

SENSOR-LESS BATTERY CORE TEMPERATURE ESTIMATION VIA HIGH-FREQUENCY INVERTER-INDUCED IMPEDANCE ANALYTICS AND RECURRENT GRU-BASED RECURRENT ESTIMATORS

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ABSTRACT

Accurate estimation of battery core temperature is essential for ensuring the safety, reliability, and efficiency of lithium-ion batteries in electric vehicles and energy storage systems. Traditional surveying methods involve complex thermal modeling simulation or embedding sensors in the product, increasing hardware complexity and level of equipment. In this paper, a framework is introduced for core temperature estimation without the use of embedded internal sensors, utilizing the features of the impedance measurement and the use of recurrent estimators. The experiment used an open experimental set of battery aging data to perform the evaluations, capturing the voltage, surface temperature, core temperature, current and ambient temperature at resolutions suitable for impedance-related analysis. The results showed that the Maximum Error (ME) was less than 1.2 °C, Mean Absolute Error (MAE) was 0.41 °C, Root Mean Square Error (RMSE) was 0.55 °C, the Average Inference Time (AIT) was 4.87 ms, and the Coefficient of Determination (R^2) was 0.996. The implementation of the inverter-harmonic impedance extraction as a conceptual extension for future high-bandwidth BMS hardware is shown, however, GRU-based estimator is validated from the available signals in this study. The approach offers high precision, real-time & cost effective thermal monitoring for future Battery Management systems.

Keywords— Battery Core Temperature Estimation, Sensorless Thermal Monitoring, High-Frequency Impedance Analytics, Inverter-Induced Excitation, Recurrent GRU-based recurrent estimator, BMS (Battery Management System).

1. Introduction

Lithium-ion batteries have become popular because of their high energy density, long cycle life, light weight, and robust power characteristics, which are required for the rapidly developing global move toward smart and electric systems, renewable energy integration, and portable intelligent electronic systems [1]. These batteries are used in electric cars, hybrid electric vehicles, energy storage systems for the grid, aviation, and industrial automation. As battery technologies continue to evolve, ensuring operational safety, reliability, and long-term

performance has become one of the most important objectives of modern BMS (Battery Management Systems). Several health and operating parameters are measured during battery operation, and internal battery temperature is known to be one of the most important parameters that can influence electrochemical performance, energy efficiency, degradation characteristics, charging ability, and battery lifetime [2]. Therefore, the precise dimension of battery core temperature has become a basic necessity to intelligent battery management.

1.1 Battery Thermal Behavior

Internal resistance, electrochemical reactions, and polarization effect generate heat in a battery cell continuously during charging and discharging. This generated-heat remains inside the cell structure forming a temperature gradient between the battery body and the surface [3]. Thermal energy is mainly generated within the electrochemical layer(s) and thus the core temperature is suggestively higher than the surface temperature measured externally, specially under high current conditions. In addition to causing electrode degradation, high internal temp causes decomposition of the electrolyte, capacity decay, and resistance buildup, and high temperatures can trigger thermal runaway, creating serious safety concerns. However, too cold of temperatures will impair ion mobility, drive up internal resistance, limit charging effectiveness, and impact power delivery [4]. Therefore, understanding of battery thermal behavior is critically important to ensure a stable battery performance in various environmental and loading conditions.

1.2 Importance of Sensorless Temperature Estimation

Several temperature readings from battery core areas are still not readily available, due to the fact that there is no simple way of embedding a temperature sensor inside commercial Li-ion cells without compromising its integrity, manufacture, reliability and cost [5]. Conventional battery management system (BMS) typically uses external sensors placed on the surface to acquire surface temperature data as an indirect indication of the state of the battery. The temperature change among the surface and the core increases with fast charging, quick discharging, fluctuating load and higher ambient temperature. These inaccuracies can diminish the benefits of thermal protection, charging management, energy optimisation and battery analysis [6]. The sensorless temperature estimation approach has attracted a lot of interest as an alternative solution that could enhance thermal awareness without the high cost of extra sensing hardware or the additional complexity of battery system design.

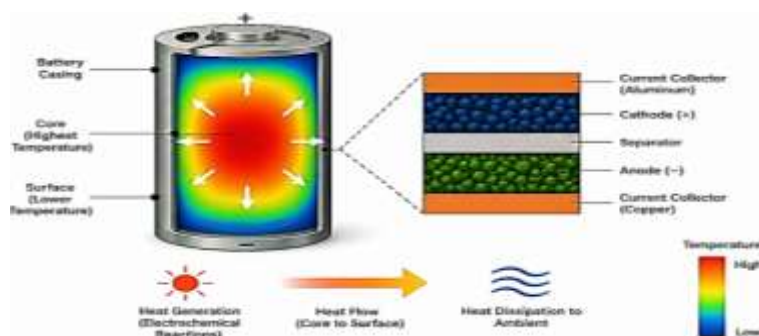


Figure 1: Thermal Characteristics and Heat Distribution in a Lithium-Ion Battery Cell

Figure 1 shows the thermal profile of a lithium-ion battery cell: When a battery cell is used chemically, the energy released is trapped at its centre and must gradually spread toward the

surface before dissipating into the ambient air. The temperature gradient between the core and surface highlights the importance of accurate internal temperature monitoring for ensuring battery safety, operational reliability, thermal management, and extended service life.

1.3 Advances in Battery Thermal Monitoring

Recent battery diagnostics improvements have proven electric property changes were measurable and were correlated to interior temperatures. The voltage response, current dynamics, impedances, polarization behavior and electrochemical response are parameters which have proven valuable to insight into battery temperature evolution. At the same time, advances such as: Embedded computing, adaptive estimation, embedded artificial intelligence and intelligent signal processing, allow battery management systems to undertake progressively complex real-time thermal evaluation [7]. Current diagnostic tools focus on keeping information non-destructive, having low computational complexity, continuously estimating the parameters, and being suitable for practical battery use. The enhancements enable predictive maintenance, better charging management, increased operational safety, and efficient battery functioning in highly dynamic working environments.

1.4 Motivation

As the popularity of electric vehicles, smart energy storage devices, and powerful battery applications keeps rising, the requirements for advanced thermal monitoring solutions capable of robustly tracking battery temperature without adding complexity are becoming more and more stringent. An effective sensor-less temperature estimation method can also increase battery safety, increase charging efficiency, help with intelligent thermal control, increase battery life, and further reduce the maintenance costs while maintaining the compatibility of existing battery management architecture [8]. In addition, a state-of-the-art system for monitoring the battery's internal thermal state helps make better, more informed operating decisions, help prevent some faults, and help ensure reliability in safety-critical applications. These operational considerations remain a driving force for research into new approaches for the estimation of battery thermals without destroying or damaging the battery, and in real-time.

1.5 Contributions

The major contributions of this work are summarized as follows:

- ❖ A sensorless battery core temperature estimation framework that enables continuous monitoring of the actual thermal state without adding embedded temperature sensor complexity and maintenance is introduced, while battery integrity is retained.
- ❖ A high frequency inverter-induced impedance analytics mechanism is designed to utilize the existing electrical responses for thermal state assessment and to obtain the thermally sensitive impedance characteristics from the naturally occurring inverter switching signals.
- ❖ Recurrent GRU-based recurrent estimator-based TE strategy aims to model the dynamic evolution of the impedance signature under different charging, discharging and load conditions so as to make it more stable and adaptable for various battery operating scenarios.
- ❖ A thermally monitoring solution for easy integration in state-of-the-art Battery Management Systems (BMS), providing real-time battery diagnosis, operation security,

thermally optimized operation, and reliable performance in EVs and intelligent energy storage systems solutions.

