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Research Article

Deep Learning for Battery Thermal Optimization: LSTM, GRU, BiLSTM, and DNN in IoT-Driven Energy Systems

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ABSTRACT

Electric vehicle (EV) efficiency, reliability and safety are all greatly influenced by battery thermal management systems (BTMS). This study investigates the optimization of BTMS utilizing cutting-edge machine learning models, including Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Bidirectional LSTM (BiLSTM) and Deep Neural Networks (DNN). Using a rich data set of batteries made up with ionized lithium metrics observed in diverse temperatures. This study constructs forecasting models to estimate the state of charge (SoC) and temperature in battery systems. Comparative analysis reveals that DNN excels in predictive accuracy for stable conditions, while BiLSTM offers superior performance in dynamic and high-temperature scenarios.

The work emphasizes challenges and merits combining aging effects into SoC and temperature predictions, providing a holistic approach to understanding long-term battery behaviour. By replacing costly physical prototyping with simulation-based evaluations, this research provides a transformative framework for rapid BTMS development. The proposed framework not only enhances the accuracy of thermal and charge state predictions but also provides a cost-effective simulation-based methodology for testing and optimization. The findings opens pave a path for innovative, reliable, as well as adaptable solutions for battery management that enhance adoption related to sustainable energy techniques. By helping to create more resilient, dependable and effective thermal management techniques for EV batteries, the current research prepares the foundation for future advances in battery optimization.

Keywords: Battery Thermal Management System, BiLSTM ,DNN, GRU and LSTM ,EV performance, Reliability , Thermal optimization,

1. INTRODUCTION

Considering the number of important challenges, lithium-ion batteries are a very practical option for energy storage systems. As a replacement of the combustion engine vehicles, electric vehicles have come out as savior of our world [1]. In most of the electronic devices and electric vehicles, lithium batteries are used, which resulted in the development of V2G (vehicle-to-grid) techniques [2]. One possible means of dealing with the problem of climate change is electrifying transportation. Electric vehicles' entrance on the market has had a major influence on a number of industries, most notably the electrical grid.

A numbers of measures have been put in place to encourage the deployment of electric vehicles, and the growing trend of acceptance over the past decade has been encouraging [3]. Although LIBs are the foundation of electric cars, they have several significant problems including inadequate thermal efficiency, thermal runaway, fire dangers and a higher rate of discharge in environments with low and high temperatures. Thus, while dealing with this issue, the majority of researchers have developed novel techniques for managing and preserving the (Lithium Ion Battery)LIBs' overall thermal performance [4]. Understanding the battery's power density, durability, temperature tolerance, and adaptable electrochemical function is vital. In electric vehicles and renewable energy storage devices BMS are vitally important [5].

In order to ensure battery safety and address the expected difficulties, Recent improvements in the system include upgrades to the battery's thermal management. By accelerating heat transmission, the BTMS technology improves battery safety by ensuring battery performance based on mechanical, electrochemical, and thermo kinetic properties under both regular and unusual operating situations. It is also critical to maintain the proper operating temperature and avoid overheating for safe operation. Thus, a crucial research objective is to create a BTM system that is dependable and safe [6].

A novel BMS system that utilizes the most advanced computational Methods of intelligence, For example data analytics, neural networks, and machine learning algorithms. The suggested system seeks to offer adaptive control techniques and real-time prediction capabilities that are significantly better than those of conventional BMS by utilizing these technologies. A more detailed knowledge of battery performance and the capacity to make preventive modifications that can greatly improve battery efficiency and lifetime are made possible by the use of such advanced technologies [7].

To precisely make an estimate of the SoC and temperature, a comparative study of simulation data is carried out in this research paper. The structure of this document is as follows: The dataset, pre-processing, and RNN, BiLSTM and DNN architectures utilized for optimization are all explained in detail in Section 2. The impact of age and temperature and elaborates the technique related to simulation data utilized in section 3. The detection of the level of difficulty analysis and the temperature and SoC estimation are shown and discussed in Section 4 ultimately; Section 5 presents the manuscript's conclusions.

1.1. **Literature Review**

It is well Known that the battery belongs to the most significant components of an electric vehicle, a lot of research has focused on developing an accurate temperature management system that improves the battery's lifespan and performance. With an emphasis on cooling technologies, the paper seeks to critically evaluate the studies and research that have been done thus far about the kind, architecture, and principle of operation of BTMS which are adopted into building of Lithium ion batteries of different shapes [8]. Better thermal management requirements and a more efficient thermal management system will be required for EVs. This research presents a cooling approach that may be utilized for both active and passive liquid cooling systems. The elements of coolant and refrigerant circulation are modelled [9]. Figure 1 show the battery pack cooling classification used in BTMS.The batteries must operate between 285 K and 310 K, requiring efficient BTMS. Advancing these systems demands research, collaboration, and testing for reliable and eco-friendly lithium-ion battery management [10].

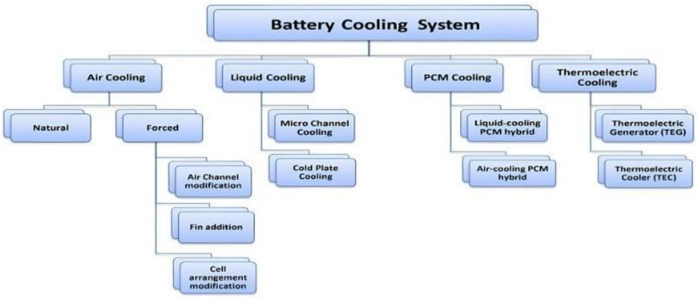

Figure 1. Classification of battery pack cooling methods [10]

Battery management research is essential as the performance of battery directly affects the vehicle power and range. A correct evaluation temperature and state of charge of the battery are essential to the vehicle overall performance, driveability and safety [11]. Using the liquid for cooling and a machine learning model, this work investigates a thermal management system to predict the thermal health of battery EVs. Real-world data on EV operation, cooling, and battery has been collected. Important factors that influence battery health related to heat were found [12]. Material research that was previously unreachable has improved thanks to artificial intelligence (AI); for instance, machine learning (ML) has been able to forecast certain previously unheard-of thermal attributes [13]. To increase EV performance, a battery thermal management system is essential. Overview of BTMS used in EV development was provided in this study using machine learning methods in estimating while the performance of BTMS on the basis of fast charging [14]. Advanced methods are required in this quickly expanding manufacturing so that we can precisely evaluate the condition of the battery. This is quite challenging procedure because of the complex nature of battery chemistry, temperature, and age [15]. Furthermore, Improvement in steadiness of grid as well as using sources such as renewable energy depends on precise SoC estimate [16]. Battery SoC refers to the battery's duration between charges [17-18]. The only way to assess SoC indirectly is to use variables like current, voltage and temperature [19].

In electric vehicles precise approximation of SoC of the battery and the study analyzes SVM, Neural Networks, Ensemble Methods, and Gaussian Process Regression. Provided algorithms are compared for their ability to provide a model for the complex, nonlinear relationship between real-time driving data and SoC, aiming to enhance battery management and vehicle performance [20]. Several approaches of estimating SoC. Terminal voltage, open circuit voltage, coulomb counting, and a dynamic strategy based on the Unscented Kalman Filter (EKF) will all be covered in this research [21]. The differences between data-driven and model-based SoC estimation are described in terms of estimate error, advantages, disadvantages, and the estimation model or algorithm [22]. Predictive methods based on ML and an interactive logical approach serve to predict a power electronics package's thermal properties as well as to assess some related contributions of thermal management methods and encapsulation material properties to hotspot temperatures. [23].

