International Journal of Pattern Recognition and Artificial Intelligence

IOT APPLIED BATTERY MANAGEMENT SYSTEM IN ELECTRIC VEHICLE POWERED WITH AI

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In electric vehicles (EVs) the main source of energy is the lithium-ion batteries offering the necessary energy density and efficiency. One of the key elements to consider in order to be safe and perform well is accurate monitoring. Operating conditions are very critical to the functioning of the battery. Fire risks may be caused by unexpected events, like overheating, overcharging, and traditional Battery Management Systems (BMS) may not have accurate real-time predictive functionality during dynamic driving and charging. In order to address these limitations, the proposed study will use a hybrid LSTM (Long Short-Term Memory) + GRU (Gated Recurrent Unit) model with a hybrid optimizer (a hybrid of adaptive gradient and momentum-based methods). The hybrid model leverages the long-term memory retention capabilities of LSTM and the computational efficiency of GRU, while the hybrid optimizer offers benefits in terms of increased convergence speed and predictive accuracy. The battery parameters, including current, voltage, and temperature, are continuously monitored through IoT-enabled embedded controllers, and real-time communication is facilitated using Node-RED and MQTT protocols. The model is trained and tested with the EVIoT-PredictiveMaint Dataset, which has large-scale real-world EV data on the battery. The hybrid LSTM + GRU model that has hybrid optimizer performs better than the standard deep learning models with an accuracy of 91%, precision of 89, recall of 90 and F1-score of 88. The suggested system will provide scalable, smart, and secure real-time EV battery management through the combination of AI prediction and IoT monitoring to create the next generation of electric vehicles.

Keywords: battery management, Artificial intelligence, hybrid algorithm, internet of things, electric vehicles

1. Introduction

The demand for the use of electric vehicles (EVs) is growing as a result of the increasing expense of fuel. Due to these factors, several automakers are investigating gas substitutes. Utilizing electrical sources reduces pollutants, therefore they could be good for the environment. In terms of energy efficiency and environmental protection, EVs provide significant benefits. The electric vehicles are mostly referred to lithium-ion battery because substantially more compact and longer life cycle (6-10 times) than lead acid. Overcharging and extreme discharges are two common causes of the lithium-ion battery life cycle reduction. Conversely, EV batteries are usually large in size and design, which makes them have a small driving range.

The expansion of electric vehicle adoption is often challenged by safety concerns related to current battery technologies. Overcharging a battery can significantly shorten its lifespan and, in extreme cases, lead to hazardous events such as fire. To mitigate such risks, electric vehicles rely on battery monitoring systems that alert drivers about the battery's condition. Traditional systems were limited to basic functionalities such as monitoring, detecting irregularities, and issuing warnings through a simple dashboard indicator. However, with advancements in notification technologies, the integration of the Internet of Things has greatly enhanced these systems. Modern IoT-enabled solutions not only keep drivers informed but also provide manufacturers and service providers with real-time battery health data, making them an essential component of preventive maintenance strategies. IoT extends internet connectivity to everyday devices and objects, broadening its scope beyond traditional applications and providing users with seamless access to information. Battery monitoring systems based on IoT in electric vehicles alert drivers and transmit real-time information to manufacturers to enable predictive maintenance. In recent years, numerous Artificial Intelligence -based methods for SoC estimation have also been developed, further enhancing the accuracy and reliability of battery monitoring systems. These strategies might potentially outperform more traditional ones. In order to find correlations and patterns between the cell calculation parameters and the SOC, the approaches employ a special learning capacity of the AI model for training. For estimation of SOH, SOC, SOP and SOS taken into the one of the AI technologies that represented the LSTM and GRU hybrid algorithm to be an exploitation their values.

2. Related work

2.1. *Battery energy management system*

Ghalkhani et al., (2017) The most expensive part of an EV and the main contributor to the cost difference between those cars and those powered by an ICE is the battery pack. Construction of a typical EV typically costs $12,000 more than that of equivalent ICE-powered cars in the small and midsize automobile classes. Because of SBMS constraints, most original equipment manufacturers overengineer battery by 10% to 14% in order to slow down the pace of battery degradation. By incorporating precise and reliable SOC, SOH, and SOP estimate algorithms onboard the BMS, this over-engineering might be reduced. A carefully designed Battery Management System is necessary to provide the security, reliability, and the overall efficiency of lithium-ion battery systems, because LIBs can charge faster compared to various other battery technologies (Ali et al., 2019). It is a challenging task to measure the state of charge of Li-ion battery since it is a nonlinear, complex, and time-dependent electrochemical system. The methods of SOC estimation can be broadly divided into four major groups namely direct measurement methods, accounting-based estimation methods, model-driven methods and intelligent computing methods. Their benefits, shortcomings, and estimate mistakes from previous research are discussed critically. To enhance online estimate, several suggestions are made depending on technological advancement.

Ibrahem et al., (2023) The increased use of renewable source of energy and its fluctuating production have created many stability, reliability and power quality problems. The potential solution of these problems using renewable energy sources is provided by energy storage systems in such situations. In order to address these issues, a range of ESS solutions have been published in the literature; nevertheless, a single ESS does not fully cover all of the demands for all processes and has a variety of tradeoffs with regard to system performance throughout its entirety.

Sekhar Raghu Raman et al., (2021) The integration of super-capacitors into the body of an electric vehicle improves its acceleration and regenerative braking capabilities, lengthens the Li-ion battery's useful life, and maximizes space by providing more room for the battery, which is the vehicle's primary energy source. Super capacitor integration inside the automobile body requires specialized packaging techniques to reduce space requirements and encourage dispersed energy storage inside a vehicle.

Vishnu et al., (2023) The efficiency and security of HSEV power distribution depends on energy management systems. New adaptive Intelligent Hybrid Source Energy Management Strategy is also being developed towards control of energy in the hybrid sources. In order to make the most out of the sources of energy at hand and get the necessary power to the motor, the IHSEMS uses fuzzy logic controller and absolute energy-sharing strategy.

Chao-Tsung Ma., (2020) The ANFIS can effectively be trained to extract the nonlinear characteristics of charging and discharging of a battery. The given technique involves the Coulomb counting technique, as well as an efficiency correcting system, and a reference SOC is also provided as a checking system to ensure the reliability of the system.

Seydali Ferahtia et al., (2023) The proposed Energy Management System integrates the Bald Eagle Search algorithm with an external energy maximization strategy. Experiments were conducted under the controlled conditions in a flat surface with a temperature in the air of 25 0 C and in the absence of wind. The efficiency of the suggested approach was measured as compared to the use of state machine control, conventional PI control, and other methods of energy consumption minimization.

