate is set to 5×10^{-4} . The hybrid model employs four layers, using the tanh activation function for the GRU/LSTM units.

The LSTM (Long Short-Term Memory) is a special type of recurrent neural network (RNN) designed to better capture long-term dependencies in temporal sequences. Compared to classical RNNs, LSTM networks offer better performance for state-of-charge (SoC) monitoring thanks to their ability to retain relevant information over long periods. An LSTM network consists of one or more LSTM cells, whose internal structure is shown in Figure 3 below. There are three gates in an LSTM cell: the forget gate (in blue), the input gate (in orange), and the output gate (in yellow). The LSTM unit uses as input the current element of the sequence, denoted x_t , and the output of the previous time step h_{t-1} , as well as the previous memory state c_{t-1} . Outputs h_t and c_t are then kept for the next iteration.

The forget gate determines which information should be erased or retained in memory. It is generally defined by the following equation:

$$f_t = \sigma(W_f[h_{t-1} + b_f]), \quad (3)$$

where σ is a sigmoid function. W_f and b_f represent the weight matrix and bias associated with the forgetting gate, respectively. The entry gate, on the other hand, updates the cells. The entry formula can be formulated as follows:

$$i_t = \sigma(W_i[h_{t-1}, x_t + b_i]); \quad (4)$$

$$c_t = \tanh(w_c[h_{t-1}, x_t + b_c]). \quad (5)$$

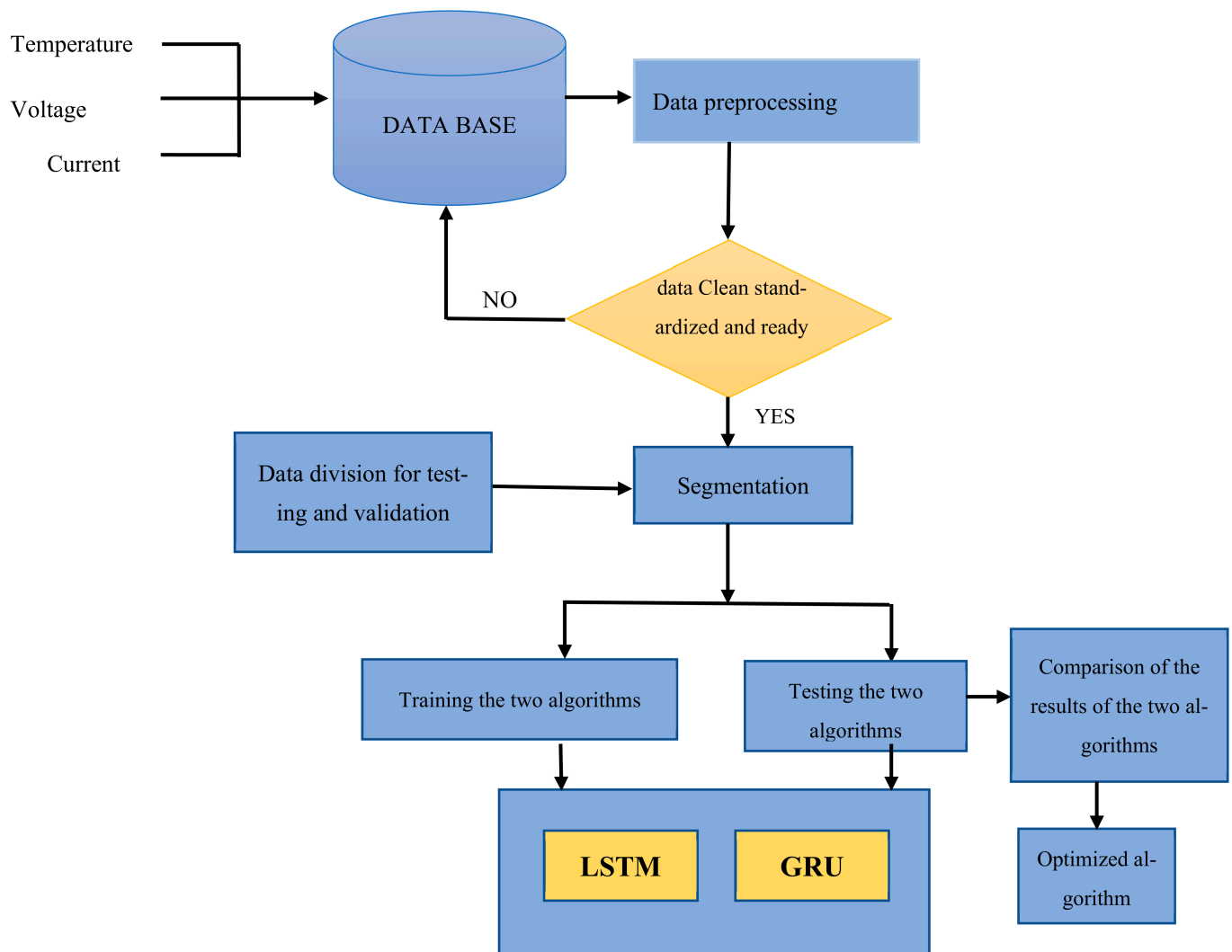


Figure 2. Proposed general architecture.