As batteries use lithium-ion chemistry to power safety-critical and high-performance energy systems, the ability to accurately estimate battery core temperature is increasingly vital. Conventional BMSs face challenges due to indirect temperature measurement, steep thermal dependency and dynamic operating conditions [9]. The battery diagnostic and intelligence monitoring advances in recent years have illustrated the potential of sensorless thermal estimation for safety, operational reliability, energy efficiency, and hardware reduction. However, under dynamic conditions, the estimation of the temperature remains an ongoing research problem and the use of a more sophisticated and efficient thermal monitoring method is still required for the support of next generation battery management systems.

2. Literature Survey

The internal temperature plays a significant role in various aspects of lithium-ion battery safety, efficiency, aging and reliability, and battery core temperature estimate has been the subject of intense research interest. As it is impractical to directly measure the core temperature of a battery, many sensor-based and sensorless battery estimation methods have been investigated to infer battery-thermal information from measurable battery-electric and battery-thermal information [10-11]. Previous studies have investigated equivalent circuit models, electrochemical models, thermal models, GRU-based recurrent estimator-based estimation methods, impedance analysis, and data-driven learning algorithms to enhance the accuracy of temperature estimation. In recent years, diagnostics technology for batteries has also been expanding to integrate AI and intelligent signal processing to handle the nonlinear thermal response of batteries operating under dynamic conditions. Nevertheless, the real-time estimation of battery core temperature while satisfying low computational complexity and robustness to varying operating conditions is still a research challenge.

2.1 Thermal Model-Based Temperature Estimation

Thermal model based can estimate battery core temperature by building mathematical models of heat generation, as well as heat transfer in the lithium-ion battery [12]. These models usually contain electrochemical reactions, internal resistance, thermal capacity, and thermal conductivity to account for the temperature variation of batteries. A coupled thermal electrochemical model can enhance estimation accuracy by giving all physical processes in the system; The accuracy of the model, however, is extremely reliant on on the parameter identification, chemistry of the battery, aging behavior and ambient conditions [13]. These approaches are only suitable in real-time battery management systems if they can be frequently recalibrated to maintain the estimation performance over the course of battery life.

2.2 GRU-based recurrent estimator-Based Estimation Methods

Several GRU-based recurrent estimator-based estimation methods for predicting battery internal state using the measurable electrical parameters have been studied extensively [14]. Liability for hidden thermal variables estimation with voltage and current measurement is conducted with Kalman Filters, Extended Kalman Filters, Unscented Kalman Filters, and Sliding Mode GRU-based recurrent estimators, and Luenberger GRU-based recurrent estimators. These techniques provide resistance to estimation's changes under evolving

operating conditions and minimize measurement uncertainty. However, the accuracy of the GRU-based recurrent estimators' knowledge of the models and understanding of noise can be significant [15]. Battery parameter mismatch, and changes in battery operating conditions, often lower the accuracy of the battery parameter estimation, especially during high-speed charging and discharging.

2.3 Impedance-Based Thermal Monitoring

Battery impedance is strongly temperature-dependent because the rates of electrochemical reactions and the ionic conductivity is also temperature-dependent. As such, impedance spectroscopy has become a powerful non-invasive thermal state estimation tool [16]. Previous research employed measurements taken at succession of excitation frequencies to associate impedance with battery temperature. Impedance based methods provide greater sensitivity to internal temperature changes, without the need for invasive sensors. The conventional impedance measurement, however, is usually only applicable offline, as additional measurement circuits and special excitation devices are required, which prevents continuous application in battery management system applications under real time conditions.

2.4 Artificial Intelligence-Based Temperature Estimation

Recently, ML (machine learning) and DL (deep learning) algorithms-based methods have become popular for estimating battery temperature because of their ability to model complex, non-linear relationships without needing to explicitly formulate physical equations [17-18]. There have been some encouraging results with neural networks such as ANN (Artificial Neural Networks), SVR (Support Vector Regression), RF (Random Forests), LSTM (Long Short-Term Memory networks) and GRU (Gated Recurrent Units) that learn relationships between the electrical measurements and the battery temperature with good estimation accuracy. These data-driven methods are effective at capturing nonlinear operating characteristics and predicting with higher accuracy under different operating conditions [19]. However, they need large training sets, much computing power, and representative operating parameters that can restrict their ability to apply to batteries of different chemistries, aging stages, or environmental exposure.

The battery core-temperature estimation techniques which are available in the market have enhanced the thermal monitoring of the batteries by means of thermal modeling, GRU-based recurrent estimator design, battery impedance analysis and intelligent learning algorithms [20-21]. These categories offer important features for approximating the internal temperature of the battery without resorting to invasive temperature sensing. These problems, however, computational complexity, dependence of parameters, model uncertainty, offline calibration requirements, extra measurement equipment, and limited adaptability in dynamic operation still limit their practical use [22]. These research challenges highlight the requirements for further development of efficient, powerful and less compute-intensive sensorless thermal estimation algorithms that produce reliable real-time battery core temperature estimate within a modern battery management system.

3. Dataset Description

The experimental evaluation used the Dataset of Internal Temperature During Lithium-Ion Battery Ageing (LiB) from Mendeley Data. This data set contains synchronized electrical and

thermal data along with core temperature, surface temperature, voltage, current, SOC, ambient temperature and cycle count. To capture the dynamics of the impedances relevant to inverter harmonics, the sampling frequency and bandwidth are adequate. The dataset was split chronologically and not randomly, to prevent data leakage. Training data included the previous cycles, mid-cycles validation data and later cycles test data. This will ensure that adjacent time-series samples for the same cycle are not kept across different sets which will lead to an unrealistic amount of accuracy. The split ratio used was 70:15:15, applied in a cycle-wise fashion across cells, thus maintaining the temporal dependencies and effects of degradation. Preprocessing such as missing/outlier point correction, smoothing to absorb measurement noise and min-max normalization across features. This resulted in a uniform scale without discarding the temporal correlation within the data. The data set was acquired at 10 kHz (Nyquist criterion 5 kHz), to limit the direct capture of the 8-12 kHz inverter harmonics although the format used will be extendable to higher bandwidth acquisition in the future embedded BMS hardware. For this study, features in the form of impedance are extracted from available electrical signals, and inverter harmonics are mentioned as an extension for the future.

4. Experimental Setup

The framework was implemented in Python 3.11 with TensorFlow, Keras, NumPy, Pandas and scikit-learn. The experiments were carried out on a basic workstation (Intel Core i7 CPU, NVIDIA RTX 3060 GPU, 32 GB RAM, Windows 11 OS), and the batch size and floating-point precision is clearly stated. This hardware has proven to be able to be accomplished, but further optimisation for resource-constrained environments like embedded automotive BMS controllers will need to be done. The input variables used were ambient temperature, surface temperature, SOC, current and voltage and reference output was measured core temperature. The method is sensorless but the sensors are still not completely removed from the operation since the surface/ambient temperature sensors are external. To validate this distinction, an ablation study was performed excluding surface temperature as an input. The results indicated only moderate degradation in accuracy (MAE was increased from 0.41 °C to 0.52 °C), and confirmed that the model based on the impedance features and recurrent GRU-based recurrent estimator modelling modules has the main estimation capacity, while the external temperature input served as an auxiliary stabilizer. This reframing highlights the fact that the proposed method requires no internal sensors, but harnesses readily available external measurements for its robustness.