2.2. *Thermal conditioning*

The system that controls the battery temperature is one of an EV's most important parts. Therefore, a key topic of research is the appropriate battery operating temperature range during charging and discharging mode as well as the associated thermal management. For the battery to operate for longer and be safe in electric vehicles (EVs), the recommended temperature range of 25 °C to 40 °C must be maintained throughout charging and discharging cycles. Battery packs may catch fire due to thermal runaway. Several C-rates were tried on a 10 Ah pouch Li-ion cell to determine the constant current charge/discharge's time-dependent thermal behavior. In a confined space where the battery was housed, a temperature of 14 °C was maintained **(Feng et al., 2018)**. To analyze battery **temperature distribution and the energy efficiency of BTMS, Yao et al. (2021) and Shim et al. (2022)** employed a heater and refrigerant-based BTMS integrated with an air-conditioning unit for a battery module. Their results indicated an increase in the average coefficient of performance of the BTMS at 25 °C, 30 °C, and 35 °C, along with an enhancement in average energy efficiency from 2.63% to 5.07%. Furthermore, when high thermal conductivity nanoparticles were incorporated into a composite PCM with 12 wt% expanded graphite (EG), the battery pack's heat dissipation showed greater responsiveness at higher flow rates compared to pure PCM. Experiments by **Peng et al. (2022)** further confirmed the beneficial effects of composite PCM in battery thermal management systems.

2.3. *Battery energy management system using IoT technology*

Mohd Helmy Abd Wahab et al., (2018) proposed battery energy management monitoring through iot technology using sensors and to find the vehicle location with help of GPS and GSM module. Design of hardware including arduino, voltage sensor, current sensor, GPS and GSM. The level of voltage and location of vehicle as processed by arduino controller and send information for user phone. This study experiments divided two category such as monitoring device and user interface section.

Harish et al., (2018) Lead Acid batteries which are generally embraced in vehicle batteries should be well monitored to be able to work at any situation. Therefore, it would require a more organized battery management system that ensures that the output of the battery is monitored at an appropriate frequency. These parameters can be calculated using a variety of coherent techniques. But because the battery's materials, the environment it is in, and the strain it is under, all have an impact on these characteristics, these approaches are unable to produce accurate findings.

Ramesh Kumar et al., (2018) For industry to run smoothly, a robust battery system is required. It should be mentioned that these batteries cost substantially more and that continued use might result in problems. Additionally, the lead-acid battery recycling process for broken batteries could be harmful to the environment. The lead-acid batteries' electrolyte temperature and backup hours are being tracked in this study. In this method, the average current, voltage, remaining capacity, full charge capacity, and humidity are all monitored. High levels of surveillance are in place. The battery's lifespan will be extended. IOT interference for in-the-moment observation.

Prakash Pawar and Panduranga Vittal., (2019) Under the suppositions of a demand response event, the maximum demand limit limitation with various scenarios, and modifying the priority assigned to each appliance, experimental work is executed. Based on user comfort levels with sensory information components and usage time, SEMS adds cost-optimization algorithms. We built a home area network with dependable ZigBee connectivity, and we developed an IoT environment for data analytics and archiving.

Younes Boujoudar et al., (2021) A micro grid system with grid-connected solar panels and lithium-ion battery energy storage devices is advised to employ an intelligent control mechanism. This power controller takes advantage of a Smart controller on the bidirectional DC/DC converter to control both battery discharging and charging. Its main novelty is that it combines the artificial neural networks to not only control the converter in both directions, but also predicts the state of charge of the battery.

P. Sivaraman et al., (2020) It evaluates measurement-based power, state of charge, state of health, and overall battery condition. A core function of the BMS is cell balancing, where it continuously monitors each individual cell or parallel-connected cell group and actively balances them during operation. To guarantee the battery's safe functioning, it also performs battery diagnostics. BMS will notify or alert for cell replacement if it determines that any one of the cells is weak. Additionally, it offers protection from overcharging, undercharging, overcurrent, undervoltage, short circuits, and temperature changes (low and high temperature).

S.Prabakaran et al., (2023) The processed data is then transmitted to the cloud server via the wireless communication module for further management and analysis. In addition, that the creating a distinct charge curve for each recharge session with the help of clever cloud software, the battery cells' lifespan may be prolonged. This ensures that the battery is charged all the way up. A smart IOT-based battery management system may be created and put into use utilizing LoRaWAN technology, which has a long range and uses minimal energy **Dayal Chandra Sati et al., (2021)**

Dapai Shi, Jingyuan Zhao et al., (2023) It offers vital services like cell balance and assessment of battery condition (together with state of charge, thermal, health, and safety). Its main duty is to provide secure battery operation the massive quantity of data that batteries generate over the course of their operational lives, cloud computing is quickly becoming the preferred method for data storage and analysis in the scientific community. This cloud-based digital explanation offers a more adaptable and effective replacement for conventional approaches, which sometimes need for substantial hardware expenditures. To extract patterns and insights from enormous volumes of observational data, machine learning is increasingly becoming a necessary technique.

M. Bharathi et al., (2022) the use of electric vehicles may tackle the issue of air pollution, maintain a pollution-free environment, and ensure that the world can continue to exist with clean air. EVs resemble devices that run on a battery that is charging. The state of an EV is influenced by the battery's operation. The problems that can tell the performance of a battery are voltage, current and temperature.

A. Prabha et al., (2022) a computer model based on an artificial intelligence capable of predicting SoC of batteries. The battery management system was developed based on core dataset built on a Mendeley data and has added all the significant components of a battery. The artificial intelligence model is constructed based on the Artificial Neural Network framework. It is to be noted that minimum training loss and maximum accuracy may not always translate to validation phase. Upon validation, the model shows excellent performance, which predicts the state of charge of the battery with accuracy of over 0.98 with a loss of less than 0.05.

Rachit Raj et al., (2022) Battery management systems are crucial to the industry's ability to provide better performance and enable greater ranges as the market for electric vehicles grows. To ensure the overall system's safety, effectiveness, and dependability, battery packs must be continuously checked. This is accomplished by tracking the current, voltage, temperature, and other variables, which are then analyzed using a variety of algorithms. Based on the dataset gathered/simulated for the individual Li-ion cells, the SoC of the battery pack is calculated using ANN/AI-ML based control system. A single inductor technique of cell balancing is utilized to guarantee that voltage/SoC remains constant for the various cells in the battery pack.

V. G. G, A. N, J. S et al., (2022) A system for tracking and examining lithium-ion battery data, including current, temperature, voltage, and charge and discharge cycles, has been created. For electric vehicles to have better battery performance, the battery temperature has to be continuously checked and maintained. The lifetime, safety, and mileage of an electric car are all impacted by the battery's performance, which is the main power source for the vehicle. The system is composed of an IOT-based data transmission module and a microcontroller-based circuit for handling sensors.