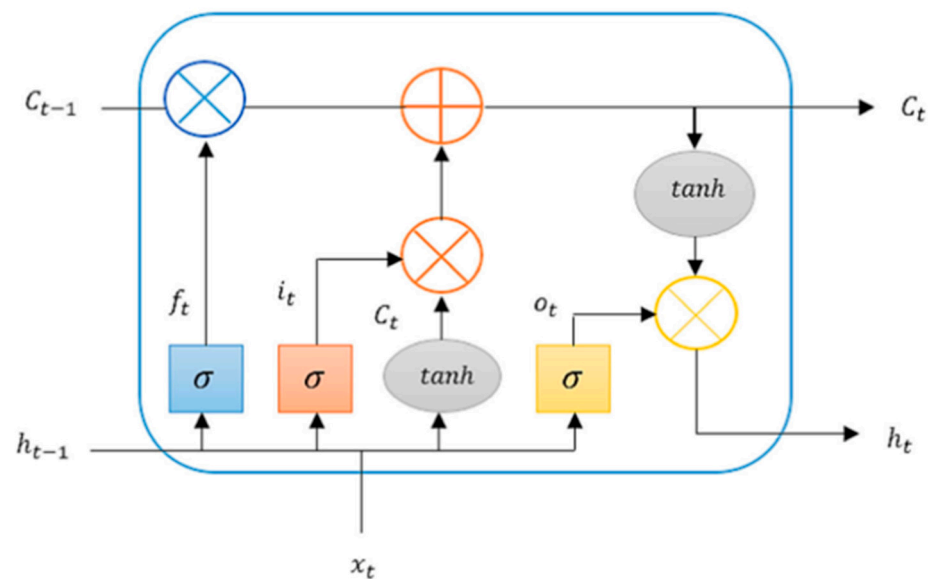


Figure 3. LSTM model structure.

2.2. Presentation of Performance Coefficients

To evaluate network performance, we use the mean squared error (MSE) and the root mean squared error (RMSE). These measures allow us to quantify the network's accuracy relative to the target or reference value.

$$MSE = \frac{1}{N} \sum_{i=1}^N (p_i - O_i)^2, \quad (6)$$

where P_i is the real value and O_i is the predicted value, as follows:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (p_i - O_i)^2}. \quad (7)$$

Figure 4 shows the general flowchart of the overall implementation procedure.

Tables 1 and 2 present the battery parameters and a summary of the simulation parameters, respectively.

Table 1. Technical specifications of the battery and fields of application.

Battery Type	Rated Voltage (V)	Energy Density (Wh/kg)	Lifespan (Cycles)	Yield (%)	Charging Time	Cost (€/kWh)	Main Applications
Lithium-ion (Li-ion)	3.2–3.7 V par cellule	150–250	1000–3000	90–98	1–4 h	100–300	Electric vehicles, smartphones, laptops

Table 2. Summary of simulation parameters.

Setting	Numerical Values
Rated voltage	12 V
Maximum discharge current	7 A
Rated capacity	7 Ah
Charging voltage range	13.5 V to 14.5 V
Internal resistance	0.0021 Ω
Internal polarization capacity	28,000 μ F
Polarization resistance	0.017 Ω
Resistance to concentration	0.029 Ω
Capacity for deconcentration	32,000 μ F
Number of hidden sofas	4 (LSTM ou GRU)
Neurons/couch	100 'n, 80 'n, 60 'n, 40 'n
Internal activation	Tanh (states) + sigmoid (gates)
Exit	1 value (estimated SoC)

Battery voltage, current, and temperature are used as input variables for estimating the state-of-charge (SoC) of electric vehicle batteries. The SoC is the primary output variable to be predicted. Dissipated power determined by the voltage-current product provides additional energy information, reflecting internal losses and changes in operating state, particularly during charge and discharge cycles. Its inclusion in LSTM and GRU models improves the accuracy of the SoC estimation by accounting for both thermal effects and the complex energy dynamics of the battery system. In the current literature, such as in [4], the four-layer model offers a better compromise for datasets and hyperparameters such as the learning rate (LR), which typically has a value between 0.001 and 0.0005 Adam, and for batch sizes ranging from 64 to 256 with a sequence length between 100 and 500 time steps.