Most promising cooling techniques in EV is liquid cooling for preserving the optimal temperature and stability. However, liquid cooling requires addressing challenges like thermal conductivity, energy efficiency, and integration complexities for establishing a BTMS [24]. The battery temperature must be maintained within the designated range using passive as well as active cooling principles. Phase transitions and heat pipes are two ways that materials such as Phase Change Materials consume and reserve heat. effectively transmit heat via condensation and vaporization, and hydrogels soak up and discharge water to regulate temperature in passive cooling systems. PCMs offer reliable temperature control, but their poor thermal conductivity limits how effective they can be [25]. Notwithstanding its drawbacks, including expense, safety issues, and recycling difficulties, LIBs are essential to the acceptance of EVs. The parameters to be estimated using machine learning-based methodologies are the state of power (SoP), SoC, the state of health (SoH). Accurate LIB prediction and management in EVs are crucial [26]. Batteries which are lithium ionised power devices, EVs, as well as renewable energy storage but generate heat during charge and discharge, risking shorter lifespan, reduced performance, and safety issues. Machine learning offers a transformative solution by analysing vast data to enhance thermal management and predict battery temperatures effectively [27]. Determining the exact level of charge is necessary for reliable operation along with effective battery management in renewable energy systems. The 70% was performed for training purposes the artificial neural network model and remaining 30% from the total data was utilized for carrying out tests as well as to validate the same [28].

1.2. Research Motivation

The prediction of SOC and temperature has been investigated using a variety of deep learning models, including LSTM, GRU, BiLSTM and DNN. Each model, however, has unique pros and cons that influence whether it is appropriate for forecasting for the future or real-time applications. A comparison of these models' strengths and weaknesses in battery prediction tasks is shown in Table 1.

Table 1: Comparative Analysis of Deep Learning Models for SOC and Temperature Prediction in EV Batteries [32].

Model	Characteristics	Limitations
LSTM (Long Short-Term Memory)	- Designed to handle long-term dependencies in sequential data. - Uses memory cells with three gates: input, forget, and output. - Effective for time series prediction, NLP, and speech recognition.	- High computational complexity. - Requires more training time due to multiple gates. - Susceptible to over fitting on small datasets.
GRU (Gated Recurrent Unit)	- Simplified version of LSTM with two gates: update and reset. - Faster and requires fewer parameters than LSTM. - Suitable for sequential data tasks like speech recognition and time-series forecasting.	- Less expressive than LSTM for very long sequences. - Does not capture as long dependencies as LSTM in certain cases.
BiLSTM (Bidirectional LSTM)	- Consists of two LSTM layers processing sequences in forward and backward directions. - Captures both past and future contexts. - Improves accuracy in NLP and speech processing tasks.	- Doubles the computational cost compared to LSTM. - Requires more memory for storing both forward and backward passes.
DNN (Deep Neural Network)	- Fully connected layers with nonlinear activation functions. - General-purpose deep learning model for classification and regression.	- Lacks memory mechanisms for handling sequential dependencies. - Prone to over fitting, requiring large datasets for effective learning.

Model	Characteristics	Limitations
	- Can approximate complex functions given sufficient data and training.	- Computationally expensive for very deep architectures.

Current technology faces challenges in accurately forecasting the important parameters of LIBs like the SoH and SoC due to their complex structure, sensitivity to external factors, and cell variations. The traditional methods have limitations, significant progress has been made by combining system bound and evidence-based approaches in order improving real-time status prediction [29]. An accurate long-term battery estimation under diverse conditions demands faster, more reliable methods. Research focuses on overcoming these challenges through advanced algorithms comprehensive modelling, and sensitive sensors to understand the battery complexity in a better way [30].

Monitoring the temperature is important when assessing the lithium-ion battery beneficial capacity. However, with large-scale electric vehicle battery packs, monitoring the temperature of individual cells is difficult with the complexity of sensor handling. A sensor-free battery temperature prediction technique was developed to deal with the issue. based on deep learning is proposed, offering both high accuracy and fast runtime performance. This method makes use of short periods of discharge current and battery voltage as inputs to a deep neural network model for predicting temperature [31]. Deep learning (DL), an advanced aspect of artificial intelligence and machine learning, performed better than conventional ML techniques, particularly when working with huge and unstructured datasets. Speech recognition, healthcare, driverless cars, cyber security, predictive analytics, and other fields are all impacted. However, creating efficient deep learning models is difficult due to the dynamic and intricate nature of real-world issues [32]. Traditional forecasting methods struggle to predict battery performance across diverse usage and environmental conditions. Advances in Artificial Intelligence (AI) have revolutionized battery management by replacing basic mathematical models with machine learning principles like support vector machines, decision trees, and regression, enhancing state estimation for temperature and SoC. However, many studies still rely on simple ML models that cannot effectively handle time-series data. AI methods for enhancing fault analysis, thermal management, and battery health diagnostics are becoming growing in popularity, aiming to enhance EV safety, reliability and performance [33].

1.3. Novelty of work:

To amplify consistency of state of charge and battery temperature estimates, this work analyzes the application of powerful LSTM, GRU, BiLSTM and DNN models via capturing the complex, nonlinear relationships which exist between temperature and input variables, these models provide significant improvements in predictive performance. Supervised learning is shown to excel in accurately estimating SoC and battery temperature across varying ambient conditions. This proves particularly valuable, as conventional estimation methods often fall short in handling such complexities [34] require the use of specific models developed for certain temperature settings [35].

This study makes several notable contributions to battery management systems (BMS) research:

1. To estimate temperature and SoC, advanced models (LSTM, GRU, BiLSTM and DNN) using significant simulation datasets are trained and further evaluated via MAE, RMSE, and R^2 metrics.

2. Simulated data enables accurate SoC and temperature estimation, showcasing simulation as a cost-effective tool for BMS development.

3. Aging effects on a 3S4P battery pack under varying temperatures are analyzed, offering insights into long-term performance optimization.

4. A diversified dataset (current, voltage, temperature, aging effects) is used for the first time, improving SoC estimation and accommodating dynamic conditions.

5. Comparative analysis highlights the superior precision of DNN models, paving the way for hybrid architectures.

6. The study validates model accuracy under varying ambient conditions (-20°C to 60°C) and aging effects, emphasizing robustness for practical applications.

7. Simulation-based testing accelerates battery design and management system innovation by reducing dependency on costly physical tests.

This comprehensive approach improves BMS reliability, efficiency, and scalability.

2. MODEL EVALUATION

Three separate assessment indicators are used to evaluate how effective of the suggested method. These are mean absolute error (MAE) and roots mean square error RMSE. MAE shows how well the model predicts the value in comparison to the actual value, while RMSE shows how resilient the model is. Lastly, Equation (03) is used to assess the R^2 score, which measures how closely the actual value matched the values that the model predicted. The formulae for MAE, RMSE, and R^2 score are defined as follows for certain n number of entities.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \bar{y}_i| \qquad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \bar{y}_i)^2} \qquad (2)$$

$$R^2 = 1 - \frac{\frac{1}{n}\sum_{i=1}^{n} (y_i - \tilde{y})^2}{\frac{1}{n}\sum_{i=1}^{n} (y_i - \bar{y}_i)^2} \qquad (3)$$

Where the effective results from simulation dataset is y_i, the approximate results given by the posed model is $\bar{y}_i$, as well as the mean of real value is $\tilde{y}$ [36].

3. METHODOLOGY

3.1. An analysis of the Specified Neural Networks as well as Their Theoretical Background

This section highlights use of advanced models LSTM, GRU, BiLSTM and DNN for evaluating the temperature and SoC in lithium ionised battery packs. The complicated, nonlinear relations between input parameters (like temperature) and the SoC output, as well as vice versa, are well represented by these models. A concise mathematical foundation for each neural network is provided, along with a detailed comparison of their strengths and limitations in achieving accurate temperature and SoC estimations.