Dandge Vishal J et al., (2021) the power that propagates to the car vehicle is gradually reducing, and performance is affected negatively. This is the main issue of concern of battery makers. To conduct direct monitoring, this study proposes that IoT solutions be implemented to monitor the operations of the vehicle. In case the performance of a battery is decreased, the system can detect it and inform the user, who can then do further action.

Dr. Shakunthala C et al., (2022) the most crucial component of delivering clean mobility for electric cars (EVs) is their batteries. Battery management system is the name of an electrical controller that controls and monitors how battery packs are charged and discharged. Because the cell infrastructure is crucial to the survival, functionality, and well-being of drivers, current electric vehicles require battery tracking. The development and improvement of electric cars has a huge potential for usage of Internet of Things (IoT) technical advancements. Currently, EVs are receiving a lot of attention because of how long their batteries last and how little pollution they produce. The main issues that EVs are now facing are the constrained cell capacity and the dearth of facilities for battery or recharging.

2.4. *Artificial intelligence*

AI modeling requires machine learning because it allows systems to improve their performance over data-driven decisions lacking the essential for explicit programming. Using connections and patterns found by machine learning algorithms, big datasets are examined to make predictions and determinations.**Aykol et al. (2020)** state that machine learning usually uses test data to accurately predict battery behavior by using a programmable function with changeable parameters. This enables extrapolation to different battery systems. An example of a battery management system is transferring learning, which uses data-driven techniques to manage activities for each individual's health status forecast **Jiang et al., (2022).** Although machine learning has proved effective in navigating the continuously increasing time-series data, it possesses a number of limitations in addressing complex spatiotemporal systems. Since deep learning can automatically extract spatiotemporal data, it has recently attracted a lot of attention. Issues that the artificial intelligence community has previously regarded unsolvable have greatly improved because too deep learning. It has demonstrated to be especially successful in finding multifaceted structures in massive data sets for battery systems, according to **Samanta et al., (2021)** and **Sharma et al., (2022)**. As a result, complicated physical processes would be better understood and forecasting models for long-range spatial relationships over various timelines would be more accurate. **Shi et al., (2023) and Shi et al., (2021).**

2.5. *Summary*

In above literature reviews state that battery management system which applied in different applications such as thermal management, Artificial intelligence and internet of technology. The next category thermal management which affects the battery to reduce over heat in battery packs. The IoT technology that monitored the battery parameters temperature, voltage, current and SOC were updated in user interface with the assistance of cloud web server. The analysis of battery management system is a machine learning that analyses the parameters of the dataset.

3. Methodology

This proposed system will involve the use of Iot and artificial intelligence technologies which are categorized into three parts which include control system, battery monitoring system as well as IoT technology. These technologies are continuously monitoring and evaluated the battery state and through the data in serial communication. The overall process has been discussed below conversation and architecture shown in figure 1. The battery monitoring system consists of sensors like voltage, current, and temperature which produced values. The current, voltage, SOC and temperature values were updated to ESP32 controller and through on raspberry pi for the purpose of serial communication. Data acquisition, controlling of electric vehicles and data assembling which controlled by using control system. The purpose of IoT technology used in battery monitoring parameters and updated on cloud server. To create user interface using python programming language which supports parameter identification. The hybrid algorithm involved in battery management system which enhance the SOC and SOH parameters for the step-by-step procedure.

3.1. *Dataset Description*

The EVIoT-PredictiveMaint Dataset is a comprehensive real-world dataset collected from IoT-enabled electric vehicles (EVs) operating in diverse environments. The dataset captures multi-modal telemetry, environmental conditions, and historical maintenance records at 15-minute intervals over a 5-year period. It is specifically designed for multi-horizon predictive maintenance in EV fleet management, supporting federated learning applications for failure prediction, maintenance scheduling, and component health assessment. With 175,393 records, this dataset is ideal for research in predictive maintenance, failure analysis, and energy optimization in electric vehicle fleets. It includes sensor data, telematics, environmental conditions, and maintenance history to facilitate advanced machine learning models for predicting vehicle reliability and optimizing maintenance strategies. https://www.kaggle.com/datasets/datasetengineer/eviot-predictivemaint-dataset