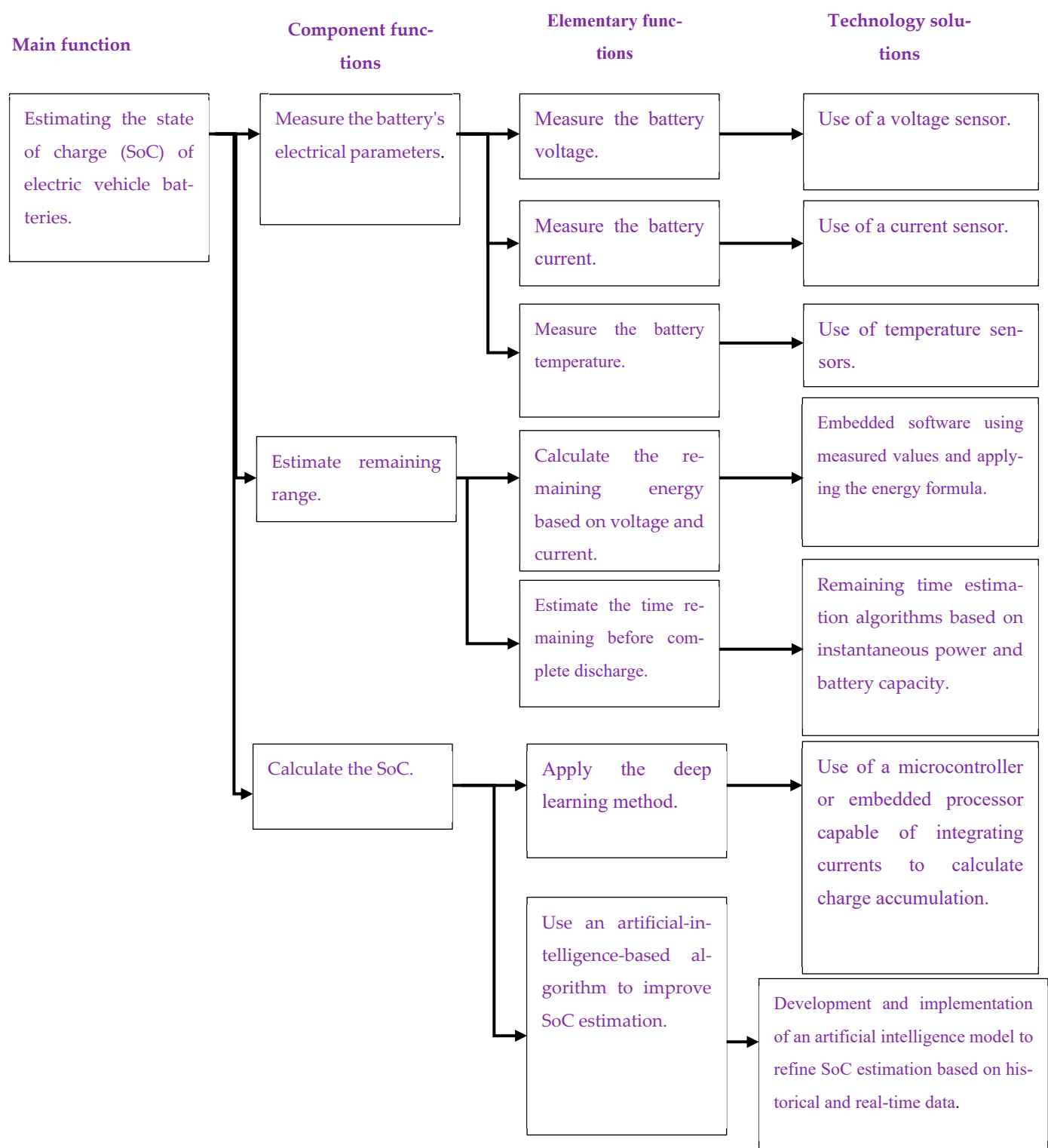


Figure 4. General implementation diagram.

3. Experimental Prototype for Battery State-of-Charge (SoC) Estimation

Figure 5 shows the final SoC map developed for battery estimation, which incorporates several key components. Table 3 lists these key components and their associated functions.

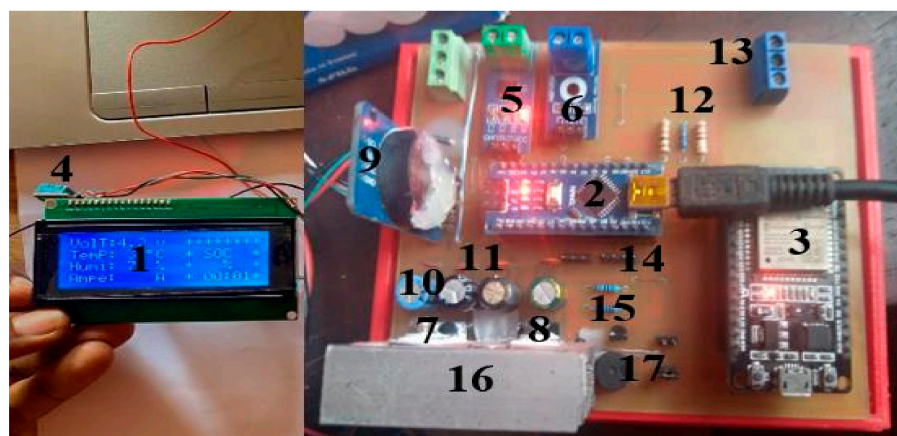


Figure 5. Map developed for estimating the state-of-charge (SoC) of batteries.