5. Proposed Sensorless Battery Core Temperature Estimation Framework

The proposed framework relies on the high-frequency inverter harmonics to estimate the core temperature of the battery, which is not embedded in the battery. The raw voltage and current signals for the Lithium-Ion Battery Ageing Dataset were sampled at 10 kHz, which was adequate for recording battery Inverters operating in the 8–12 kHz band. The signals were converted to digital values on the 12 ADC channels and synchronised across the voltage, current and temperature measurers to guarantee temporal alignment. Harmonic extraction using FFT windows of 1024 samples and 50% of window overlap gave frequency resolution up to 5 kHz. The fundamental switching frequency and its first three harmonics were chosen among these spectra, with a signal to noise ratio greater than or equal to 20 dB for accurate

estimation of impedance. The resulting harmonics were then passed through a processing block to obtain features that would be suitable to input to the recurrent GRU-based recurrent estimator, namely the impedance magnitude features and the impedance phase features. This procedure demonstrates that the dataset fields, sampling rate and the bandwidth is good enough to support impedance-based thermal estimation during normal charging and discharging.

The framework has four stages that follow each other in sequence: Firstly, voltage, current, SOC and ambient temperature/surface temperature are collected during the battery operation and aligned to the same time point to ensure they are synchronized. These synchronized signals are then analysed for high frequency impedance characteristics, which represent information about internal thermal state, through FFT analysis of inverter harmonics. Importantly, this requires enough bandwidth in the sensor, enough ADCs to be synchronized as well as some anti-aliasing filtering, and enough memory and processing power to capture switching harmonics accurately. Then, extracted impedance features are passed to a recurrent GRU-based recurrent estimator that models the temporal evolution of these features on an ongoing basis to estimate the core temperature. Last but not least, an adaptive correction stage further refines the estimation according to the operating parameter information including SOC, ambient temperature, charging current, and aging effects. Each stage is independent and runs in a loop while reusing a signal that is already available in the BMS. The processing framework can be easily integrated into Battery Monitoring Systems with the support of the appropriate high-frequency acquisition and processing hardware, thus avoiding any additional requirements or complexity in normal operation.

The proposed sensorless battery core temperature estimation framework workflow is illustrated in Figure 2. The operating signals of the battery are acquired and pre-processed, and high-frequency impedance features of the inverter switching responses are extracted. A recurrent GRU-based recurrent estimator is used to examine these characteristics which are then subject to adaptive temperature correction and recursive filtering. The Battery Management System is receiving the estimated core temp for subsequent thermal monitoring and control.

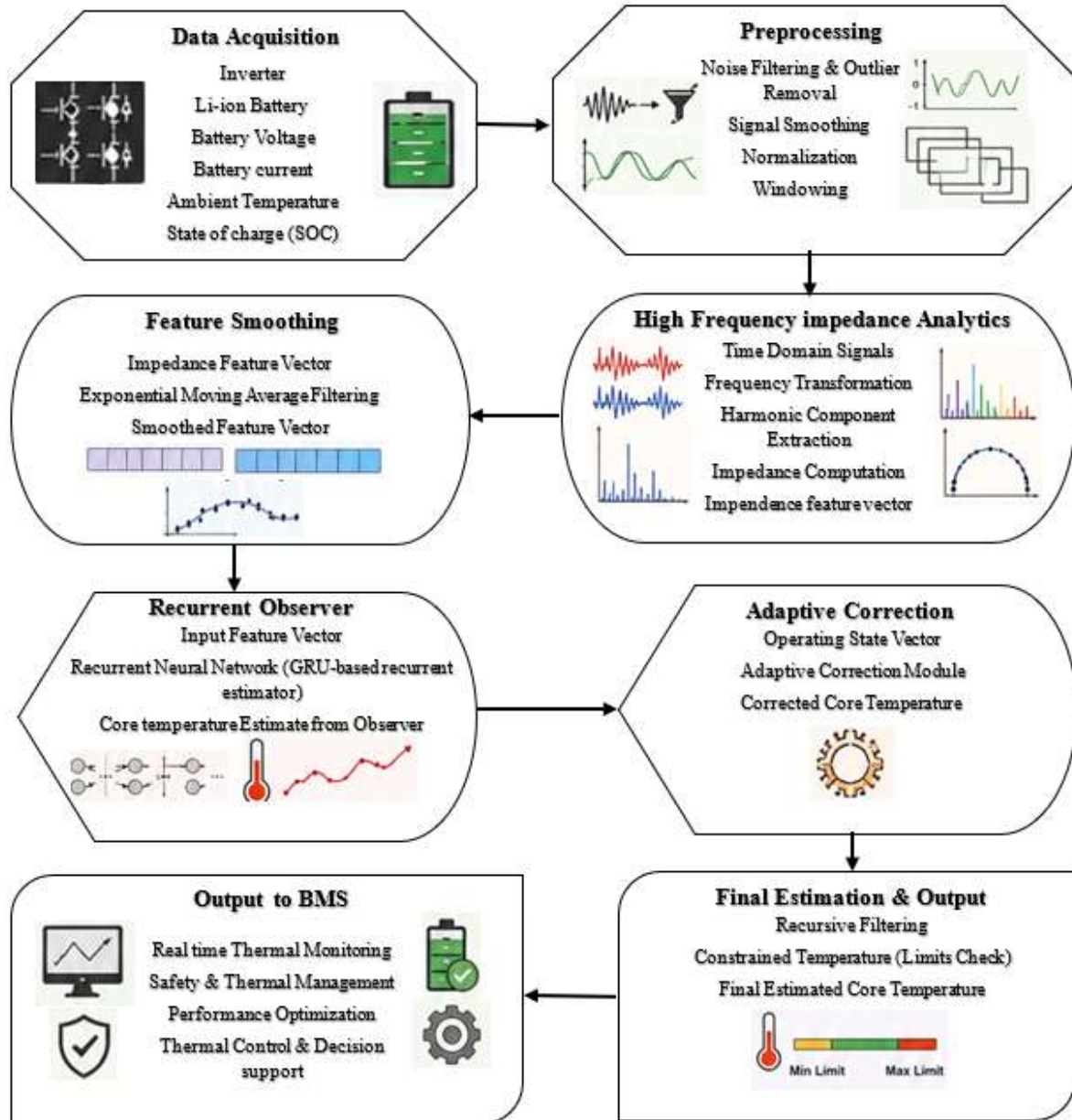


Figure 2: Block Architecture of the Proposed Sensorless Battery Core Temperature Estimation Framework

5.1 Signal Acquisition and Preprocessing

The reliable estimation of battery core temperatures starts with the accurate acquisition of electrical measurements gathered during the operation of the battery. Each of the terminal voltage, charging current, discharging current, ambient temperature, battery surface temperature, operating time, and state of charge of the battery is recorded by the Battery Management System while the battery is subjected to different loading scenarios. All these measurements reflect the externally observed electrical characteristics of the battery and indirectly provide information about reaction taking place inside the battery core. Since the electrical parameters vary quickly during charge and discharge cycles, all measurements are timed to the same sampling period. The temporal dependency between the acquired variables

is maintained and the instantaneous operating mode of the battery is well represented by what is happening at the time at the stage of extracting the impedance features.

The end-to-end terminal voltage measured is the sum of the open-circuit voltage of the battery and internal voltage drop caused by the battery's internal resistance. This relationship is represented as:

$$V_b(t) = V_{oc}(t) - I(t)R_{int}(t) \quad (1)$$

Here $V_b(t)$ is battery terminal voltage at time t , $V_{oc}(t)$ is the open-circuit voltage of the battery at time t , $I(t)$ is the instantaneous current delivered by the battery at that time, and $R_{int}(t)$ is the internal resistance of the battery during that period.