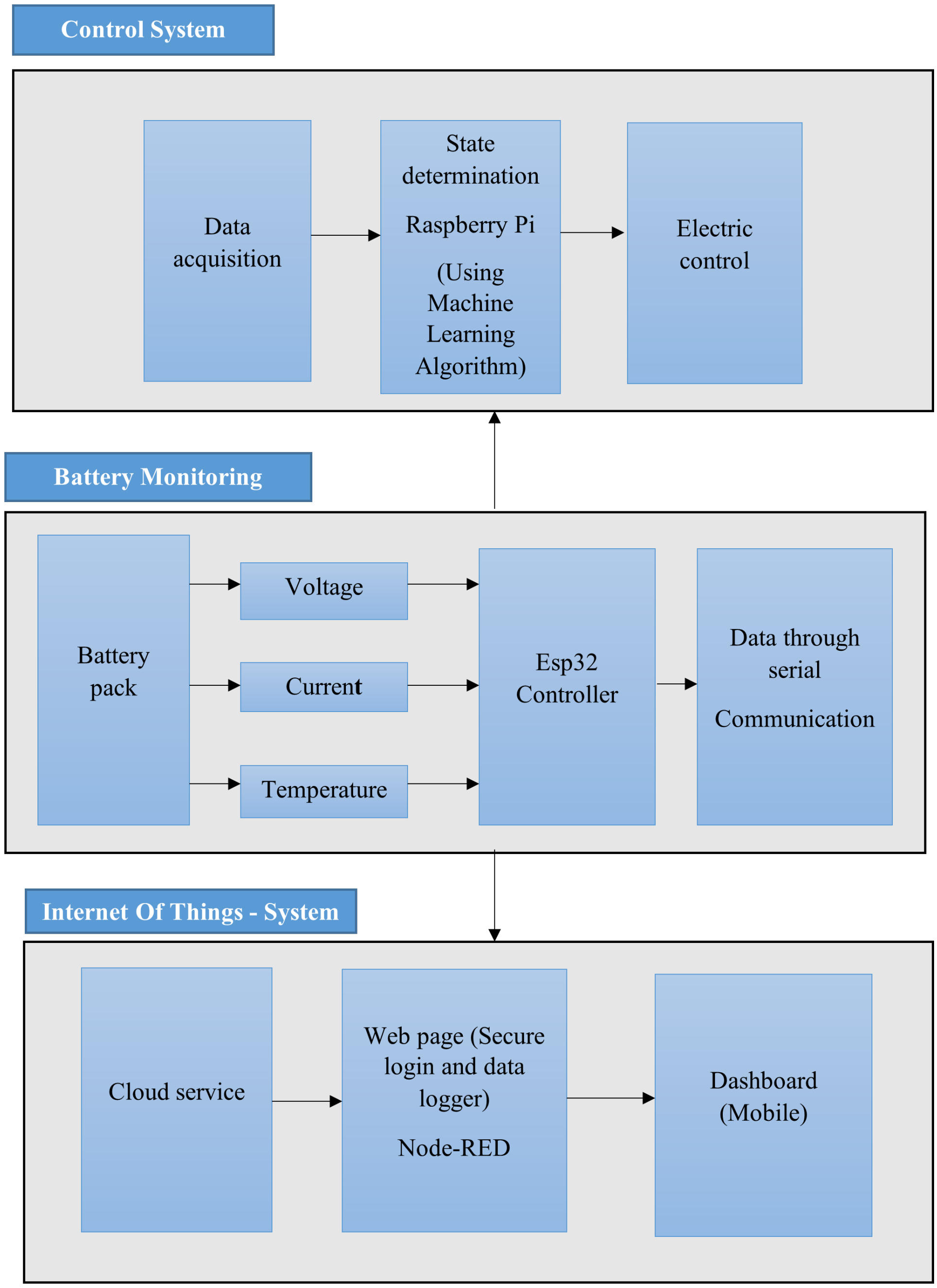

Fig. 1. Architectural overview of the proposed system

3.2. *Battery monitoring system*

The strategies of hardware and software are used in battery management system which regulates battery for efficient functioning. Battery management and battery monitoring approaches consist of various sensors, charging and discharging condition, current level, voltage level and temperature. One of the greatest advances in

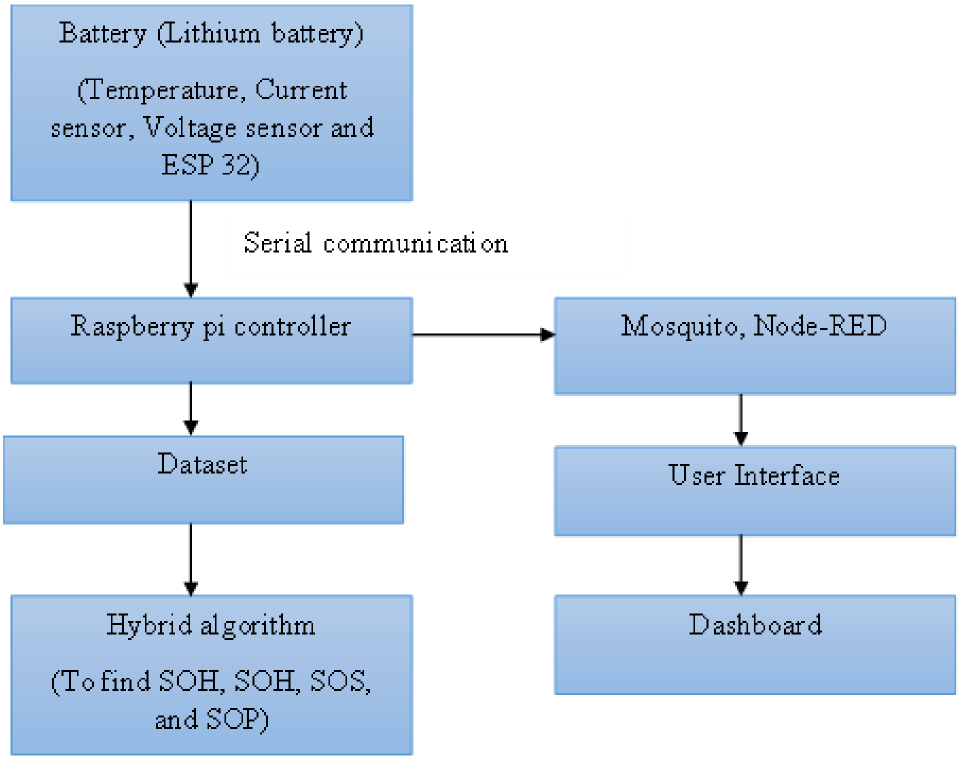

Fig. 2. Flow chart of proposed system

electrochemistry is lithium-ion batteries, and their applications as ESS have increased significantly. In today's world equivalent circuit (RC network) models are routinely used to construct battery models for SOC calculation. The SOH estimate was taken into consideration when simulating and developing the battery degradation model constructed on capacity fading. The physical characteristics of each anode and cathode individually were largely responsible for determining these model parameters. But in a dynamic environment, outside variables like the surrounding temperature and the discharge current load will lead to errors in these stationary models.

The battery status monitoring using current sensor, voltage sensor and temperature sensor which produces the output level of voltage, current and temperature values updated to the ESP- 32 controller. This controller is chip and embedded device which is in build wi-fi and Bluetooth connectivity. The ESP 32 controller reads the analog or digital values, inter interface connectivity. The bunch of values are updated ESP 32 to serial communication that is a Raspberry pi controller.

3.3. *Control system*

The Raspberry pi controller is a mini computer that connected port keyboard, mouse like computer. The number of values is stored in this controller up to number of days and act as own server accessibility. This controller operated using Raspbian OS which supported on embedded system and IoT technology like node red and mosquito messenger. This controller supported on python language and learning algorithms. Python is one of the programming languages which several packages of library was installed easily and also maintain machine learning, deep learning and artificial intelligence.

While there are many conventional approaches, AI-based techniques are rising in prominence as a means of enhancing dynamic reactivity and reliability. Currently, BMSs are installed with a preset control algorithm that is not changed or adjusted during the course of the system's lifespan. The batteries do, however, have a rather lengthy lifespan, with many having guarantees of between five and ten years. Due to the length of time, the operational environment may change over the system's lifecycle. To increase performance characteristics, the control approach might need to be adjusted. Beyond the precision of its computations, the importance of SOH and SOC for the BMS goes beyond that. A BMS is in charge of both informing the user with information about the batteries and safeguarding the batteries. Particularly with Li-ion batteries, the estimations of SOH and SOC have an impact on the instructions sent to the battery.

3.4. *Hybrid model using Long-Short-Term Memory (LSTM) with Gated recurrent unit (GRU)*

A neural network models the dynamic behavior of a system, where the fundamental component is the memory cell. In the first hidden layer, features are extracted and organized. The second hidden layer highlights variations through the diversity of connections between gates and memory cells, which regulate how efficiently the cell states are maintained over time. The output layer is based on an LSTM block and the LSTM architecture is used to model and identify the battery system.

The LSTM models are popular to predict the battery life accurately in the case of renewable energy and IoT systems [?] used an LSTM-based approach to predict battery degradation patterns, which showed its capacity to address its time-series dependencies and nonlinear changes of battery behavior. These findings supported the hypothesis that LSTM can accurately predict battery health and remaining useful life and is important in maximizing the energy storage infrastructure in IoT-enabled networks. This method emphasizes the fact that LSTM can be used to make more accurate predictions about managing the battery and assist in real-time decision-making in intelligent energy use.