Table 3. Essential components and their associated functions.

No.	Designations	Functions
1.	2004-I2c LCD Screen (HITACHI, Tokyo, Japan)	Enables real-time display of measured data (voltage, current, temperature) as well as the SoC. Thanks to the I2C interface, it simplifies wiring while offering efficient local monitoring of the embedded system.
2.	Arduino NANO board	Ensures the acquisition of data from the sensors (voltage, current, temperature) and their initial processing.
3.	ESP32-Wroom-32	It ensures data transmission to the Arduino IoT Cloud platform via its integrated Wi-Fi connectivity. It complements the Arduino Nano board by adding wireless communication functionality to the embedded system.
4.	DHT 11 Temperature Sensor	Measures the ambient temperature around the battery. This data is used to improve the SoC estimation, as temperature directly influences battery performance and behavior.
5.	ACS712 Current Sensor	Allows for the measurement of current flowing through the battery in real time. This information is essential for accurate SoC estimation, as the current directly influences the variation in charge.
6.	Voltage sensor	Allows the voltage across the battery terminals to be measured. This data, combined with current and temperature, is used to accurately estimate the battery's state-of-charge (SoC).
7.	Regulator 7805	Provides a stable 5 V supply needed to power the Arduino Nano.
8.	ANS1117 Regulator	Ensures a stable power supply by providing a regulated 3.3 V voltage to power the ESP32-WROOM-32.
9.	RTC DS3231	Provides an accurate real-time clock to the embedded system, enabling the dating and synchronization of battery measurements, which is essential for time-series data analysis.
10.	Polarized capacitor	The polarized capacitor is used to stabilize the power supply by filtering voltage fluctuations.
11.	Non-polarized capacitor	The non-polarized capacitor is used to filter out interference and high-frequency signals in the circuit.
12.	Resistance	Resistance limits the electric current in the circuit.
13.	Bogner	Allows for easy and secure connection of external components.
14.	Male connection bar	Serves to establish reliable electrical connections between the system and external components.
15.	BC547 NPN Transistor	Acts as a switch or amplifier in the circuit, allowing control of the flow of electric current based on the received signal.

Table 3. *Cont.*

No.	Designations	Functions
16.	Radiator	The radiator helps to dissipate the heat generated by certain electronic components (such as voltage regulators) in order to prevent them from overheating.
17.	Buzzel Active	Used to emit an audible warning signal if critical temperature thresholds are exceeded around the battery.

4. Results

This section presents the results obtained from the proposed methods and an experimental validation using the proposed map. The first 500 data pairs used for model training are shown in Figures 6–10 below, illustrating the joint evolution of the input parameters, including dissipated power, over time.

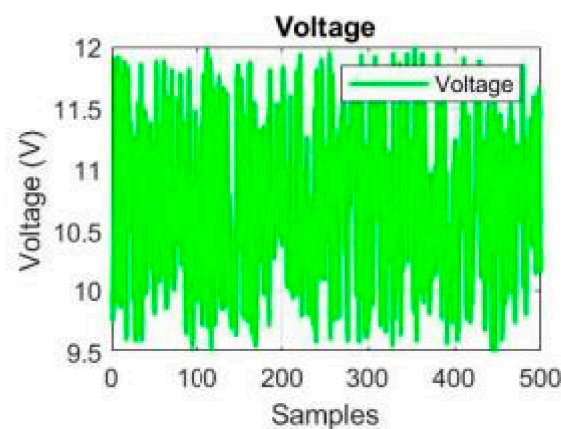


Figure 6. Voltage input.

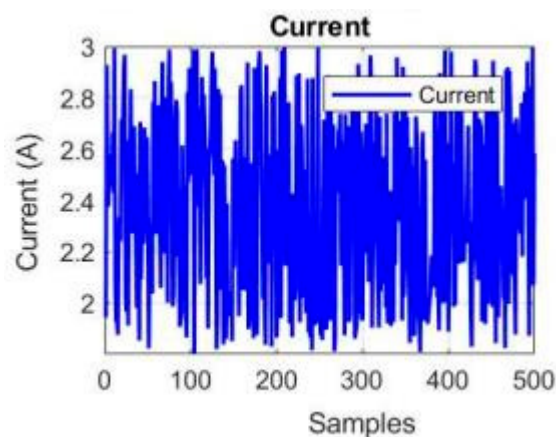


Figure 7. Current input.