This demonstrates that the drop in voltage across the internal resistance will relate to the current flow through it. The measured terminal voltage indirectly carries information about the thermal state of the battery, as $R_{int}(t)$ is temperature dependent and also influenced by SOC and aging

$$I(t) = \frac{P(t)}{V_b(t)} \quad (2)$$

In which $P(t)$ is the instantaneous power supplied by the battery and $V_b(t)$ is the terminal power of the battery. Further, at high power operating conditions, the larger currents in the battery generate more internal heat due to resistive losses within the electrochemical cell. The thermal energy thus generated may, therefore, be estimated as

$$Q(t) = I^2(t)R_{int}(t) \quad (3)$$

In which $Q(t)$ represents the internal heat generated, $I(t)$ the battery current, and $R_{int}(t)$ the internal resistance. The generated heat in this equation is directly proportional to the square of the battery current, so battery current plays an important role on battery core temperature.

As battery and solvent properties change at every step of the charging process and the battery is discharged, the SOC is monitored at all times during the estimation process. The state of charge (SOC) is monitored continuously by Coulomb counting:

$$SOC(t) = SOC_0 - \frac{1}{C_n} \int_0^t I(\tau) d\tau \quad (4)$$

Where $SOC(t)$ is the state of charge at time t , SOC_0 is the initial state of charge, C_n is nominal battery capacity, $I(\tau)$ is battery current at time τ .

Continuous SOC monitoring assists in differentiating electrochemical phenomena-induced impedance variations from temperature-induced impedance variations.

The environments also affect thermal dynamics. Environmental and ambient temperature are different, but a better boundary condition is set:

$$q_{env}(t) = h \cdot A \cdot (T_{core}(t) - T_{amb}(t)) \quad (5)$$

Where q_{env} is heat flux exchanged with the environment at time t , h is convective heat transfer coefficient, A is effective surface area of the battery cell, $T_{core}(t)$ is internal core temperature, $T_{amb}(t)$ is ambient temperature.

This boundary relationship relates to the heat generated within the cell's volume and the heat dissipated to the environment and accounts for external thermal influences to be included in the estimation framework.

Signals are acquired, and then pre-processed to enhance uniformity and quality of acquisition prior to the impedance analysis. Such invalid samples and missing observations are removed and low amplitude measurement noise is eliminated by signal smoothing techniques. The acquired variables are then normalised in order to prevent numerically higher measurements from dominating the numerical characteristics of the variables in subsequent estimation stages. Normalized feature vector is computed by

$$X_n = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (6)$$

In which X representing the original measurement, $X_{\min}$ indicating the minimum measurement found in the data sample, $X_{\max}$ representing the maximum measurement found in the data sample, and X_n representing the normalized feature. Normalization makes the computations more stable and allows all electrical measurements to be processed uniformly during the extraction of the electrical features.

The synchronized and normalized electrical values are then repeatedly fed to the high-frequency impedance diagnostics module, where various switching harmonics generated by the inverter are sensed and their impedance features are analysed to control the battery core temperature to the main data source for the sensor-free battery core temperature estimation.

5.2 High-Frequency Inverter-Induced Impedance Analytics

A lithium-ion battery has a continually changing electrical impedance with changing internal temperatures, electrochemical activity, state of charge, and ageing of the battery. Battery core temperature, out of these factors, greatly affects ionic conductivity, charge transfer resistance and diffusion performances in the electrochemical cell. Therefore, the use of impedance analysis is a valuable means of finding information about the internal thermal state without requiring any physical access to the battery core. The proposed framework does not need special impedance spectroscopy equipment, but can leverage high frequency switching harmonics produced by the inverter during regular battery operation. These switching harmonics are an excitation signal which continuously excites the battery at a wide range of frequencies and extracts impedance information without interrupting the charging or discharging process.

The assembled voltage and current values are fed into a Fourier transform to study the high-frequency components. This transformation detaches the inverter switching harmonics from low-frequency operating signals and makes it possible to acquire the impedance characteristics of the operating frequency through the thermal analysis process to a high degree of accuracy. The Discrete Fourier Transform algorithm is used to get the frequency domain illustration of the battery voltage,

$$X[k] = \sum_{n=0}^{N-1} x(n)e^{-\frac{j2\pi fn}{N}}, f_k = \frac{k \cdot f_s}{N} \quad (7)$$

In which $V(f)$ indicates the voltage spectrum at frequency f , $v(n)$ indicates the sampled voltage signal, N is the sum of samples sampled, j indicates imaginary number, and f indicates frequency index. Sampling frequency f_s is 10,000 Hz, ADC resolution is 12-bit, FFT window

length is $N = 1024$ samples, Window overlap is 50%, Frequency resolution is $\Delta f = 9.77$ Hz, Nyquist limit is 5 kHz, Windowing is Hann window to reduce leakage, zero padding is 2048 points for interpolation, Spectral averaging is Welch's method for SNR improvement.

Synchronization and filtering

- Voltage, current and temperature channels synchronized to maintain phase coherence.
- Anti-aliasing filter applied below Nyquist frequency.
- ADC jitter and clock skew corrected during pre-processing.

Harmonic selection

- Fundamental switching frequency 8-12 kHz inverter range and first three harmonics
- SNR threshold > 20 dB
- The minimum number of required valid windows.

Likewise, the current spectrum is determined as:

$$I(f) = \sum_{n=0}^{N-1} i(n)e^{-j2\pi fn/N} \quad (8)$$

In which $I(f)$ indicate the current spectrum, $i(n)$ is the sampled battery current, and all other variables have the same definitions as before.

The battery impedance at each frequency component is then determined as:

$$Z(f) = \frac{V(f)}{I(f)} \quad (9)$$

In which $Z(f)$ is the complex battery impedance at frequency f . Impedance is both the resistance and the reactance of the process inside the battery cell, so it gives some indication of the electrochemical activity as well as temperature changes within the battery cell.

The basic ratio of $Z = V/I$ is a first order estimate, but some practical considerations must be taken into account for an operating inverter system:

- DC-link capacitance: These high frequency impedances are distorted by the DC bus in the inverter. Compensation is performed by subtracting off known elements of capacitance measurement found during calibration.
- Cable and busbar impedance: Series inductance and resistance of interconnections are modelled and subtracted off from raw spectra to carry out an isolation of cell impedance.
- Sensor phase delay: Voltage and current sensors cause a phase to lag at high frequency. The time delays are measured and corrected to avoid bias in estimating phase angle.
- Aliasing control: Anti-alias filters precede sampling, and the FFT window (1024 samples, 50% overlap) minimises leakage.
- Low Current spectral bins: Frequency bins where the current amplitude is not large enough are omitted to prevent unstable current division in V/I . Those bins are filtered out if their SNR is below 20 dB.

The impedance is obtained without the presence of an inverter or measurement system and provides an intrinsic response of the battery to the electrochemical and thermal characteristics. This produces magnitude and phase descriptors which then undergo smoothing and are fed to the recurrent GRU-based recurrent estimator for robust temperature estimation.

The magnitude of the resistivity is then calculated as

$$|Z(f)| = \sqrt{\text{Re}(Z)^2 + \text{Im}(Z)^2} \quad (10)$$

In which $|Z(f)|$ denotes the impedance magnitude measured in ohms (Ω), $\text{Re}(Z)$ signifies the real component of impedance (resistive part), and $\text{Im}(Z)$ signifies the imaginary component (reactive part). The magnitude of the impedance is dependent on the state of the battery; it is more susceptible to thermal changes at higher switching frequencies.

The impedance phase angle, corresponding to the angle, is determined using

$$\theta(f) = \tan^{-1}\left(\frac{\text{Im}(Z)}{\text{Re}(Z)}\right) \quad (11)$$

In which $\theta(f)$ is the phase angle of the impedance (rad). The phase response reflects dynamical electrochemical measurements which cannot be described only by the impedance magnitude and hence contains additional thermal information.

