Hybrid Chaotic Attractor Recurrent Network Transnet Architecture for Accurate State of Charge Estimation of Li-Ion Batteries in EV Application

[1]Ch. Leela Kumari, [1]D. Ravi Kishore, [2]M Pavan Kalyan, [2]K Bhavani Shankar, [2]K Sai Krishna
[1]Godavari Global University, Rajahmundry, India
[2]Godavari Institute of Engineering and Technology (A), Rajahmundry, India

Abstract. Main objectives of the study are to design and validate a novel state of charge (SoC) estimation framework for Lithium-Ion Batteries (LIBs) in Electric Vehicle (EV) Energy Storage Systems (ESSs), integrating the chaotic attractor recurrent network (CARN) with transformer techniques. This hybrid approach aims to overcome limitations in conventional battery management systems (BMSs), particularly in handling noisy inputs, long-range dependencies, and data imbalance. These objectives were achieved by implementing a structured methodology that incorporates data balancing to mitigate skewed datasets, exploratory data analysis (EDA) for anomaly detection and pattern recognition, and feature scaling for input normalization, thereby ensuring robust and effective model training. The hybrid classification model leverages the temporal pattern recognition capability of ARN alongside the strong attention mechanism of the Transformer, enabling superior adaptability under diverse operating conditions. Implemented in Python, the proposed method was rigorously tested across multiple scenarios to confirm its reliability and accuracy. The most important results are the reduced root mean square error (RMSE) of 0.9671, mean square error (MSE) of 0.9352, mean absolute error (MAE) of 0.793, and an enhanced R^2-score of 99.86%, which collectively demonstrate significant improvements over conventional estimation techniques. The significance of obtained results lies in validating the proposed model's ability to deliver highly accurate, robust, and real-time SoC prediction, thereby contributing to safer and more efficient battery management in EVs. This study highlights the potential of hybrid deep learning architectures to advance ESS safety, optimize energy utilization, and support sustainable electric mobility.
Keywords: lithium-ion batteries, battery management systems, chaotic attractor recurrent network and transformer, data processing, exploratory data analysis, Python.

DOI: https://doi.org/10.52254/1857-0070.2026.1-69.15
UDC: 621.352:629.331:004.032.26

Arhitectură hibridă CARN-Transnet pentru estimarea precisă a SOC-ului bateriilor Li-ion în aplicațiile EV

Ch. Leela Kumari[1], D. Ravi Kishore[1], M Pavan Kalyan[2], K Bhavani Shankar[2], K Sai Krishna[2]
[1]Universitatea Globală Godavari, Rajahmundry, India
[2]Institutul de Inginerie și Tehnologie Godavari (A), Rajahmundry, India

Abstract. Obiectivele principale ale studiului sunt proiectarea și validarea unui cadru inovator de estimare a stării de încărcare (SoC) pentru bateriile litiu-ion (LIB) din sistemele de stocare a energiei (ESS) ale vehiculelor electrice (EV), integrând rețeaua recurentă de atractori haotici (CARN) cu tehnici de transformare. Această abordare hibridă vizează depășirea limitărilor sistemelor convenționale de gestionare a bateriilor (BMS), în special în ceea ce privește gestionarea intrărilor zgomotoase, dependențele pe termen lung și dezechilibrul datelor. Aceste obiective au fost atinse prin implementarea unei metodologii structurate care include echilibrarea datelor pentru a atenua seturile de date distorsionate, analiza exploratorie a datelor (EDA) pentru detectarea anomaliilor și recunoașterea modelelor, precum și scalarea caracteristicilor pentru normalizarea intrărilor, asigurând astfel o instruire robustă și eficientă a modelului. Modelul de clasificare hibrid utilizează capacitatea de recunoaștere a modelelor temporale a ARN împreună cu mecanismul puternic de atenție al Transformer, permițând o adaptabilitate superioară în diverse condiții de funcționare. Implementată în Python, metoda propusă a fost testată riguros în mai multe scenarii pentru a confirma fiabilitatea și acuratețea sa. Cele mai importante rezultate sunt reducerea erorii medii pătrate (RMSE) la 0.9671, a erorii medii pătrate (MSE) la 0.9352, a erorii medii absolute (MAE) la 0.793 și îmbunătățirea scorului R^2 la 99.86%, care demonstrează în ansamblu îmbunătățiri semnificative față de tehnicile de estimare convenționale. Semnificația rezultatelor obținute constă în validarea modelului propus.
Cuvinte-cheie: baterii litiu-ion, sisteme de management al bateriilor, rețea recurentă de atracție haotică (CARN) și transformator, prelucrarea datelor, analiză exploratorie a datelor, Python.