Figure 6 shows the evolution of the battery voltage over 500 samples. Significant fluctuations are observed, with values ranging from 9.5 V to 12 V. This noise makes estimating the SoC (state-of-charge) from voltage alone difficult. Therefore, the use of deep learning models such as LSTM and GRU is justified, as they allow for the extraction of relevant information despite signal variability.

Figure 7 illustrates the variation in the current drawn by the battery over 500 samples. The signal exhibits strong fluctuations between 1.8 A and 3 A, indicating unstable or noisy behavior. As with the voltage, this variability complicates the direct estimation of the SoC.

The LSTM and GRU models allow us to leverage the noisy time-domain data to improve the accuracy of the estimation.

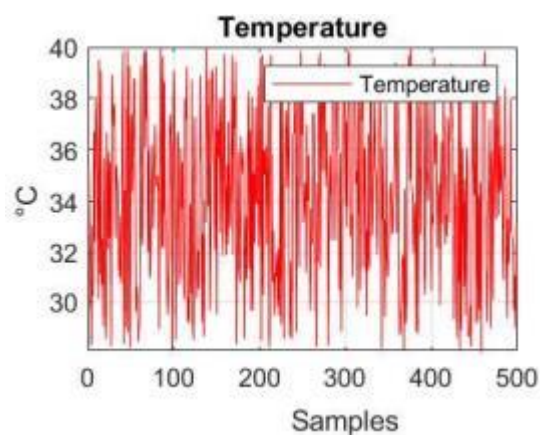


Figure 8. Temperature input.

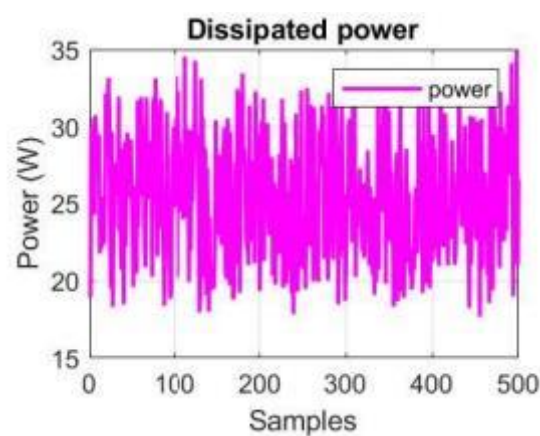


Figure 9. Dissipated power.

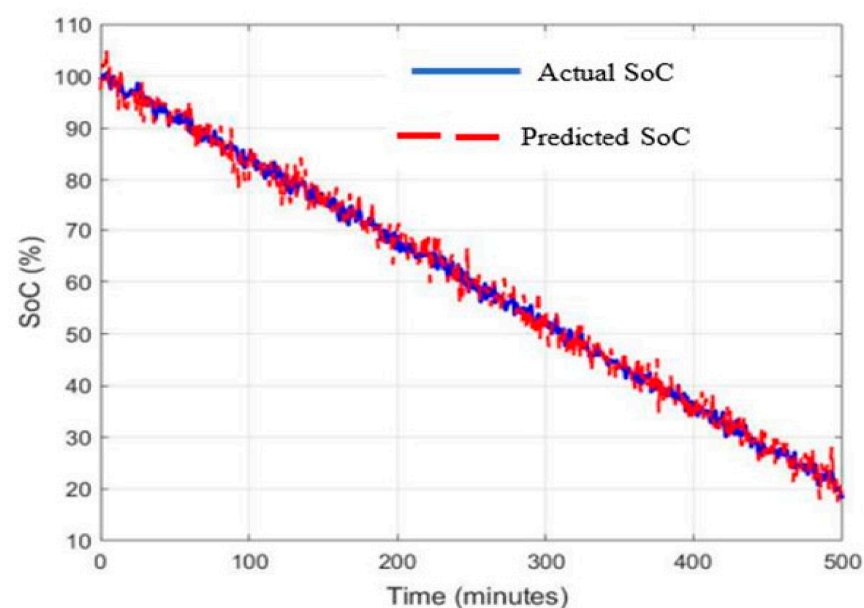


Figure 10. SoC output.