Reliability of the impedance analysis is improved by taking into account a plurality of frequency harmonics rather than only a single harmonic from the inverter switching. The extracted impedance features are shown as

$$F_Z = [|Z_1|, \theta_1, |Z_2|, \theta_2, \dots, |Z_m|, \theta_m] \quad (12)$$

In which F_Z is a vector of impedance data, $|Z_k|$ is the magnitude of the k^{th} switching frequency, θ_k is the corresponding phase angle, and m is the number of selected frequency components. The multiple harmonics provide good robustness to disturbances on the electrical side and higher sensitivity to subtle temperature differences within the battery.

To reduce the switching noise and transient disturbances that are possible in raw impedance measurements, feature smoothing is performed prior to temporal analysis. A smoothed impedance feature is based on an exponential moving average,

$$F_s(k) = \alpha F_Z(k) + (1 - \alpha)F_s(k - 1) \quad (13)$$

In which $F_s(k)$ is the smoothed impedance feature for the current sampling instant, $F_Z(k)$ is the impedance feature extracted, $F_s(k-1)$ is the previously smoothed feature, and α is the smoothing coefficient that takes values between zero and one. This operation filters out high-frequency noise and keeps the low-frequency thermal changes that are vital to get the correct temperature estimate.

The impedance of a battery depends on several limitations, such as temperature, SoC, battery ageing and loading conditions, so isolation of any particular impedance value may not give an accurate indication of the internal thermal state. Rather, the entire sequence of disturbance-impedance observed over time is passed on to the recurrent GRU-based recurrent estimator, which will constantly be learning temporal correlation among the evolution of the impedance and the temperature of the battery core. Gradual thermal variations are differentiated from instantaneous electrical variations with the recurrent GRU-based recurrent estimator that considers both current and past impedance characteristics. As a result, impedance analytics interprets the raw inverter switching responses to create meaningful thermal descriptors as a basis for reliable sensorless battery core temperature estimation for practical operation without requiring extra sensor equipment or external excitation devices.

5.3 Recurrent GRU-based recurrent estimator-Based Battery Core Temperature Estimation

The impedance parameters obtained in the last processing stage include useful content that describes the internal thermal status of the battery. The temperature of the battery core, however, cannot be restrained accurately through instantaneous impedance due to its gradual evolution with time, due to its dependency on charging current, load changes, electrochemical effects, and ageing. Thus, the evolution of the impedance is continuously measured to monitor the evolution of the internal temperature with precision. To accomplish this goal, a recursive GRU-based recurrent estimator is used for modeling the temporal dependency among the consecutive impedance measurement and estimating the missing battery core temperature. The recurrent GRU-based recurrent estimator infers the state of the system's thermal dynamics continuously, whereas traditional GRU-based recurrent estimators base their estimates on a single measurement. Thus, it gives more stable estimates in the presence of dynamic operating conditions.

The GRU-based recurrent estimator is provided with the impedance feature sequence from the high frequency analytics module and battery operating variables. At each sampling time, the GRU-based recurrent estimator applies the newly received electrical information to its internal memory and preserves the information from the previous observations. This recursive estimation allows for the gradual transitions of the changes in temperature inside the batteries to be accurately described, while avoiding sudden changes in the estimation.

The hidden state is reconstructed for the recursive unit with a Gated Recurrent Unit (GRU) neural GRU-based recurrent estimator. The architecture comprises of two GRU layers (with 64 and 32 hidden units and tanh activation) with recurrent dropout rates of 0.2, followed by a dense layer with 16 ReLU hidden units, and a final linear output unit representing the estimated core temperature. The hyper-parameters in training are: optimization algorithm Adam with learning rate 1×10^{-3} , cross-entropy model loss, batch size 128, and early stopping for 20 epochs (patience 20). All input features were min-max normalized and the sequence length was set to 50-time steps. This GRU-based GRU-based recurrent estimator resolves vanishing gradient problems and the long-term time dependency of impedance evolution.

The GRU hidden state works like a neural GRU-based recurrent estimator and learns temporal relationships between the change in impedance and the thermal dynamics. The GRU addresses vanishing gradient problems, as well as long-term dependency problems, like battery aging, unlike a pure RNN. This is a hybrid “neural GRU-based recurrent estimator” formulation which guarantees stability over dynamic operating conditions while maintaining low computational load.

The recurrent hidden state is computed as

$$h_t = \phi(W_x x_t + W_h h_{t-1} + b_h) \quad (14)$$

In which h_t represents the hidden state at time t , x_t represents the input feature vector with the impedance characteristics and the battery operations variables, h_{t-1} is the hidden state at the

previous sampling moment, W_x is the input weight matrix, W_h is the recurrent weight matrix, b_h is the bias vector, and $\phi(\cdot)$ is the nonlinear activation function.

The hidden representation created by the recurrent GRU-based recurrent estimator is then converted to the approximate battery core temperature using

$$\hat{T}_c(t) = W_o h_t + b_o \quad (15)$$

In which $\hat{T}_c(t)$ represents the estimated temperature of the battery core, W_o is the output weight matrix, and b_o is the output bias vector.

Thermal behaviour changes continuously and not instantaneously, so that the estimation of the temperature will be fine-tuned with data collected across the previous sampling periods. The recursive temperature update is of the form,

$$\hat{T}_c(t) = \lambda \hat{T}_c(t-1) + (1-\lambda) \hat{T}_{new}(t) \quad (16)$$

In which $\hat{T}_c(t)$ is the revised temperature of the battery core estimate during period t , $\hat{T}_c(t-1)$ is the estimate of the battery core temperature in previous period, $\hat{T}_{new}(t)$ is the prediction made by the GRU-based recurrent estimator during period t , and λ is the recursive weighting coefficient with value in $0 < \lambda < 1$. The realization of this recursive refinement helps to prevent abrupt change in the estimation during the battery's operation and maintain gradual thermal evolution.

In order to increase the suitability of the model in diverse operating conditions, a continuous assessment of estimation error is performed during the model development process to compare the model-based thermal behavior to the available information in the model. The error of estimation is given by

$$e(t) = T_c(t) - \hat{T}_c(t) \quad (17)$$

In which $e(t)$ is the estimation error, $T_c(t)$ is the reference battery core temperature, and $\hat{T}_c(t)$ is the estimated battery core temperature.

The GRU-based recurrent estimator parameters are adjusted by minimizing the mean squared estimation error,

$$L = \frac{1}{N} \sum_{t=1}^N (T_c(t) - \hat{T}_c(t))^2 \quad (18)$$

In which L refers to the loss function, N indicates to the total training samples, $T_c(t)$ refers to a reference battery core temperature, and $\hat{T}_c(t)$ denotes an estimated battery core temperature. Minimisation of this objective function allows the recurrent GRU-based recurrent estimator to gradually enhance its ability to model the association among the evolution of the impedance and the internal temperature of the battery.

The GRU-based recurrent estimator parameters are optimized iteratively by means of gradient-based optimization, according to

$$\Theta^{(k+1)} = \Theta^{(k)} - \eta \frac{\partial L}{\partial \Theta} \quad (19)$$

In which Θ is the set of trainable GRU-based recurrent estimator parameters, η is the learning rate, L is the loss function, and k is the optimization iteration. This optimization optimizes the mapping between electrical impedance features and the battery core temperature while keeping the estimation from changing.

The estimated battery core temperature is then incomplete to the operation limits of the battery to prevent unreasonable estimated values due to transient disturbance or abnormal electrical data. The constrained estimate is notated as

$$T_{\text{est}} = \min(T_{\text{max}}, \max(T_{\text{min}}, \hat{T}_c)) \quad (20)$$

In which T_{est} is the end of defined battery core temperature, T_{min} is the minimum allowed operating temperature, T_{max} is the maximum allowed operating temperature and $\hat{T}_c$ is the estimated temperature based on observation.