The battery health prediction is not the only example of the LSTM networks useful in the area of the energy management in the electric vehicles introduced [?,?] an LSTM-based framework to control the EV charging in the commercial-building prosumer setting. The application of LSTM networks integrated explained the issues of urban climate variability by integrating the time sequence learning potential of LSTM [?].

Step: 1 Collection of predicted data from Raspberry pi and calculate the training soft max average vectors.

$$g_i(X) = \frac{K_i\, p(\omega_i)}{\sum_{i=1}^{L} k_1\, p(\omega)} \tag{1}$$

Step: 2 A particular group of Hidden Layers is selected by a number of criteria.

$$g_i(X) = g_i(X) \tag{2}$$

Step: 3 The training and testing data set uses dataset division of the values.

Step 4: Model Evaluation can be used to determine the structure of the data in the absence of reliable training data.

Step 5: Classified output.
The RNN was developed largely to address the challenges of LSTM retention and vanishing gradients in backpropagation. One of its notable variants is the GRU. The GRU (Figure 3) is designed with only two gates an update gate and a reset gate making it simpler to interpret, computationally less complex, and faster to train compared to traditional RNNs. The reset gate determines how much past information should be forgotten, where a stronger reset effect discards more historical data. The update gate, on the other hand, balances the contribution of new input with the previous hidden state to form the current hidden state. battery prediction deep learning model involving a multivariate Gated Recurrent Unit (GRU) network. They use a set of input features to learn more complicated temporal dependencies between battery degradation and their approach GRU architecture has

drawn interest in battery management since it can work with sequential data and yet it is computationally efficient. GRU can perform more precise tracking of the nonlinear dynamics of batteries by maximizing its time-based learning and feature extraction capabilities [?].

$$g_r = \sigma(W_r\,[s_{t-1}, x_t] + b_r) \tag{3}$$

$$g_z = \sigma(W_z\,[s_{t-1}, x_t] + b_z) \tag{4}$$

$$\hat{s}_t = \tanh(W_h\,[\,g_r * s_{t-1},\, x_t] + b_s) \tag{5}$$

$$s_t = (1 - g_z) * s_{t-1} + g_z * \hat{s}_t \tag{6}$$

The sigmoid function is,

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{7}$$

The tan function is,

$$\tanh(x) = \frac{e^{2x} - 1}{e^{2x} + 1} \tag{8}$$

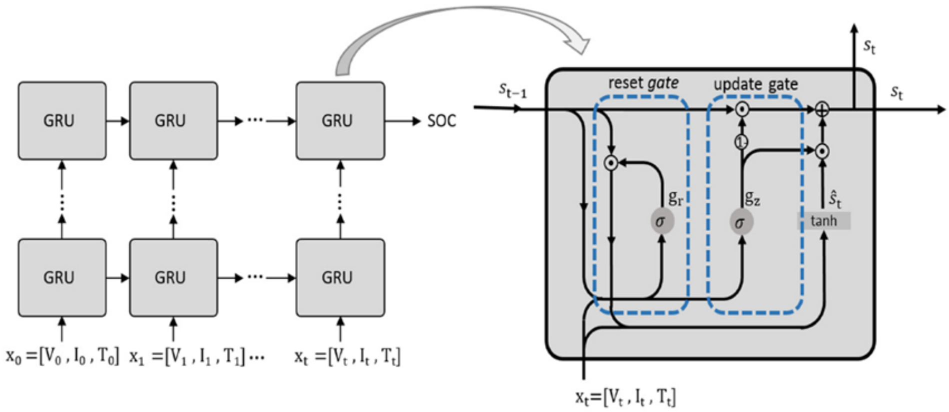

Fig. 3. Architecture of GRU

The GRU design was suitable to large time series data since it enabled the use of the same constraints at the new time steps.

The table 1 hyperparameter values determine the learning of the hybrid LSTM-GRU model. Learning rate and batch size of 0.001 and 64 respectively are balanced. A dropout of 0.2 is used to avoid overfitting, and 100 epochs are used to achieve convergence. The hybrid optimizer enhances precision and early stopping using validation split helps to protect reliability, thus, the model is resilient to predicting EV batteries.

Table 1. Hyperparameter Settings for Hybrid LSTM–GRU Model

Hyperparameter	Value
Learning rate	0.001
Batch size	64
Number of epochs	100
Dropout rate	0.2
Optimizer	Hybrid optimizer (adaptive gradient + momentum-based)
Loss function	Mean Squared Error (MSE)
Activation functions	Sigmoid, Tanh (hidden layers); Softmax (output layer)
Hidden units	128 per layer
Number of layers	2 LSTM layers + 2 GRU layers
Validation split	20%
Early stopping	Patience = 10 epochs

3.5. *IOT system*

Let's now examine the function of the BMS in an EV, specifically how the BMS may progress technology by incorporating IoT and AI. The BMS of an EV is equipped with several sensors to track voltage, current, temperature. Every nanosecond, these parameters are gathered. An edge intelligence system is utilized in EVs and intelligent cars to lessen dependent on the cloud.

By reducing the power consumption of the motor, edge intelligence can reduce some anomalies, such as the maximum temperature. The motor won't take too much power and overheat the battery, even if this could make the EV a little bit slower. In order to maximize the State of Health, edge intelligence may also govern the State of Charge. The values are updated on login our web page based on cloud help of Node-RED and Mosquito.

3.6. *Node RED*

A programming environment or tool is called Node Red. Node-RED uses graphical flows and nodes, which are distinct parts of a flow, to create programs. Node-RED's ability to be both functional and graphical, allowing you to build programs visually and giving you a ton of functional control through JavaScript, is the feature I enjoy it the most. Node-RED's main programming language of choice is JavaScript. Node-RED is the name of an internal browser-based programming environment.