Figure 8 shows the evolution of the battery temperature over 500 samples. Significant fluctuations were observed, with values ranging from 28 °C to 40 °C. This variability can

affect battery performance and influence the SoC estimation. Integrating temperature as an input variable into LSTM and GRU models improves prediction accuracy by accounting for the thermal impact on battery behavior. In an African context, rising temperatures are the primary factor that disrupts SoC estimation through four mechanisms: (a) The apparent capacity, which increases sharply; thus, at 40 °C, a battery develops 3 to 8% more Ah than, or even exceeds, its capacity at 25 °C. This has a direct impact on the Coulomb value if the actual charge Q is not modified and temperature-corrected, as in [4]. (b) Internal resistance decreases by a factor of 1.5 to 2 between 25 °C and 45 °C, and the discharge voltage increases, directly impacting the SoC estimate. (c) Accelerated aging, according to Arrhenius' law, causes the SOH value to decrease twice as fast for every 10 °C increase. (d) Above 35 °C, a BMS without temperature compensation is inaccurate by at least 5%, and above 40 °C, the error exceeds 12%, as demonstrated by [4].

Figure 9 shows the power dissipated (P) over 500 samples. It varies significantly between approximately 18 W and 34 W. These fluctuations are due to a variable charging profile applied to the battery during the simulation.

Figure 10 shows the evolution of the battery's state-of-charge (SoC) over 500 samples. The blue curve corresponds to the actual SoC, while the red curve represents the SoC predicted by the model. The two curves are generally close, despite some discrepancies, particularly at the beginning of the simulation. This confirms the ability of the LSTM and GRU models to efficiently estimate the SoC, even in the presence of variable input signals.

To summarize the results obtained during SoC estimation, using the LSTM and GRU models, Table 4 presents a summary based on the specific characteristics of each architecture and the quantitative performance measured during the simulations.

Table 4. Prediction results.

Algorithms	Duration of the Training (s)	MSE	RMSE	Precision (%)
LSTM	234	0.0901	0.2965	80
GRU	206	0.0715	0.2589	83.6

4.1. Graphical Data

To analyze battery behavior during a discharge cycle, experimental data were recorded and then plotted as curves. These graphs allow us to observe the evolution of key quantities such as voltage, current, temperature, and state-of-charge (SoC) over time. The goal is to better understand battery dynamics and to provide a relevant dataset for training deep learning models (LSTM and GRU) used for SoC estimation. Figures 11–14 provide visual representations that form an essential basis for evaluating the relevance of the input variables and the quality of the predictions generated by the models. Indeed, the GRU model is used for its real-time SoC advantage as it is lighter and the loss of accuracy is minimal if the settings are optimal. Regarding hyperparameters, the learning rate varies between 0.0005 and 0.003, whereas the startup time with the LSTM model is 0.003. Furthermore, the batch size varies between 128 and 256 for the GRU model, with an inference time of 3.2 ms for the GRU versus 4.5 ms for the LSTM under the same configuration. Hence the choice of the GRU. Thus, generally speaking, if the MAE < 1.5% at 450 °C, then the LSTM model retains the advantage. However, if the MAE < 2% with a strong real-time constraint, GRU is the recommended model.

Indeed, the noise from the sensor hinders good GRU learning, and it forgets very quickly, especially when the temperature becomes considerably high, between 40 and 45 degrees. Furthermore, the GRU is not a purely physical process; it requires very dynamic, real-time training to maintain its accuracy. Hence the need to create a hybrid system to obtain greater

results. However, additional specific conditions or constraints are necessary for a better comparative study.

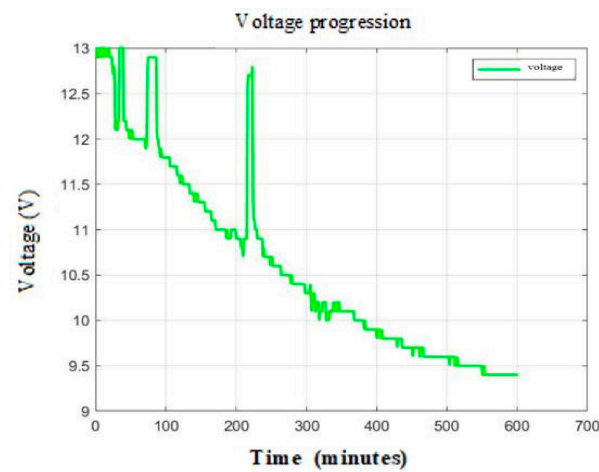


Figure 11. Experimental Voltage.

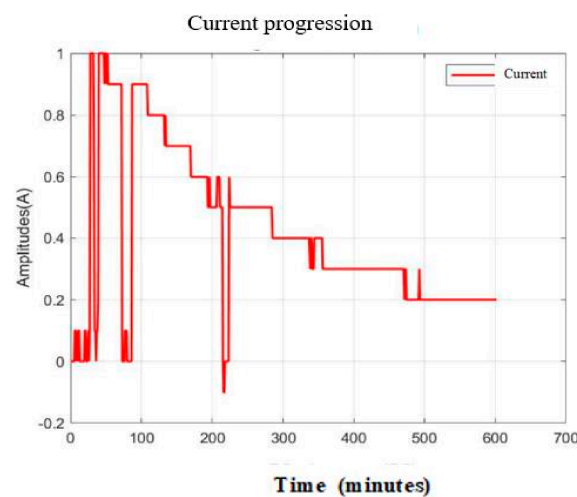


Figure 12. Experimental current.