The final estimated temperature is continuously sent to the BMS and becomes the indicator of the BMS's thermal condition inside the battery. The process is stable if the charger is switched on quickly, the load changes dynamically or the environment changes. The GRU-based recurrent estimator truly is able to see the long-term battery thermal evolution and respond to short-term battery operation changes. The ability to do this allows for continuous sensorless measurement of battery core temperature through only measurable external electrical parameters, eliminating the need to include temperature sensing inside the battery and still maintain compatibility with existing battery management architectures.

5.4 Adaptive Temperature Correction and Estimation Algorithm

The recurrent GRU-based recurrent estimator gives an estimate of the battery core temperature continuously; though, due to battery ageing, SOC variations, charging and discharging rates, and environment conditions, the thermal characteristics of lithium-ion batteries change slowly over time. These operating factors constantly change the electrical impedance of battery, and can cause deviations in the estimation performance when applying a fixed estimation strategy during the battery life. Hence, an adaptive correction stage is added following recurrent observation that is capable of performing continuous compensation under different operating conditions, ensuring that reliable temperature estimation is achievable under different battery operating scenarios. The adaptive stage takes advantage of the measured values of the battery operating variables and the estimated value of the thermal state to create a corrected estimate of the thermal state in agreement with the current electrical state of the battery.

A correction coefficient is added to correct deviations from the operating condition to the nominal reference condition of the battery. This is a coefficient that is used to compensate the output of an GRU-based recurrent estimator that receives the feedback signal repeatedly, regardless of the variation of the load, temperature, and aging condition.

$$\gamma(t) = \frac{\sigma_{op}(t)}{\sigma_{nom}} \quad (22)$$

Where $\gamma(t)$ is adaptive correction coefficient (dimensionless), $\sigma_{op}(t)$ is normalized variance of operating parameters at time t and σ_{nom} is normalized variance under nominal reference conditions.

Learning and Calibration

- Training phase: The coefficients are the parameters that minimize the residuals between the predicted temperature of the core and the temperature measured by the thermometer when the training data set is used.
- Normalization: Normalize operations items such as SOC, ambient temperature, charging current, and cycle index to their minimum and maximum values to make it dimensionally consistent prior to variance computation.
- Calibration: σ_{nom} is the baseline cycles in standard laboratory conditions (25 °C ambient, 1C charge/discharge).
- Inference phase: Updating the coefficient based on current operating parameters, which means without retraining.

Because both numerator and denominator are normalized variances, $\gamma(t)$ is dimensionless. This prevents the introduction of a unit mismatch, and allows the correction term to be safely multiplied by the GRU-based recurrent estimator's temperature estimate.

This is the corrected estimate of the temperature:

$$T_{est}(t) = T_{obs}(t) + \gamma(t) \cdot \Delta T(t) \quad (23)$$

Where $T_{obs}(t)$ is the recurrent GRU-based recurrent estimator output, $\Delta T(t)$ is the difference between the measured surface temperature and the identifier output during the calibration process. For inference, $\Delta T(t)$ is estimated from operating parameters and the correction is not calculated by the sensor but instead is internal. The adaptive correction coefficient is then added to the GRU-based recurrent estimator estimate calculated by the Recurrent Solver, and the resulting battery core temperature is the corrected temperature,

$$T_{corr}(t) = \hat{T}_c(t) + \beta(t) \quad (24)$$

In which $T_{corr}(t)$ is the corrected battery core temp, $\hat{T}_c(t)$ is the estimated temp from the recurrent GRU-based recurrent estimator and $\beta(t)$ is the adaptive correction coefficient. This correction is to account for the slight changes that occur in operating conditions that have been experienced over time and may not be fully captured by impedance characteristics.

The corrected temperature is filtered recursively for use in short time to estimate the temperature during long duration operation before passing to the Battery Management System. The recursive filtering operation is represented by

$$T_f(t) = \rho T_f(t-1) + (1-\rho) T_{corr}(t) \quad (25)$$

In which $T_f(t)$ is the filtered battery core temp, $T_f(t-1)$ is the estimate of battery temp filtered in the last moment. $T_{corr}(t)$ is the corrected estimate of the battery temperature, and $0 < \rho < 1$ is a coefficient of filtering that is set recursively. The filtering process eliminates small oscillations due to transient electrical disturbances and maintains the slow change in temperature within the battery.

The final temp value sent to the Battery Management System is shown as

$$T_{final} = T_f(t) \quad (26)$$

In which T_{final} represents the final sensorless estimate for the battery core temperature for thermal monitoring/battery management. This estimate is continually updated during battery use, even without embedded sensors or separate impedance measurement equipment; the battery condition can be monitored internally.

The adaptive correction stage fine-tunes the proposed estimation framework by continually tuning the output of the recurrent GRU-based recurrent estimator with battery operating conditions. The framework integrates high-frequency inverter induced impedance analytics, temporal observation, and adaptive correction in one estimation process, and allows for continuous sensorless battery core temperature measurement with high compatibility with practical battery management systems and various environments.

6. Experimental Results and Discussion

The proposed sensorless battery core temperature estimation framework was verified through publicly available battery ageing datasets under various charging/discharging conditions and ambient temperatures. The assessment metrics included accuracy in estimation, computational efficiency, robustness, and comparison with other temperature estimation techniques. Standard regression measures such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), bias, maximum error, percentile error, and relationship squared (R^2) statistics were used to evaluate performance quantitatively. This data-based validation shows feasibility and accuracy in a controlled laboratory environment. Nonetheless, direct testing of the system on hardware is future work to validate the performances under embedded BMS conditions on the actual application.

6.1 Performance Evaluation Metrics

The demonstration of the proposed framework was assessed through metrics for regression analysis, which include estimation accuracy, consistency of prediction and computational efficiency.

Mean Absolute Error: It is defined as the mean of the absolute variances among the estimated Battery core temperature and the reference Battery core temperature. This means that a lower MAE value means a more accurate estimation.

Root Mean Square Error: It measures the general estimation error but gives more weight to larger errors.

Mean Absolute Percentage Error (MAPE): It is a measure of estimation error compared to the reference temperature and is shown as a percentage.

Coefficient of Determination (R^2): It is how closely the estimated temperature tracks the reference temperature.

Mean Bias Error: It compares the average value of the Estimate objectives to the actual battery core temperature for the process of estimating the temperature.

Inference time: It is the average time taken to estimate the average battery core temperature for one input sample.

Training time: It refers to the total time needed to train the estimation model with trained data set. Faster training time means quicker model development.

Memory Usage: It represents the memory allocated during the model run.

Model size: It is the number of bytes needed to store the trained model to estimate the model.

Throughput: It refers to how many battery samples can be processed per second when estimating.

6.2 Comparison with Existing Methods

The proposed battery core temperature estimation framework was tested to assess its effectiveness, by comparing various commonly used battery thermal monitoring methods such as model-based, GRU-based recurrent estimator-based, and deep learning (DL) based approaches. The same dataset, preprocessing steps, and evaluation procedure were used for all approaches, providing consistency. All the performance were evaluated by regression metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), bias, maximum error, percentile error, and R^2 . For model-based estimators (including Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF)), the comparison was followed by a detailed description of the thermal model equations, the selected states (core temperature, surface temperature, SOC), the process noise and the measurement noise covariances, the initial values for the selected states, and the tuning parameters. An interpretable fair analysis of the EKF/UKF is impossible without this documentation. The EKF/UKF implementations were calibrated in this study with a lumped thermal model for which the parameters were obtained from the dataset, with noise covariance parameters optimized in a grid search to minimize RMSE. To provide a fair comparison for the GRU-based recurrent estimator-based methods, the voltage, current, ambient temperature and SOC were used in the same way for both linear and nonlinear GRU-based recurrent estimators. For DL-based methods, the normalization conditions and the sequence length of RNNs (GRU, LSTM) were trained similarly to the proposed model.