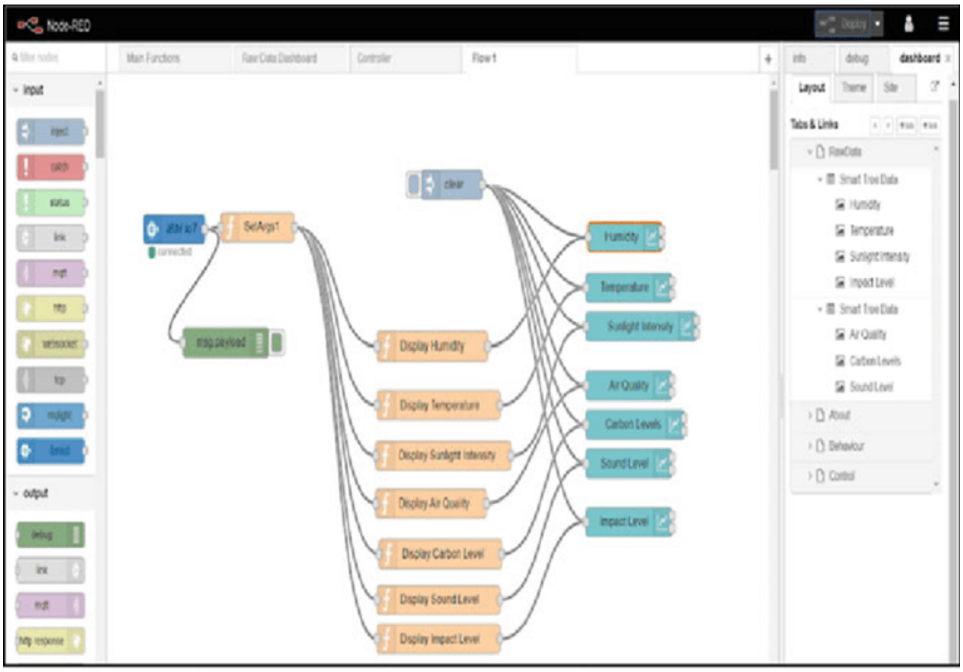

Fig. 4. Working of Node-RED

3.7. *Mosquitto MQTT*

The most recent 5.0 iteration of the MQTT protocol is implemented by the message broker Mosquitto. Intelligent energy management network using IoT to charge electric vehicle (EV) charging stations using MQTT (Message Queuing Telemetry Transport) as a standard communication issue. MQTT helps to create real-time, light, and reliable data flow between distributed sensors, charging stations and cloud servers to monitor and control the flows of energy efficiently. The framework showed better energy usage, load balancing and efficiency in EV charter infrastructure. The system is scalable to low-latency communication and incorporating MQTT together with IoT sensors is critical to the intelligence of energy management in contemporary smart-grid-enabled charging of EVs [?]. Mosquitto is the ideal option for handling the MQTT protocol on our Raspberry Pi because it is a quite lightweight application of software.

4. Result and discussion

Battery monitoring system describes battery monitoring and battery management system of results are obtained using the machine learning algorithms and to perform IoT technology of messages on our web page with particular URL. Figure. 5 depicts

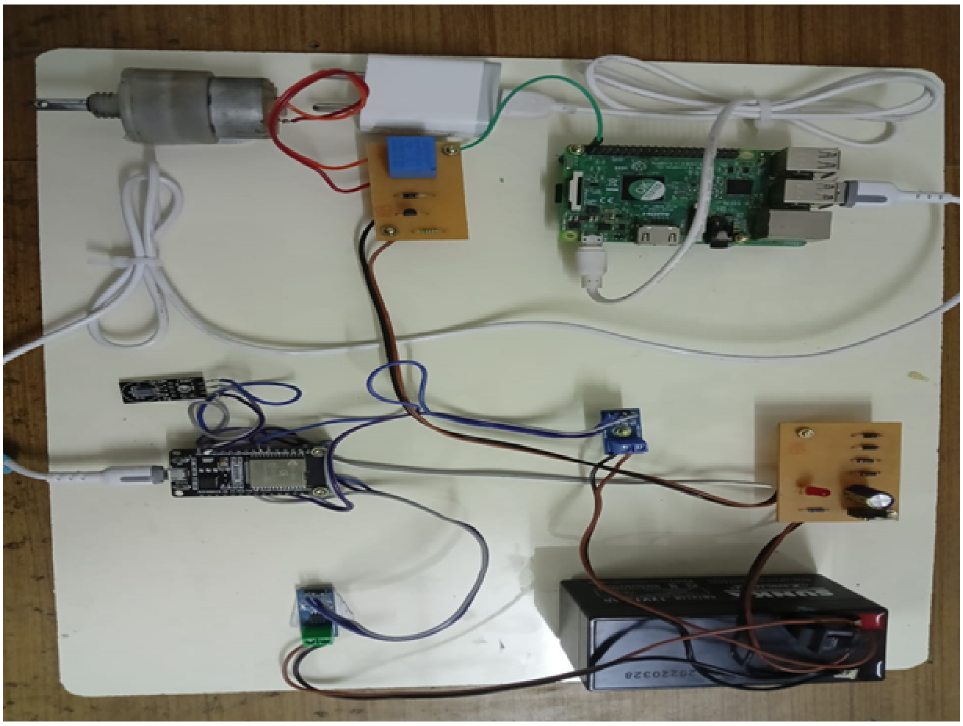

Fig. 5. Experimental setup of the battery management

the experimental configuration of the AI and IoT-powered Battery Management System. Through GPIO pins, sensors are attached to the ESP32 controller. Data is gathered from the Battery that is linked to the setup and is monitored through IoT utilizing mobile apps and online apps for parameters like current, voltage, and temperature. Through serial, an ESP32 controller transmits data to a raspberry pi. Installed on the Raspberry Pi are the Node-RED programming language and the mosquito broker, and the Node-RED programming language was used to create the user interface.

The experimental setup's real-time data sets are fed into the machine learning algorithm and trained on them. The LSTM algorithm's metrics, which are useful in assessing the algorithm's effectiveness, are also displayed in the result section. It is evident from the metrics analysis that the LSTM algorithm has a high accuracy rate of 88%.

Table.2 suggests that by comparing the outcomes of the classification report, we can see that the hybrid algorithm generates high values for Accuracy, High Precision, Recall, and F1 Score. Therefore, the hybrid approach is the most appropriate to predict the lithium-ion battery remaining charge.

Table 2. Performance comparison of different algorithm

Algorithm	Accuracy	Precision	Recall	F1 score
LSTM	72%	84%	80%	82%
GRU	76%	79%	86%	86%
Hybrid LSTM + GRU	91%	89%	90%	88%