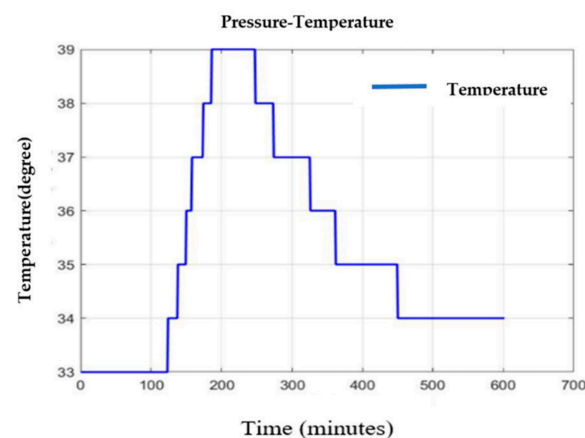


Figure 13. Experimental temperature.

Figure 11 shows the battery discharge curve over a complete cycle of approximately 600 min. A gradual decrease in voltage is observed, from an initial value close to 13 V to a cutoff voltage around 9.5 V. This evolution highlights different phases characteristics of the discharge process: a rapid initial drop, a more linear phase, and then a relatively stable

plateau before stopping. Occasional voltage variations, visible particularly around 100 and 220 min, could correspond to temporary interruptions or changes in the discharge current. This data reflects the nonlinear behavior of the battery, and allows for the evaluation of its usable capacity as well as the internal phenomena influencing its performance, such as internal resistance or temperature.

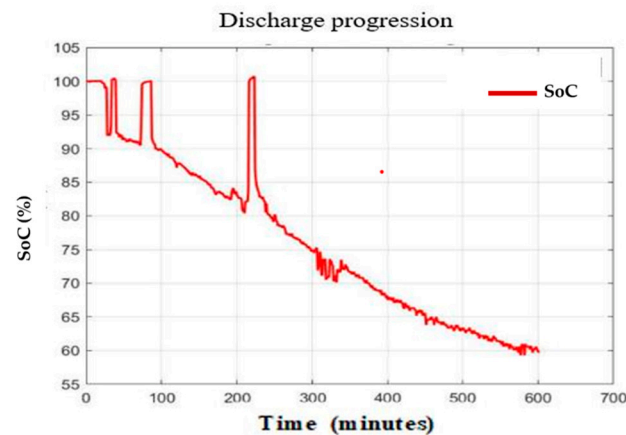


Figure 14. Experimental discharge progression.

Figure 12 illustrates the evolution of the battery discharge current during a complete cycle of approximately 600 min. The profile reveals a stepped discharge pattern: the current starts around 1 A, then gradually decreases in stages, reaching approximately 0.6 A after 200 min, 0.4 A after 300 min, and 0.2 A after 500 min. This stepped evolution could be related to the use of a variable load or a specific test protocol. The abrupt variations recorded at the beginning of the discharge suggest a stabilization phase of the system. Analyzing this curve, combined with the voltage curve, provides a better understanding of the battery's dynamic behavior and allows for an estimation of the power delivered throughout the cycle.

Figure 13 illustrates the battery temperature evolution during a complete discharge cycle. A gradual temperature increase is observed starting at the 100th minute, reaching a maximum of approximately 39 °C around the 200th minute, before gradually decreasing to stabilize at around 34 °C after 500 min. This temperature variation is likely related to heat dissipation due to the discharge current and the battery's internal resistance. Analyzing this curve allows us to assess the system's thermal behavior, a crucial factor for battery safety and durability.

Figure 14 shows the battery's state-of-charge (SoC) evolution curve throughout the discharge cycle. The SoC, initially at 100%, gradually decreases to approximately 60% after 600 min. This discharge is not strictly linear: a faster decrease is recorded at the beginning of the cycle, followed by a slower rate. Occasional increases in the state-of-charge (SoC) may occur at certain times, potentially corresponding to interruptions in discharge or recovery phases. This variation allows for an assessment of the remaining energy in the battery and an estimation of its remaining range.