3.2. Gated Recurrent Unit (GRU)

The everlasting dependability issue was addressed with the development of the GRU model. By adding a gating mechanism to a simple RNN, a GRU network is produced which allows it to control the information flow inside the neural network. With the improvement, a GRU network can effectively handle problems like vanishing of gradients or ballooning gradients during back propagation and capture huge step by step dependence in time series data. It makes use of two gates the reset gate t determines how well the fresh inputs recombined based on the previously stored data, and the update gate u defines a certain amount of historical data to be allowed through. In a GRU, unlike a typical RNN, the current by the state that's hidden h_k is not immediately impacted by the prior hidden state h_{k-1} or the input of current c_k.Figure 2 interprets the general structure of the GRU [37-38].

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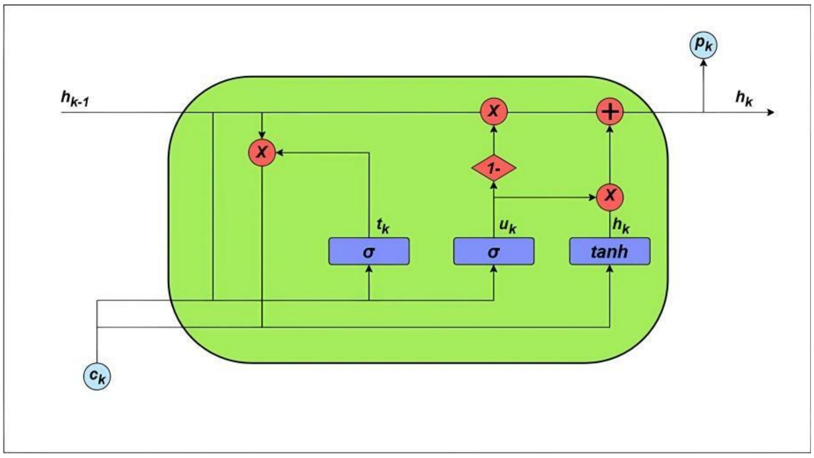

Figure 2. The gated recurrent unit's structure (GRU).

Previous state is linearly combined with the GRU activation h_{k-1} and a candidate state $\hat{h}_k$

$$h_k = (1 - u_k) * h_{k-1} + z_g * \hat{h}_k \quad (4)$$

Where u_k is known as the update gate, and a sigmoid function activates it

$$u_k = \sigma(w_z c_k + w_z . h_{k-1} + b_u \quad (5)$$

This is how the GRU candidate state is determined

$$\hat{h}_k = \tanh (w_h c_k + w_h. (t_k * h_{k-1}) + b_m \quad (6)$$

Where t_k The sigmoid function is responsible for activating the reset gate

$$t_k = \sigma(w_r c_k + w_r h_{k-1} + b_r) \quad (7)$$

3.3. Long Short-Term Memory Network (LSTM)

In order to solve the gradient vanishing problem, a particular kind of RNN called the LSTM was created. Both short-term and long-term memories are addressed by LSTM, which makes use of the idea of gates to simplify and expedite computation. Similar RNN, the LSTM is composed of three different varieties of gates: output gate (o), forgetting gate (f), and input gate (i). Figure 3 displays the primary structure of an LSTM unit [39- 40]. What data is kept in the long-term memory is decided the input gate. This gate is used to extract information from variables that aren't useful. Using the current input, newly computed long-term memory and prior short-term memory, output gate sets up a new short-term memory at the next time step, which is then transmitted to the cell. Furthermore, the results of the current time method may be extracted through this unseen state. Because it may provide an output that ranges from zero to one, the sigmoid function is selected as each of the three gates mechanisms. The information flowing through the gates is influenced by this feature. Furthermore, Ref. [41] highlights how unsymmetrical activation functions, such the hyperbolic tangent function, with back-propagation learning, can converge faster in large networks than comparable methods using non-symmetrical activation functions, the function of sigmoid [42]. Each component of the cell is displayed below

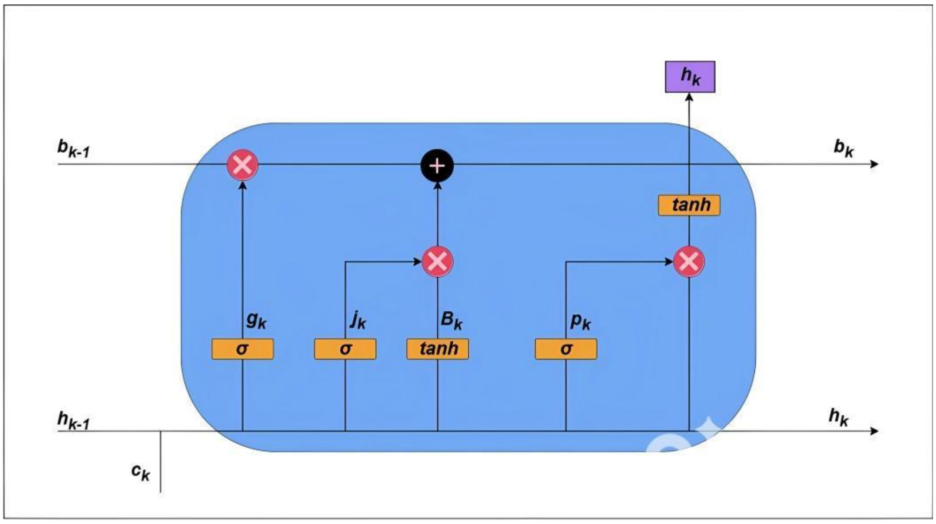

Figure 3. The long short-term memory's (LSTM) structure

Evaluating the gating units:

$$j_k = \sigma(w_{cj}c_k + w_{hj}.h_{k-1} + b_j) \quad (8)$$

$$g_k = (w_{cg}c_k + w_{hg}.h_{k-1} + b_g) \quad (9)$$

$$p_k = (w_{cp}c_k + w_{hp}.h_{k-1} + b_p) \quad (10)$$

Updating memory unit:

$$b_k = g_k b_{k-1} + j_k \tanh(w_{cb}c_k + w_{hb}h_{k-1} + b_c) \quad (11)$$

Calculating the output of LSTM unit:

$$h_k = p_k \tanh(b_k) \quad (12)$$

3.4. Bidirectional LSTM

It has been shown that BiLSTMs are particularly useful when input context is required. For activities like classifying observations. An information moves from the back end to the front end of a unidirectional LSTM. As seen in figure 4, bi-directional LSTM, on the other hand, employs two hidden states to allow information to flow both forward and backward in addition to backward to forward. Bi-LSTMs thus have more knowledge of the situation. To increase the amount of input data that the network could use, BiLSTMs were employed. RNN with LSTM and RNN with BiLSTM structures [43] BRNN essentially follows a procedure that divides a typical RNN's neurons into bidirectional pathways. One represents a forward state or positive time direction, while the other represents a backward situation and on the other hand negative time management. The inputs of the states in the other direction have no influence on the results of these two states. The figure 4 below describes the structure of BiLSTM.An initial data from previous and coming times of the present may be entered through two time directions. On the other hand, ordinary RNN needs delays in order to include future data.