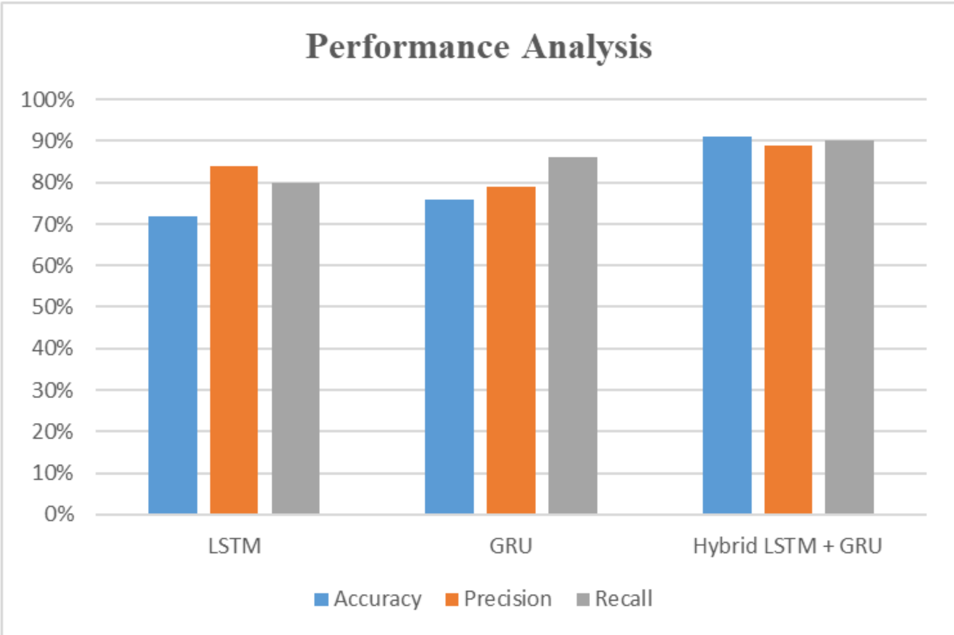

Fig. 6. Comparison of algorithm

The figure presents the performance of various deep learning models in predicting battery parameters. The LSTM model alone achieves an accuracy of 72%, precision of 84%, recall of 80%, and F1-score of 82%, which is moderately effective in identifying temporal dependencies. The GRU model performs slightly better, with an accuracy of 76 percent, precision of 79 percent, recall of 86 percent, and an F1-score of 86 percent, indicating that it is more efficient in sequence modeling. It is worth noting that the hybrid LSTM + GRU model outperforms both individual models, achieving 91% accuracy, 89% precision, 90% recall, and an 88% F1-score. The complementary nature of LSTM and GRU layers is highlighted by this improvement, as LSTM excels at maintaining long-term dependencies, while GRU is computationally efficient and learns more quickly. The findings indicate that the hybrid architecture is more dependable and robust in predicting battery management, which proves its appropriateness in providing accurate State of Charge (SoC) and State of Health (SoH) estimations in the application of electric vehicles.

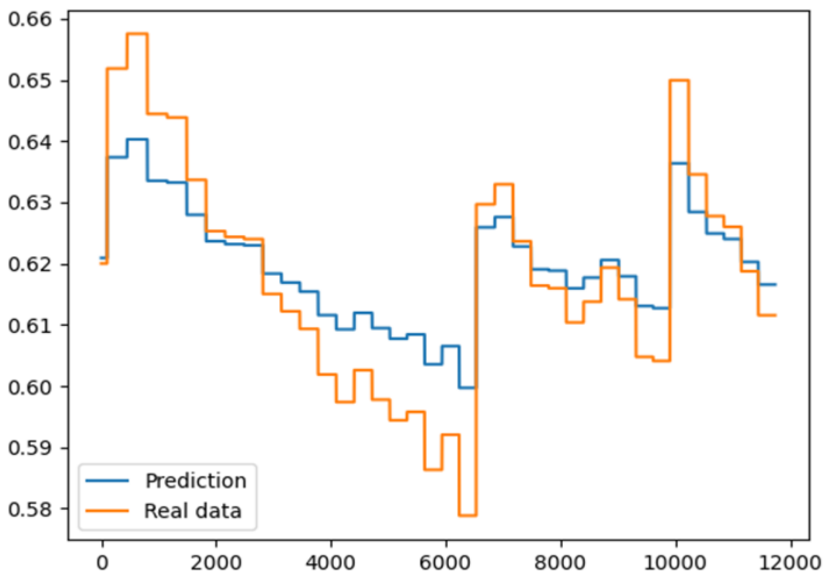

Fig. 7. Prediction of data in battery

In figure 7 represented the comparison analysis of prediction and real time data in battery and figure 8 evaluate the state of health in battery performance using LSTM algorithm The webpage user interface created by using Node-RED language shown in figure 9, the voltage, current and SoH shown in graph

The figure 9 demonstrates the tracking of electric vehicle (EV) parameters: current and voltage, in the Node-RED dashboard. The gauge is set at the current actual value which is at present 7 units, which implies that the consumption level is relatively low compared to the maximum scale of 100 units. The line graph below the gauge is a representation of the change of voltage with time. At first, the voltage is constant at approximately 30 units but in the end of the observation period, the voltage suddenly increases to about 40 units. This diagram shows the potential usefulness of Node-RED to monitor and visualize EV electrical parameters to analyse and monitor.

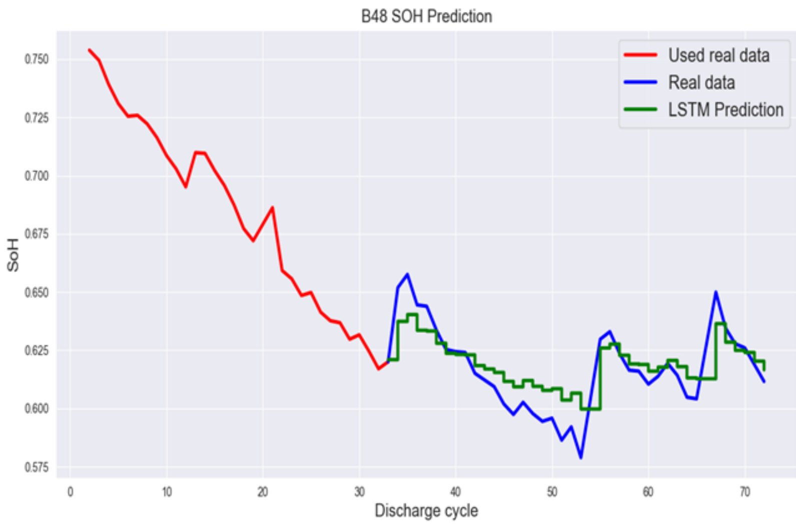

Fig. 8. Estimation of state of charge

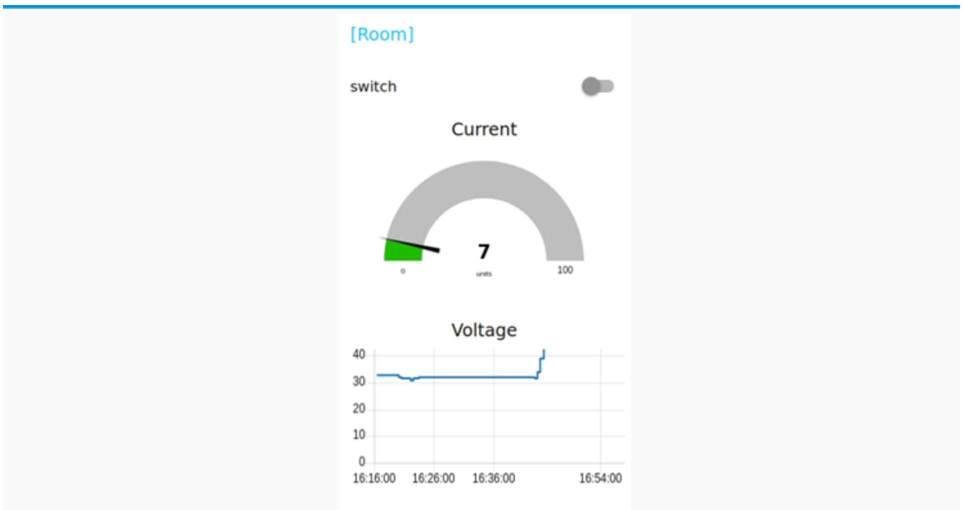

Fig. 9. EV's parameter (current and voltage) in NodeRED

Comparative analysis of the numerical and experimental outcomes at different C-rates as depicted in Figure 10 is indicative of the high degree of correlation between the electrochemical-thermal model and the actual behavior of the battery. The temperature increases at a low discharge rate of 0.5C is low at approximately