4.2. Discussion of Results

In our study, the LSTM and GRU models achieved accuracies of 80% and 83.6%, respectively, slightly higher performances than reported in the literature for similar configurations. Notably, the GRU model once again stands out, offering a better compromise between accuracy, error (MSE and RMSE), and training time. Indeed, despite a training time very close to that of the reference model (206 s vs. 204 s), our GRU model exhibits better accuracy (83.6% vs. 83%) and a reduction in RMSE to 0.2589. These results confirm the GRU's ability

to effectively capture the nonlinear dynamics of voltage, current, and temperature signals, while maintaining a less complex structure than the LSTM, which may explain its slightly shorter training time. As for the LSTM model, although it shows a slight increase in MSE and RMSE compared to the reference, it maintains stable performance with 80% accuracy, demonstrating its robustness. This slight variation can be attributed to the nature of the data used, the training parameters, or the quality of the input signals (real vs. simulated). In conclusion, the performance achieved in this work validates the relevance of using GRU and LSTM networks for SoC estimation. The improvement obtained, particularly with GRU, fully justifies the chosen approach for this project, demonstrating that our method is competitive with existing work in the literature. Table 5 presents a validation against recent literature with the results confirming the approach developed by the work [26], which presents a comparative study of three polymerization techniques, significantly reducing eddy current losses in the nuclei. More specifically, the nucleus polymerized by VGAC shows a 50% reduction in eddy current losses compared to the unpolymerized nucleus.

Table 5. Validation in relation to recent literature.

Ref.	Title	Methods Used	General Objective	Specific Objectives	Results
[14]	Battery electric vehicle charge state estimation based on deep learning and cloud-integrated IoT.	Deep learning	Accurately estimate the state-of-charge of electric vehicle batteries.	- Prevent the battery from overcharging and discharging. - Increase battery lifespan. - Know the battery's capacity	The LSTM algorithm achieves 79% accuracy, with an MSE of 0.0848 and an RMSE of 0.2912, but requires more training time. The more efficient GRU algorithm offers 83% accuracy, with an MSE of 0.0624 and an RMSE of 0.2498.
[9]	Improving the estimation of the state-of-charge of electric vehicle batteries through deep learning.	Deep learning	Accurately estimate the state-of-charge of electric vehicle batteries.	- Determine the remaining range of EVs. - Determine the operating time of battery-powered equipment.	The LSTM algorithm achieves an accuracy of 60.7%, with an MSE of 10.8469 and an RMSE of 11.8127. The GRU, less efficient in this case, has an accuracy of 53.4%, with an MSE of 13.4434 and an RMSE of 18.5928.
In this work	Contribution to the experimental study of state-of-charge (SoC) estimation of electric vehicle batteries.	Deep learning	Design an embedded system to evaluate the state-of-charge (SoC) of an electric vehicle battery.	- Design and implement an accurate state-of-charge estimation algorithm. - Develop an efficient and secure data transmission solution. - Optimize the system's energy management.	The LSTM algorithm achieves 80% accuracy, with an MSE of 0.0901 and an RMSE of 0.2965, but requires more training time (234 s). The more efficient GRU algorithm offers 83.6% accuracy, with an MSE of 0.0715, an RMSE of 0.2589, and a reduced training time of 206 s.

4.3. Challenge and Future Scope

The experimental characterization of state-of-charge (SoC) estimation for electric vehicle batteries requires consideration of several elements.

- A comparative study of machine learning models available in the current literature with experimental validation.
- The use of intelligent methods to optimize the parameters of LSTM and GRU methods, with the aim of proposing an optimal hybrid version.
- Extending the analysis windows according to different temperature scenarios for better comparison with other methods, such as the Kalman algorithm.
- Developing an experimental study based on various standardized data from the main electric vehicle manufacturers.
- Improving the accuracy of the developed models by taking into account SOH aging and temperature self-calibration.

- Proposing battery management systems (BMSs) compliant with ISO 12405 standards [27] with closed enclosures for temperatures of 550 °C, for example.

5. Conclusions

This article proposed the design of an embedded system capable of evaluating and transmitting the state-of-charge (SoC) of an electric vehicle battery in real time to a cloud platform, while optimizing energy consumption and data reliability. This involved experimental prototyping combining the development of two deep learning models, LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit), in the MATLAB environment. The main contributions are:

- (i) The development and deployment of two machine learning algorithms to estimate the state-of-charge of electric vehicle batteries.
- (ii) An experimental implementation with a prototype to validate the process of estimating the state-of-charge of EV batteries.
- (iii) A comparative study and classification of battery state-of-charge estimation methods in accordance with current literature.

The results obtained show that the GRU model offers the best performance, with an accuracy of 83.6%, a mean squared error (MSE) of 0.0715, and a mean squared error (RMSE) of 0.2589, thus validating the relevance of the proposed approach for intelligent state-of-charge estimation in a real-world application context. This work also provides a solid foundation for future prospects, including the optimization of estimation algorithms, the miniaturization of the embedded system, industrial integration, and the large-scale commercialization of real-time state-of-charge (SoC) estimation and control systems for electric vehicle batteries on a cloud platform, while optimizing energy consumption and data reliability, all contributing to the sustainable development of the automotive sector.

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