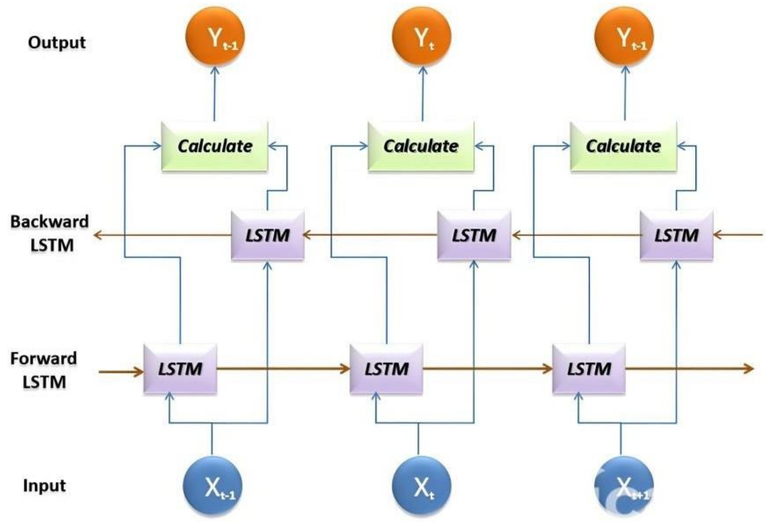

Figure 4. Bidirectional LSTM

3.5. Deep Neural Networks

Neural networks that are fed forward are some of the most used varieties of neural networks, are highly predictive. Each artificial neuron is made up of one input node and one output node that is connected to the initial nodes. With a weight w_{jk}, the output nodes of one unseen layer have connections to the succeeding layer's nodes [44], the aggregate code to a hidden neuron I is calculated using the following formula, which takes consideration of the biases and weights of each and every film [45].

$$z_k = \sum_{j=1}^{n} a_j w_{jk} + b_k \tag{13}$$

where a_j shows the input of the hidden film z and the unseen layer k [44], b_k is bias of the unseen layer k neuron, as well as z_k is total input of the unseen layer k neuron. You can utilize a variety of initiation functions on the unseen layer. The following layer receives the output from the unseen neuron after it is applied to the input:

$$h_k = f(z_k) = \frac{1}{1+\exp(-z_k)} \tag{14}$$

As a feed forward network, The MLP model demonstrates how every layer is linked from the input to the output in one directive [46]. DNN architecture for evaluating battery temperature and state of charge is shown in Figure 5. Temperature of battery or state of charge is output, while its temperature or SoC is the input. SoC and temperature of Li-ion battery probably successfully and precisely estimated using the DNN [47]. This estimate was done using MATLAB package contains toolboxes that train the input data using neural networks to produce an estimating model that can forecast a battery pack's temperature and SoC.

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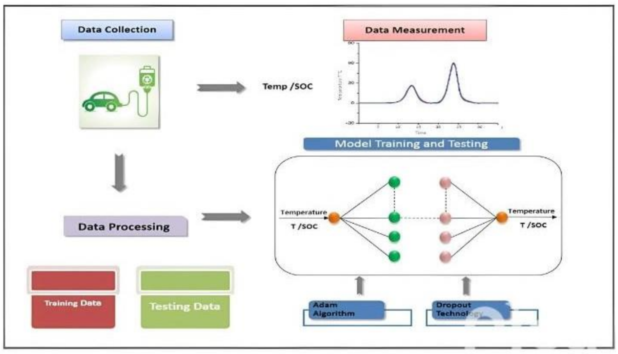


Figure 5. Proposed flow diagram for the deep learning estimation process SOC and Temperature of 3S4P Li-ion battery pack.

Table.2.Description of parameters for LSTM, GRU, BiLSTM and DNN

Parameter	LSTM	GRU	BILSTM	DNN
Number of layers	4	4	4	8
Layer size	50	50	50	64,32,16
Batch size	32	32	32	64
Epochs	100	100	100	100
Learning rate	0.01	0.01	0.01	0.001
Optimizer	Adam	Adam	Adam	Adam
Loss function	MSE	MSE	MSE	MSE
Training epochs	100	100	100	100

3.6 Real-Time Validation:

Opal-RT hardware-in-the-loop (HIL) simulation was used to validate the dataset used in this study in a different paper that is still being reviewed. This guarantees that the dataset accurately depicts battery behavior in real time and is suitable for optimization. MATLAB-enabled host PC with RT-LAB connections makes up the OPAL-RT laboratory configuration [49], as shown in Figure 6. Simulation and practical application results were in accordance. The RTS and host PC are connected via a TCP/IP cable that creates an interlink. The suggested control method on a Simulink/MATLAB platform is significantly upgraded by using RT-LAB, which is already included with MATLAB. As shown in Figure 7, the 3S4P battery pack's temperature and SoC simulation results can be verified in OPAL-RT.

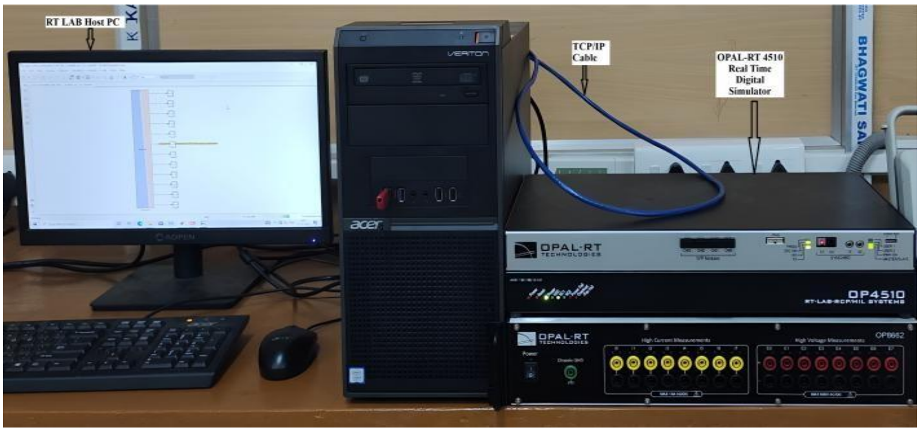
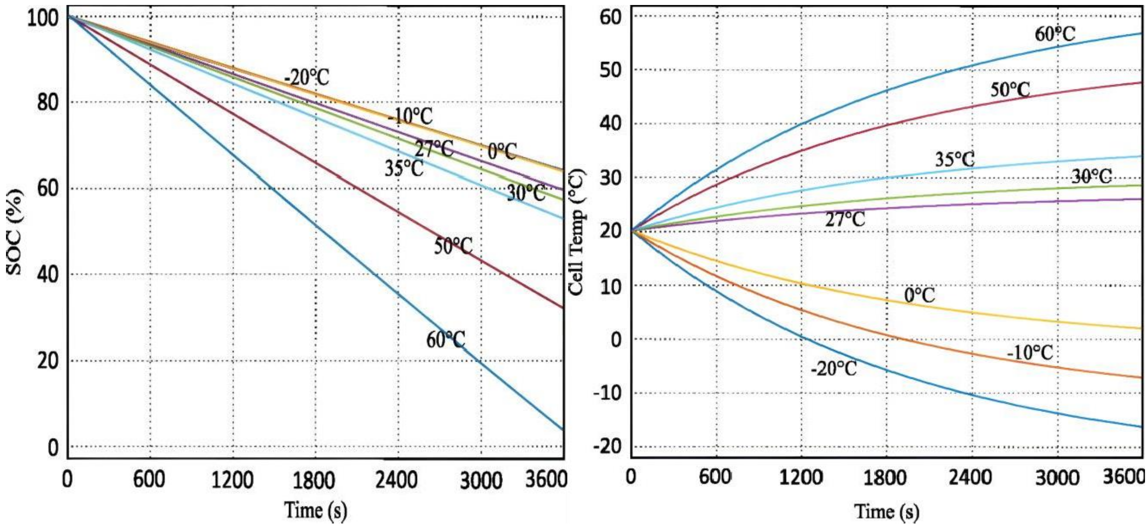


Figure 6 Real-time digital simulation platform installed in the lab.



(a) (b)

Figure 7: Real time SoC and Temperature at different Atmospheric Temperatures of battery pack.