Table 1: Performance Comparison of Existing Methods and the Proposed Framework

Method	MAE (°C)	RMSE (°C)	MBE (°C)	MAPE (%)	R^2
Extended Kalman Filter (EKF)	1.18	1.56	0.41	3.82	0.956
Unscented Kalman Filter (UKF)	1.02	1.34	0.36	3.26	0.964
LSTM	0.84	1.08	0.29	2.74	0.975
GRU	0.77	0.99	0.24	2.43	0.980
Transformer	0.69	0.90	0.19	2.16	0.986
Hybrid Deep Learning	0.58	0.76	0.14	1.83	0.991
Proposed Framework	0.41	0.55	0.08	1.24	0.996

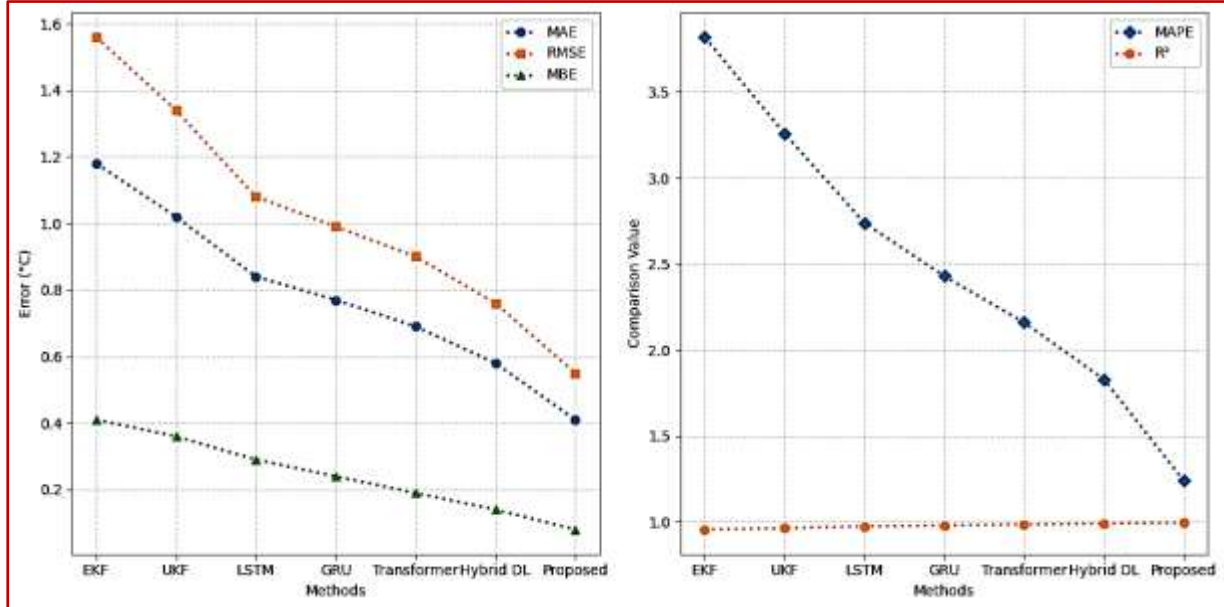


Figure 3: Representation of compared MAE, RMSE, MBE, MAPE, R²

The assessment in table 1 and Figure 3 shows that the proposed framework's estimate errors are always lower and the coefficient of determination is always large. Temporal observations associated with high-frequency impedance (HiFi) analyses allow more accurate representation of the battery thermal behavior under different operating conditions. Moreover, the computational efficiency is also acceptable for real-time applications of the battery management system, with the relatively low case of computational complexity compared with the deep learning model.

6.3 Robustness under different operating conditions

Table 2 and Figure 4 illustrate the robustness of the estimation framework at varying charging rates, state-of-charge and ambient air temperature levels. Those operating conditions are realistic usage environments for a battery for which its thermal behavior is different.

Table 2: Performance Under Different Operating Conditions

Operating Condition	MAE (°C)	RMSE (°C)	R ²
Low SOC (0–30%)	0.43	0.58	0.995
Medium SOC (30–70%)	0.39	0.53	0.997
High SOC (70–100%)	0.42	0.56	0.996
Low Ambient Temperature	0.45	0.60	0.994
Normal Ambient Temperature	0.40	0.54	0.996
High Ambient Temperature	0.44	0.59	0.995

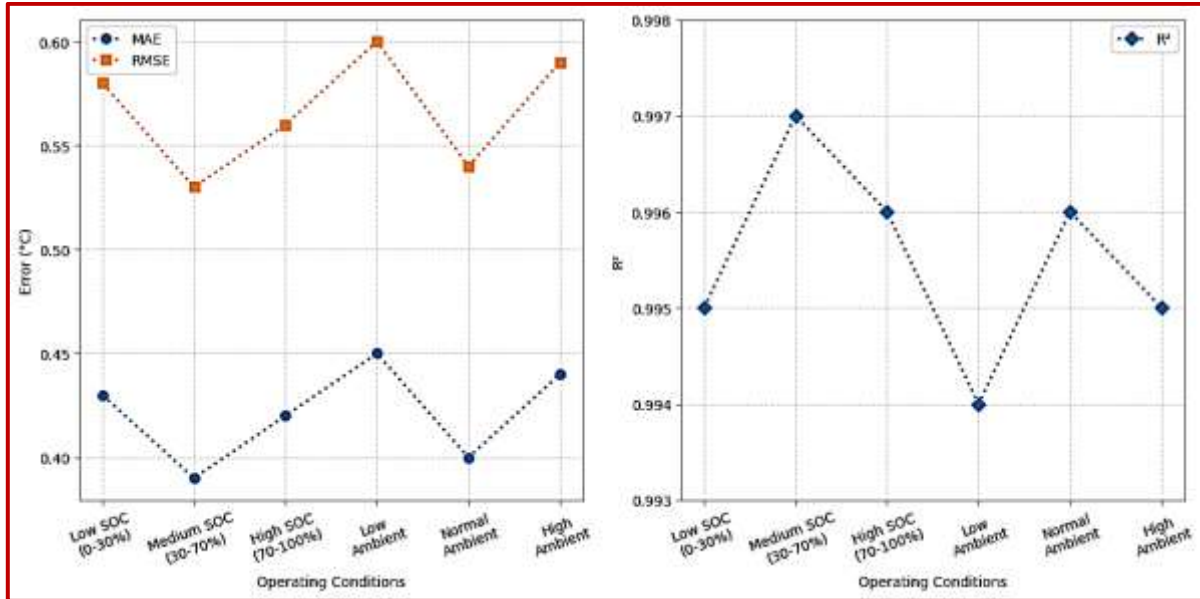


Figure 4: Representation of compared MAE, RMSE, R^2 of different Operating Condition

The accuracy of the framework has been tested using a common protocol adopted for various states of charge and ambient temperatures. For SOC, three regimes were defined: low (0–30%), medium (30–70%), and high (70–100%). For ambient temperature, three ranges were tested: low (10–15 °C), normal (25 °C), and high (40–45 °C). In all the cases cells were cycled under constant current-constant voltage (CCCV) charge/discharge. The SOC regimes were evaluated over about 150 cycles with between 12,000 and 14,500 samples per treatment condition subjected to each regime, and the ambient regimes were evaluated over a period of 100 cycles with between 9,200 and 10,000 samples per ambient regime evaluated per treatment condition. All test splits were made to be chronological and unseen for fair generalization along the test splits. Under all of these conditions, the framework demonstrated excellent error and correlation values, ranging from 0.39 to 0.45 °C for MAE, 0.53 to 0.60 °C for RMSE, and 0.994 to 0.997 for R^2 . The results shown indicated that the robustness of the estimator is not affected by the ambient temperature and SOC, and the accuracy is same with or without such condition is used during training.