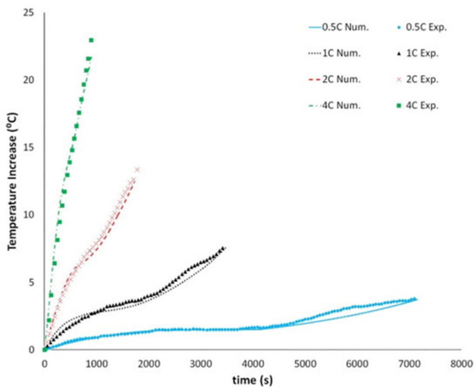

Fig. 10. Comparison of numerical and experimental results for average surface temperature under varying discharge rates

3.8 o C, which shows stable thermal behavior. But, the higher the C-rate (1C, 2C, and 4C), the higher are the temperature increases observed in the cell, which verify the first cause and effect relations. These results confirm that the model would be useful in estimating the thermal behavior of NCA Li-ion cells, so it can be used to ensure safe battery handling [?].

The trend of battery management systems (BMS) demonstrates that these systems

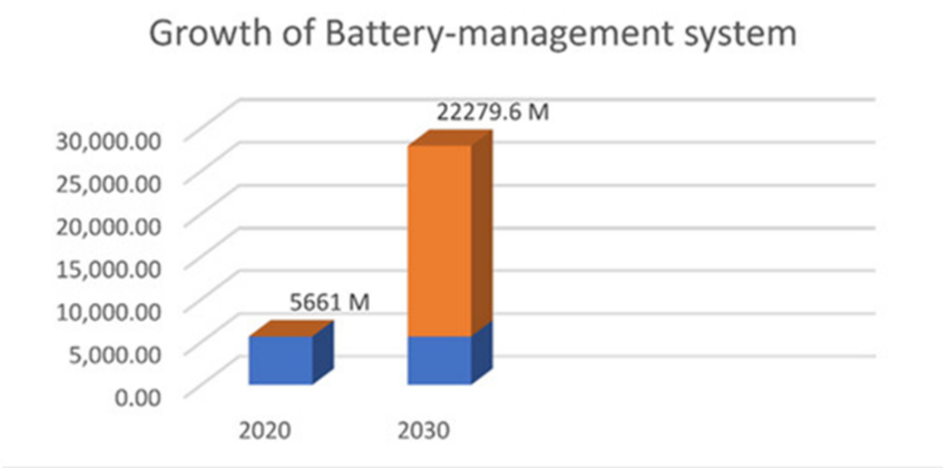

Fig. 11. Development of Battery Management Systems from 2020 to 2030

are going to increase at a very high pace between 2020 and 2030, as illustrated in the figure 11, due to the increased use of electric vehicles, renewable energy storage and handheld electronics. The BMS market value in 2020 is around 5661 million

USD, which indicates early implementation and a small penetration. The market however is estimated to explode by 2030 to approximately 22,279.6 million USD, which will be almost four times the figure. This dramatic expansion underscores the importance of safety, efficiency and long battery life that BMS is playing as it is becoming more and more the mode of operation in industries to be electrified and have sustainable energy solutions [?].

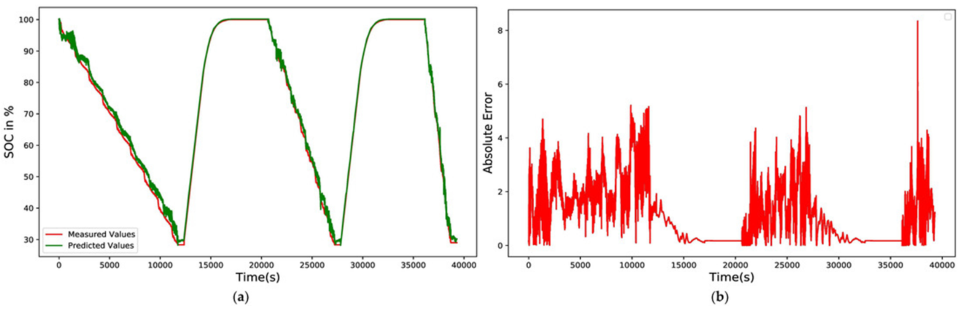

Fig. 12. Performance analysis of GRU model at -10°C with (a) measured vs. predicted SOC and (b) absolute errors

The strength and weaknesses of the GRU model in forecasting state of charge (SOC) at varying temperature conditions are shown by the performance of the model. GRU model was also reliable at 0 C and the calculated and predicted results were comparable to each other, however, the accuracy decreased with increase in temperature and highest errors were observed at 10 C. Figure 12 (a) demonstrates that the GRU model was not able to compete with LSTM-based models, which can work with larger datasets at a lower mean absolute error (MAE) and have greater accuracy. The error distribution in Figure 12 (b) shows that the error value had a maximum value of 8.34 percent at one point, but most of the error values fell below 6 percent. This indicates that, despite the fact that GRU is simple in its model and can be tested in a relatively short time, in comparison with LSTM, since it has fewer trainable parameters, the latter has a bit higher precision in predicting SOC and particularly in different thermal conditions [?].

5. Conclusion

This paper demonstrates that a hybrid LSTMGRU model, combined with a hybrid optimizer, is capable of controlling a lithium-ion battery in a battery-operated electric vehicle under varying operating conditions. The system is able to predict State of Charge (SoC) and State of Health (SoH) with accuracy, utilizing the long-term memory capabilities of LSTM and the computational efficiency of GRU. MQTT, Node-RED, and IoT-controlled embedded controllers will be integrated to provide real-time, reliable, and safe battery management. The experimental results are 91% accuracy, 89% precision, 90% recall, and 88% F1-score, which is better than the conventional models, which can be further extended to predictive maintenance of multi-cell battery packs, EV charging coupled with renewable energy sources, and edge AI applications that make faster and localized decisions. To enhance the safety, lifespan, and overall effectiveness of the next-generation battery system in electric vehicles, future studies can investigate adaptive hybrid optimizers, enhanced feature selection, and real-time anomaly detection.

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