3.7. Dataset Pre-processing

The dataset was created using a 3S4P lithium-ion battery pack with a 10.4 Ah capacity and a nominal voltage of 11.1 V [48]. During a 3600-second (1-hour) simulation were run in a range of ambient temperatures, from -20°C to 60°C, important metrics including battery voltage, temperature, current, as well as the SoC were tracked. At high temperatures (50°C–60°C), the battery overheated, causing rapid SOC depletion, reduced efficiency, and thermal runaway risk. Moderate temperatures (30°C–35°C) led to thermal imbalance and slight efficiency losses as the temperature exceeded the optimal range (28°C). At low temperatures (-20°C to -10°C), SoC remained stable initially but performance declined due to increased internal resistance and reduced electrochemical activity.

The dataset serves as a critical baseline for understanding battery performance constraints without thermal control, highlighting the need for a BTMS to maintain optimal temperatures, improve SOC retention, and ensure safety. Traditional forecasting methods struggle to predict battery performance across diverse conditions but advancements in AI are transforming battery management. Pre-processing the dataset involves down sampling by selecting every 10,000th row, reducing data size while retaining essential trends and patterns for efficient analysis and visualization.

3.7. Relation between SOC and Temperature:

In BTMS, by jointly monitoring temperature and SoC can be optimize performance and longevity. Temperature makes sure thermal safety while SoC reflects remaining capacity. A detailed analysis [50-52] highlights the impact of temperature extremes on electrical and thermal balance, emphasizing its importance for battery performance, safety, and lifespan. It also explores simulation and experimental techniques to analyze battery behavior under varying conditions.

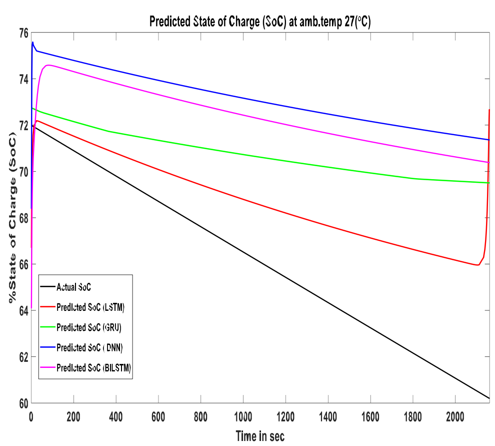
This work focuses on optimizing BTMS using deep learning models (LSTM, GRU, BiLSTM and DNN) to predict as well as control battery temperature (Temp) and State of Charge (SOC) for improved performance. Temp and SoC are key inputs, where one can predict the other. DNNs handle non-temporal relationships, while LSTM, GRU, and BiLSTM excel in time-series predictions, capturing sequential and contextual data. The goal is to ensure optimal battery performance within the 15°C–45°C range across various ambient conditions (-20°C to 60°C).

4. RESULTS AND DISCUSSION

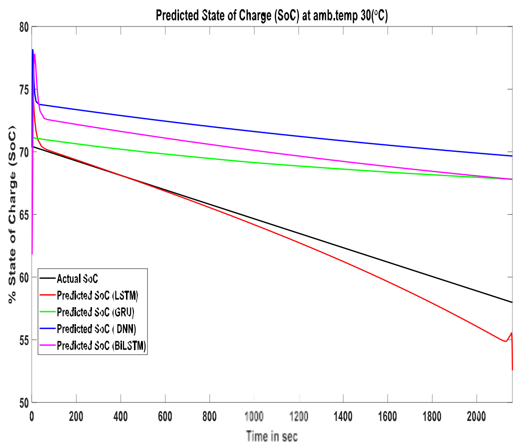
Optimizing battery performance at various ambient temperatures involves analyzing how the temperature and SoC of the battery react to various ambient Temperatures by using LSTM, GRU, BiLSTM and DNN models. The parameters used to train these models for performance evaluation as given in table.2 for getting results .The optimum range of temperature from 15 °C to 45 °C of batteries, promotes better performance, greater efficiency, and a longer lifespan.

4.1. Mode 1: SOC as Output and Temp as Input

Using LSTM, GRU, BiLSTM and DNN, one can investigate the correlation between temperature as the input and State of Charge (SOC) as the result. for a given dataset from MATLAB to upgrade the BTMS by predicting SOC under numerous ambient temperature conditions (-20°C, -10°C, 0°C, 27°C, 30°C, 35°C, 50°C, and 60°C).with SoC is the output and temperature is the input. The optimum range of temperature from 15 °C to 45 °C of batteries, promotes better performance, greater efficiency, and a longer lifespan. So from above ambient temperature conditions, consider four cases at 27°C, 30°C, 35°C, and 50°C as its analysis given in Figure 6.



(a)



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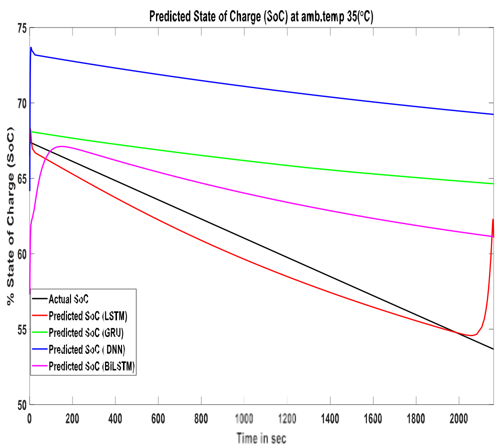
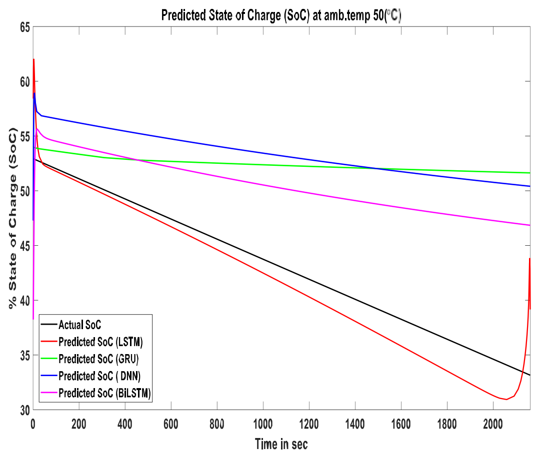


(c)



(d)

Figure 6 Model performance comparison of SoC with LSTM, GRU, DNN and BiLSTM at

(a) 27 °C (b) 30 °C (c) 35 °C (d) 50 °C

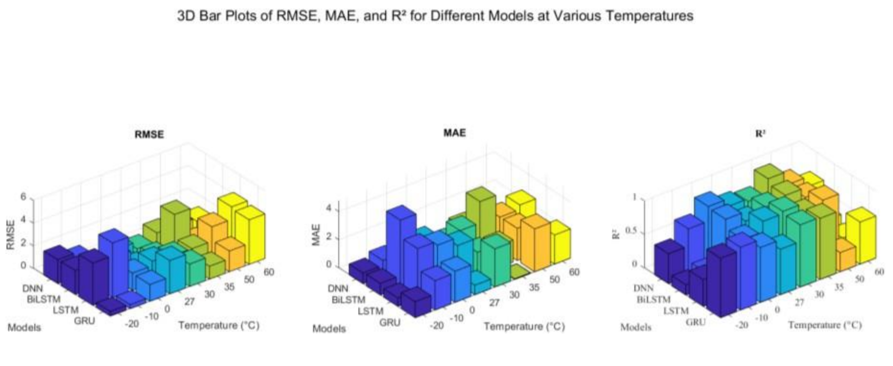
The analysis evaluates the execution of multiple machine learning models (LSTM, GRU, BiLSTM and DNN) for foreseeing the SoC of a battery under diversified ambient temperatures (27°C, 30°C, 35°C, and 50°C). Across all temperature circumstances, BiLSTM model consistently delivers the most accurate SoC predictions, closely aligning with the actual SoC curve. The DNN model also performs well, showing reliable predictions but slightly less accurate than BiLSTM. The GRU model demonstrates moderate accuracy, while the LSTM model exhibits the largest deviation, particularly over extended time periods. As the ambient temperature increases, the accuracy of all models slightly deteriorates, indicating the impact of thermal conditions on prediction performance. Overall, the BiLSTM and DNN models are the most consistent for forecasting SoC, highlighting their suitability for battery management systems under different temperature scenarios.