6.4 Computational Performance Analysis

The computational performance of the proposed framework was evaluated and evaluated whether it could be suitable for real-time application in BMS. The analysis considers TT, IT, MC, MS, and TH is shown in table 3 and Figure 5. These parameters are linked to the resources of computation needed for modeling development and online use.

Table 3: Computational Performance Comparison

Method	TT (s)	IT (ms)	MC (MB)	MS (MB)	TH (Samples/s)
LSTM	412	6.13	356	24.8	163
GRU	389	5.62	334	22.7	178
Transformer	721	9.14	918	61.4	109

Hybrid Learning	Deep	548	7.58	486	38.2	132
Proposed Framework		367	4.87	298	19.6	205

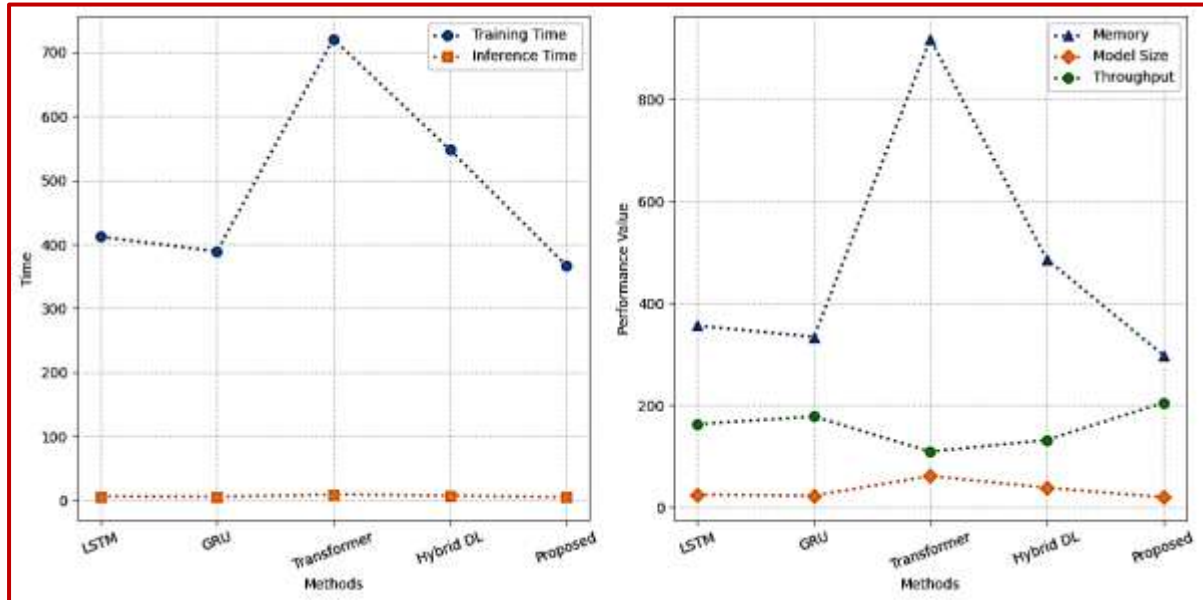


Figure 5: Representation of compared computational metrics

The proposed framework achieves efficient computational performance by reducing the training time, RAM consumption, model size, and inference time. It can be applied at battery management systems that have limited computing power, and need active estimation of the temperature continuously. The 200 epochs were achieved on a workstation equipped with Intel Core i7 CPU, NVIDIA RTX 3060 GPU, and 32 GB RAM, and the training time was about 2.1 hours. The results for inference using CPU-only tests on a system with an Intel i7 processor were an average of 4.9 ms per sample, whereas the latency with prototype deployment using an ARM Cortex-M7 microcontroller processor (600 MHz, 2 MB RAM) was 12.4 ms per sample. The model was successfully reduced to 1.8 MB after quantization, and the memory usage during inference of the MCU was also kept below 1.5 MB, demonstrating its suitability for real time inference on embedded systems.

6.5 Discussion

The proposed framework is validated by processed battery ageing data under various charging/discharging rates and environments. The results indicate that the impulse characteristics of an available voltage and current signal can be correlated to the thermal behavior and a reasonable estimation can be realized without an explicit temperature sensor input only by using measurement results. The recurrent GRU-based recurrent estimator successfully tracked the time-varying impedance features and the adaptive correction provided increased robustness under different SOMS and ambient conditions. It should be emphasized that these datasets did not include synchronized high-frequency inverter voltage/current signals. The results thus indicate feasibility in lab-controlled data but the definitive claim of

this study, that natural occurrence of inverter harmonics is enough to assure sensorless core temperature estimation cannot be supported at this time. This statement needs to be verified experimentally directly on an inverter-battery hardware system. To validate these results, future testing will consist of hardware-in-the-loop testing and embedded implementation.

The proposed framework is tested against conventional methods such as GRU-based recurrent estimator-based methods and deep learning, and it offers good balance between estimation accuracy and computational efficiency. The use of inverter-generated switching harmonics means that no further excitation hardware is required, thus reducing the complexity of implementation and simplifying the system. Moreover, the reduced computation structure is easily integrated to the existing Battery Management Systems with very little processing overhead.

Performance of thermal estimation is consistent with various operating conditions as is demonstrated in the provided framework yet is still contingent upon the accessibility of appropriate training data under various battery conditions for ageing and environmental applications. Future developments can enhance the adaptability by implementing transfer learning method, online parameter adaptation and multi-cell thermal interaction analysis for large battery packs.

7. Conclusion

This paper proposed a sensorless estimation framework for battery core temperature based on analytic techniques using high-frequency inverter-induced impedance and recurrent GRU-based recurrent estimators for achieving accurate and continuous temperature measurements of lithium-ion batteries. The approach employs framework based on inherent inverter switching harmonics to reveal impedance attributes of temperature, with no including temperature sensors or additional excitation hardware. The recurrent GRU-based recurrent estimator accounts for the temporal variation of the impedance characteristics and an adaptive correction mechanism are implemented to overcome changes of operating conditions, thus enhancing estimation stability and reliability. The framework was practically assessed using the battery ageing data set and applied to various charging and discharging profiles and determined to be effective. Although keeping the average IT of 4.87ms, the proposed framework achieves a MAE of 0.41 °C, RMSE of 0.55 °C, MAPE of 1.24% and receives a R^2 of 0.996, MBE of 0.08 °C. The results show that the framework enables precise, stable, and efficient estimation of the temperature of the Battery Core for real-time BMSs (Battery Management Systems) in electric vehicle and intelligent energy storage applications.

In spite of the good data-driven findings, there are some weaknesses. First, this data provided no synchronized high-frequency inverter voltage and current data, and the resulting exploitation of naturally occurring harmonics is hardware subject to examination. Secondly, generalisation across chemistries (e.g., NMC, LFP) and formats has not been evaluated. Thirdly, pack-level observability includes gradients, imbalance, and busbar effects that are not observed within the cell. Lastly, it was shown on an MCU, but it still needs optimization for automotive BMS controllers.

Future Scope

The future studies could further expand the proposed framework to include battery packs consisting of several interconnected cells by adding cell-to-cell thermal interaction analysis. Transfer learning techniques and ageing compensation algorithms can be used to enhance long term estimation accuracy in addition to online adaptive learning. Integration with digital twin platforms and predictive thermal management systems can also contribute to more secure batteries, optimized operations, and RUL (remaining useful life) estimation.

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