4.2. Prediction errors for state of charge for the various proposed models

Four methods are used to determine the model's overall performance LSTM, GRU, BiLSTM and DNN, and under eight different temperature conditions. The evaluation results in Figure 7 for the proposed model depict LSTM, GRU, BiLSTM and DNN while Table 3 displays the statistical analysis. Eight different temperatures were used to determine the impact of the LSTM, GRU, BiLSTM and DNN. BiLSTM emerged as the most reliable, showing low RMSE, low MAE, and high R^2 values, especially at extreme temperatures. The DNN sustained at higher temperatures but did well at lower ones. The GRU had results that varied, LSTM worked well at mid-range temperatures but poorly at higher ones. All things considered, BiLSTM offered the highest accuracy and stability under all circumstances.

Table.3 Prediction errors for state of charge for the various proposed models.

Temperature (°C)	DNN RMSE	DNN MAE	DNN R^2	BiLSTM RMSE	BiLSTM MAE	BiLSTM R^2	LSTM RMSE	LSTM MAE	LSTM R^2	GRU RMSE	GRU MAE	GRU R^2
-20	2.1126	0.76	0.4463	2.1159	0.8252	0.1535	3.7181	0.6032	0.3979	0.4104	1.1402	0.8844
-10	1.4554	1.111	0.7015	1.0521	4.7643	0.224	4.8315	3.5484	0.4612	0.3582	2.0864	0.9342
0	0.15	0.8	0.9209	1.9827	0.6986	0.8998	1.5315	3.2532	0.7667	1.4811	2.2113	0.8161
27	1.0828	1.381	0.8093	0.5353	1.0631	0.7578	1.9406	2.6842	0.9237	2.9373	0.6791	0.6764
30	0.4621	0.697	0.7686	0.7708	2.3938	0.8525	1.7428	1.666	0.9573	1.9795	2.7097	0.9258
35	1.2069	1.305	0.9916	3.7752	3.9092	0.9134	1.7248	1.5566	0.8105	1.1364	0.0535	0.9093
50	1.2256	1.068	0.7932	0.7375	2.2682	0.7702	3.0005	2.282	0.8957	1.8257	3.0433	0.2858
60	0.9476	0.23	0.6491	0.4528	2.5876	0.3119	4.106	1.0197	0.2201	3.9196	2.0693	0.6262



(a) (b) (c)

Figure 7. SOC Error Evaluation for DNN, LSTM, GRU, and BiLSTM (a) MAE (b) RMSE (c) R^2

3D bar plots show that the analysis that is comparative of four machine learning models (LSTM, GRU, BiLSTM and DNN) for SoC estimation defines through Figure 7 as follows

1. DNN: performs well at all temperatures, however, in terms of RMSE and R2, it performs best at 0°C.
2. BiLSTM: Has lower performance at lower temperatures but performs well at higher temperatures.
3. LSTM: Shows higher errors compared to other models, especially at lower and higher temperatures.
4. GRU: Performs consistently well across different temperatures, with better performance at lower temperature

BiLSTM performs well at higher temperatures, whereas DNN and GRU models perform better at lower temperatures, according to the RMSE, MAE, and R2 values. In comparison to the other models, LSTM often has lesser explanatory power and larger mistakes. According to this investigation, BiLSTM may be favored for higher temperature settings while DNN and GRU models may be better suited for a wide variety of temperatures for efficient BTMS.

4.3. SoC Performance improvement at optimal range (15°C and 45°C)

The optimum range of temperature from 15°C and 45°C of batteries, where electrochemical processes work efficiently, ensuring steady performance. Temperatures above 45°C can lead to capacity loss and safety risks, while below 15°C, reactions slow down, reducing performance and increasing internal resistance. This range offers higher charge/discharge efficiency, ideal ionic conductivity, and accurate SOC estimates, while also minimizing thermal runaway risks. Therefore, the temperatures of 27 **°C**, 30 **°C** as well as 35°C are considered in the analysis.

Table.4. Average errors of model

Model	Average RMSE	Average MAE	Average R^2
DNN	0.9175	1.1273	0.8565
BiLSTM	1.3604	2.0887	0.8412
LSTM	1.8021	1.7658	0.8972
GRU	1.3511	1.4808	0.8372

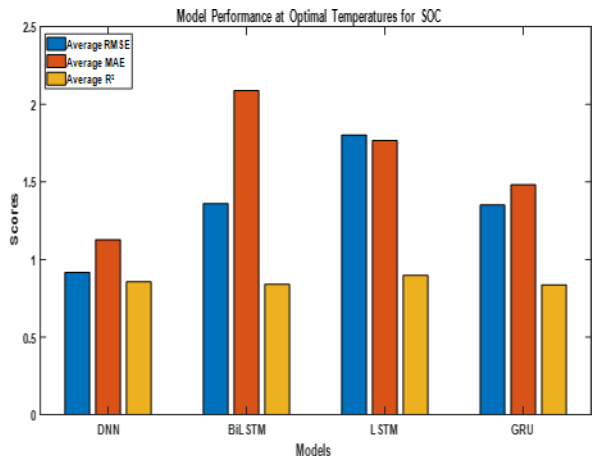
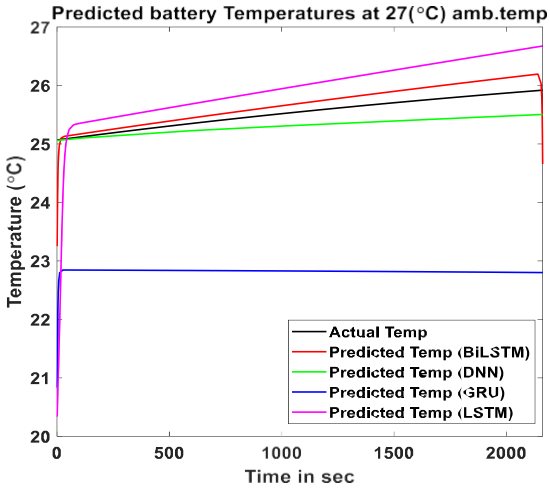


Figure 8. Model Performance at optimal temperatures for SOC Estimation.

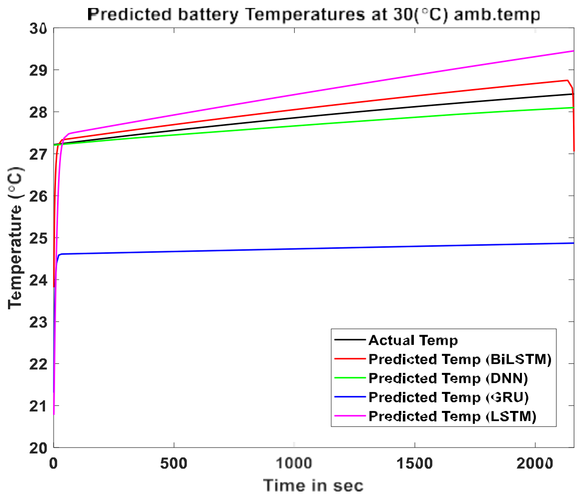
The DNN model is the most reliable with the lowest RMSE, MAE, and strong R^2. BiLSTM performs well but has higher RMSE and MAE. LSTM offers the best R^2 but struggles with higher RMSE. GRU shows moderate performance across all metrics and is the least accurate. For general use, DNN is the best, while BiLSTM and LSTM are better suited for more complex data. From Table 4 and Figure 8, DNN provides the best balance of accuracy and explanatory power. LSTM excels in variance explanation despite higher errors. BiLSTM and GRU offer moderate performance.

4.4. Mode 2: Temp as Output and SOC as Input

To analyse the corelation between temperature as the output and SoC as the input using LSTM, GRU, BiLSTM and DNN for a given dataset from MATLAB, the goal is to enhance the BTMS by predicting temperature and SoC under varying ambient temperature conditions (-20°C, -10°C, 0°C, 27°C, 30°C, 35°C, 50°C, and 60°C), with temperature being the output and SoC being the input. The optimum range of temperature from 15°C and 45°C Celsius of batteries, promotes better performance, greater efficiency, and a longer lifespan. From above ambient temperature conditions, consider four cases at 27°C, 30°C, 35°C and 50°C for analysis.



(a)



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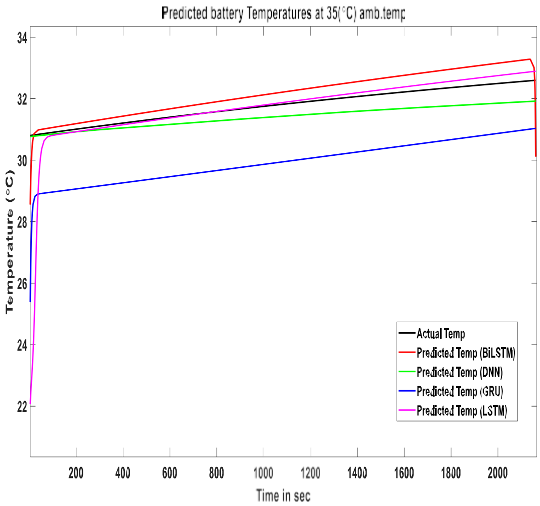

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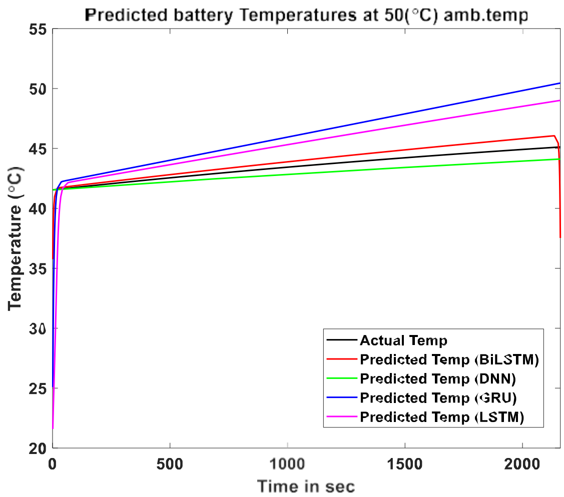

(d)

Figure 9.Model performance comparison of Temperature with BiLSTM DNN, GRU and LSTM, at

(a) 27 °C (b) 30 °C (c) 35 °C (d) 50 °C

The analysis of actual versus predicted Temperature reveals the strengths and weaknesses of various models shows in Figure 9 that BiLSTM is the most accurate model for predicting battery temperatures, closely matching actual values across all ambient conditions (27°C, 30°C, 35°C and 50°C). DNN also performs well but with slightly larger deviations. GRU under predicts temperatures consistently, while LSTM over predicts significantly, making it the least reliable. BiLSTM and DNN excel across all conditions, whereas GRU and LSTM struggle with accuracy, particularly under dynamic and high-temperature scenarios. Overall, BiLSTM is the most robust model with DNN as a reliable alternative.

4.5 Prediction errors for Temperature for the various proposed models

The overall effectiveness of the model is assessed under eight distinct temperature settings and using four different methods: LSTM, GRU, BiLSTM and DNN. Figure 10 displays the evaluation results for the suggested models LSTM, GRU, BiLSTM and DNN, while Table 5 displays the statistical analysis. Although the BiLSTM performs best overall and has a high R2 prediction accuracy, it has trouble in harsh environments. The LSTM works best in cold conditions, whereas GRU does best at warm temps. DNN is appropriate for stable environments since it provides steady but moderate performance. Combining GRU with BiLSTM could yield reliable forecasts over a variety of temperatures.

Table 5. Prediction errors for Temperature for the various proposed models

Temperature (°C)	DNN RMSE	DNN MAE	DNN R^2	BiLSTM RMSE	BiLSTM MAE	BiLSTM R^2	LSTM RMSE	LSTM MAE	LSTM R^2	GRU RMSE	GRU MAE	GRU R^2
-20	1.751	1.5291	0.6939	1.0736	1.9156	0.6664	1.0139	3.9067	0.7988	1.416	2.1762	0.416
-10	1.4856	2.453	0.7718	0.837	1.7345	0.7333	1.1592	3.0883	0.6992	2.8121	2.6402	0.3454
0	1.2273	1.1299	0.8868	4.0404	2.9681	0.6272	0.8221	1.7676	0.5183	2.6332	0.4982	0.8001
27	2.2976	0.2658	0.8283	0.2524	1.2268	0.9421	2.3483	1.3145	0.9842	0.2808	1.256	0.8903
30	0.1239	0.1119	0.8729	1.2337	2.1987	0.8481	2.2801	2.1643	0.7511	1.7236	1.6813	0.8687
35	0.1861	0.1675	0.8711	0.5775	3.5197	0.8583	0.5285	1.4241	0.9598	1.4222	0.3454	0.8687
50	0.3237	0.1977	0.3491	0.0303	2.9234	0.9998	3.4237	1.1138	0.0901	1.9277	1.8259	0.4988
60	2.2217	2.0068	0.3823	3.617	3.4851	0.6134	4.1675	3.7202	0.2772	1.4648	2.3281	0.7781

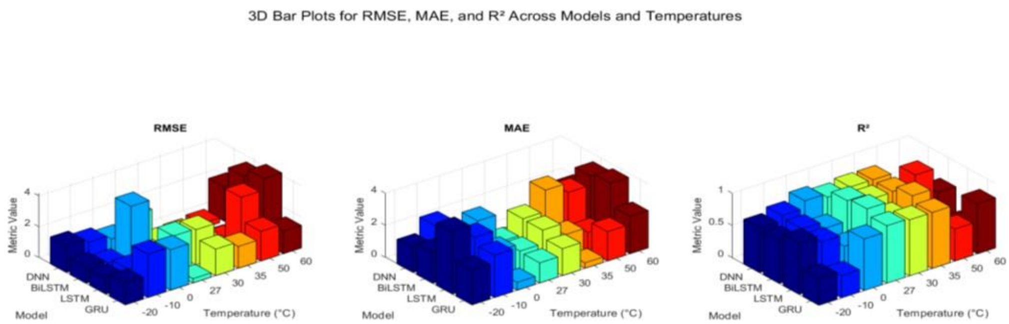

Figure10. Temperature Error Estimation for DNN, LSTM, GRU, and BiLSTM (a) RMSE (b) MAE (c) R^2

1. DNN: Shows consistent performance across various temperatures with the best RMSE and MAE at 30°C. However, its performance drops significantly at higher temperatures like 60°C.

2. BiLSTM: Has high variability in performance, with excellent results at 50°C but poor performance at 0°C.

3. LSTM: Generally shows higher errors and lower explanatory power, with the best performance at 27°C but struggles at higher temperatures.

4. GRU: Performs consistently well across different temperatures, with the best results at 27°C but slightly lower performance at -10°C.

According to the RMSE, MAE, and R2 values shown in Figure 10, the DNN and GRU models both function well at a variety of temperatures, with DNN performing best at middle temperatures. In comparison to the other models, LSTM typically exhibits larger mistakes and poorer explanatory power, whereas BiLSTM performs well at higher temperatures but is variable. This analysis emphasizes how crucial it is to choose the right model depending on particular temperature circumstances in order to have an efficient BTMS.

4.6. Temperature Performance improvement at optimal range (15°C and 45°C)

Batteries perform best in terms of SOC between 15°C and 45°C, where electrochemical reactions are efficient, ensuring stable operation. The temperature above 45°C cause degradation and safety risks, while below 15°C, performance drops and internal resistance increases. This optimal range improves charge/discharge efficiency, ionic conductivity and SOC estimation, minimizing the chance of thermal runaway and overheating. The analysis of data at 27°C, 30°C and 35°C is presented in Figure 11 and Table 6.

Table 6. Average errors of model

Model	Average RMSE	Average MAE	Average R^2
DNN	0.8692	0.1817	0.8574
BiLSTM	0.6879	2.3151	0.8828
LSTM	1.719	1.6343	0.8984
GRU	1.1422	1.0942	0.8759

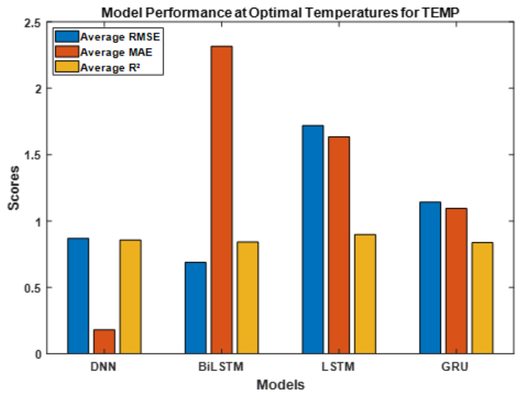

Figure 11. Model Performance at optimal temperatures for Temperature Estimation

The DNN model excels in predictive accuracy with low MAE and strong explanatory power. BiLSTM offers the highest precision with low RMSE but has greater error variability. LSTM explains variance the best but has the highest RMSE and moderate MAE. GRU delivers balanced performance with moderate error values and good explanatory power. Overall, DNN is the most accurate, BiLSTM is the most precise, LSTM explains the most variance, and GRU offers a balanced approach across all metrics.

4.7. Comparative analysis of Temperature and SoC Prediction

The provided dataset investigates the effectiveness by using Machine learning methods LSTM, GRU, BiLSTM and DNN for predicting temperature and SoC in lithium-ion batteries using different environmental conditions.

Table.6.overall performance comparison of metrics in both conditions

Dataset	**Set 1: SoC Prediction**				**Set 2: Temperature Prediction**			
Metric	**RMSE (%)**	**MAE (%)**	**R^2 (%)**	**Overall Performance (%)**	**RMSE (%)**	**MAE (%)**	**R^2 (%)**	**Overall Performance (%)**
DNN	100	100	100	66.67	120.21	98.27	70.7	82.59
BiLSTM	132.16	251.77	80.31	134.54	145.77	249.65	78.61	138.94
LSTM	261.43	225.97	89.35	166.02	196.79	231.24	63.48	154.85
GRU	162.54	190.33	99.63	117.74	171.01	159.39	68.33	120.69

Important performance variations are found with regards to RMSE, MAE, R2, and Overall Performance metrics when approaches are compared across two different datasets, as shown in Table 6 SoC prediction (Set 1) and temperature prediction (Set 2). DNN are the most effective approach in both situations. With a flawless R2 score of 100%, indicating great model accuracy, DNN provides the most accurate and balanced performance for SoC prediction, with the lowest RMSE and MAE. The overall result (66.67%) indicates a strong fit in spite of the task's complexity. In order to forecast temperature, while DNN doesn't outperform other models in terms of R^2, it still maintains the lowest MAE (98.27%) and a competitive overall performance of 82.59%. The stability across both tasks makes DNN the most reliable and efficient choice. In comparison, although models like BiLSTM and GRU show strong points in specific metrics, they fall short in overall consistency and error minimization. Therefore, DNN is the most suitable method for both SoC and temperature prediction

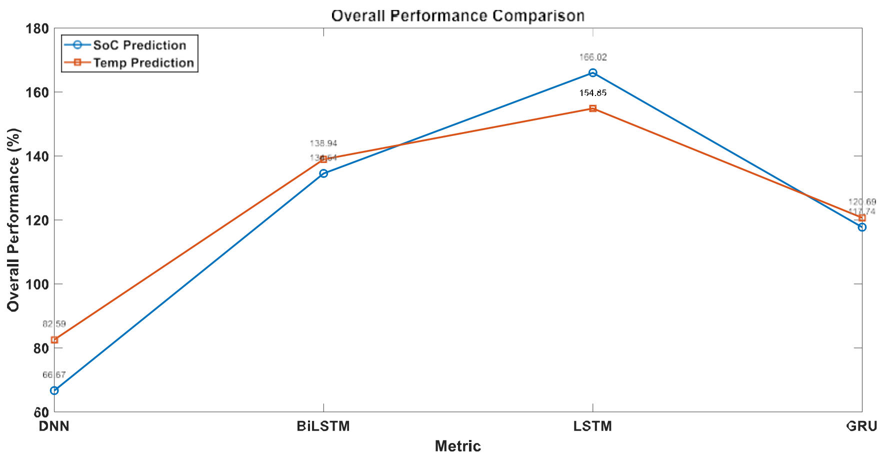

Figure12. Overall performance comparison of metrics

The analysis in Figure 12 emphasizes the importance of selecting a model that balances accuracy, consistency, and error minimization across performance indicators. While models like BiLSTM, LSTM, and GRU excel in certain areas (such as R^2), they are less consistent overall in metrics like RMSE and MAE. In contrast, the DNN model demonstrates durability and flexibility, achieving the lowest errors and competitive R^2 while maintaining stable performance across both datasets (SoC and temperature prediction). Despite, being simpler than recurrent models, DNN efficiently handles prediction tasks with reliability.

5. CONCLUSION

This study compares LSTM, GRU, BiLSTM and DNN for predicting State of Charge (SoC) and temperature within BTMS. BiLSTM outperforms others, reducing RMSE by 50.56% for SoC and 38.69% for temperature, making it ideal for dynamic and extreme conditions. LSTM excels in explaining variance, improving R^2 by 7.73% for SoC and 4.78% for temperature, and is reliable for transient behaviours. GRU provides a balanced trade-off with moderate metric improvements and efficiency in low to moderate temperatures. DNN, while stable in non-dynamic conditions, lacks adaptability.

For battery management, exact SoC and temperature estimations are crucial, with each model addressing specific needs. LSTM handles SoC transients, GRU excels in steady states, BiLSTM enhances accuracy by detecting temperature extremes, and DNN ensures stability in predictable conditions. Using LSTM for SoC decline monitoring and BiLSTM for early thermal risk detection improves safety and efficiency, while GRU and DNN reduce costs and hardware demands. The DNN is a reliable, cost-effective choice for real-world applications. Temperature prediction enhances battery safety by preventing overheating, while SoC prediction improves battery lifespan by managing charge cycles, preventing overcharging and over-discharging, and boosting energy efficiency and a hybrid model combining all four could further optimize BTMS in future.

Abbreviations

EV	Electric vehicle
RNN	Recurrent neural network
LSTM	Long short-term memory
GRU	Gated recurrent unit
SoC	State of charge
EKF	Extended Kalman filter
RMSE	Root-mean-square error
MAE	Mean absolute error
DNN	Deep neural networks
AI	Artificial Intelligence
ML	Machine Learning

Nomenclature

a_j	The input from the hidden layer j and k neurons
w_{jk}	Weight between hidden layer j and hidden layer k neurons
b_k	The hidden layer neuron j's bias
w_h	A weight matrix that includes an unseen layer and an initial layer
h_k	Current unseen state
h_{k-1}	Previous state
c_k	GRU gate input at the step k
u_k	Update gate

t_k	Reset gate
$\hat{h}_k$	Candidate state
$\underline{B_k}$	Hidden cell memory
g_k	Forget gate
p_k	Output gate
j_k	The input vector's current value

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