Гибридная архитектура Carn-Transnet для точной оценки уровня заряда литий-ионных аккумуляторов в электромобилях

[1]Ч. Лила Кумари, [1]Д. Рави Кишоре, [2]М. Паван Калян, [2]К. Бхавани Шанкар, [2]К. Сай Кришна
[1]Глобальный университет Годавари, Раджахмундри, Индия
[2]Институт инженерии и технологий Годавари (А), Раджахмундри, Индия

Аннотация. Основными целями исследования являются разработка и валидация новой системы оценки уровня заряда (SoC) литий-ионных батарей (LIB) в системах хранения энергии (ESS) электромобилей (EV) путем интеграции рекуррентной сети хаотического аттрактора (CARN) с технологиями трансформатора. Этот гибридный подход направлен на преодоление ограничений традиционных систем управления батареями (BMS), в частности при обработке зашумленных входных данных, долгосрочных зависимостей и дисбаланса данных. Эти цели были достигнуты за счет внедрения структурированной методологии, которая включает в себя балансировку данных для смягчения искаженных наборов данных, эксплораторный анализ данных (EDA) для обнаружения аномалий и распознавания образов, а также масштабирование характеристик для нормализации входных данных, что обеспечивает надежное и эффективное обучение модели. Гибридная модель классификации использует способность ARN к распознаванию временных паттернов наряду с мощным механизмом внимания Transformer, что обеспечивает превосходную адаптивность в различных условиях эксплуатации. Реализованный на Python, предложенный метод был тщательно протестирован в нескольких сценариях для подтверждения его надежности и точности. Наиболее важными результатами являются снижение среднеквадратичной ошибки (RMSE) до 0.9671, средней квадратичной ошибки (MSE) до 0.9352, средней абсолютной ошибки (MAE) до 0.793 и повышение коэффициента R^2 до 99.86 %, что в совокупности демонстрирует значительные улучшения по сравнению с традиционными методами оценки. Значение полученных результатов заключается в подтверждении достоверности предложенной модели.

Ключевые слова: литий-ионные аккумуляторы, системы управления аккумуляторами, хаотическая аттракторная рекуррентная сеть (CARN) и трансформатор, обработка данных, разведочный анализ данных, Python.

INTRODUCTION

Energy Storage Systems (ESSs) are pivotal technologies for the future development of EVs and smart grid infrastructures. Among these, lithium-ion batteries represent the most rapidly expanding ESS solution. However, despite their growing prevalence, critical issues related to the safety and effective management of LIBs remain unresolved. As a result, battery management systems have emerged as an essential component in the electrification of battery electric vehicles, offering a suite of functionalities designed to ensure safe and efficient battery operation. In recent years, the creation of intelligent and advanced state-of-charge estimation methods for LIBs has become a highly active field of research. Yet, progress is hindered by several technological challenges [1].

- Firstly, the nonlinear behaviour of LIBs stemming from their multi-scale architecture (ranging from individual materials to full battery packs) and evolving characteristics over time (such as ageing) makes accurate modelling complex.
- Secondly, internal battery conditions are difficult to monitor and are highly sensitive to changes in external environmental conditions.

The transition from laboratory-scale to industrial-scale LIBs further exacerbates this issue, as discrepancies between theoretical and real-world conditions increase [2]. Lastly, inconsistencies among LIB units compromise the performance and stability of battery packs, especially in BEV applications. Methods developed for small-scale batteries often prove inadequate when applied to large-scale systems, making precise SoC estimation a significant challenge. Therefore, the development of sophisticated SoC estimation techniques is urgently needed to address these limitations. Accurate battery state estimation is a core feature of modern BMSs in BEVs, enabling stable and efficient battery use while laying the foundation for improved safety oversight [3].

I. LITHIUM-ION BATTERY:

Lithium-ion batteries offer several key advantages, including high energy and power densities, extended cycle life, strong adaptability to environmental conditions, and elevated cell voltage. Materials used in lithium-ion battery cells perform optimally within a defined safe operating window. This window outlines the acceptable temperature and voltage ranges, along with the maximum allowable current during both charging and discharging processes [4]. There are multiple types of lithium-ion chemistries, each with its unique strengths. For instance, Lithium

Cobalt Oxide (LCO) is known for its high specific energy, while Lithium Manganese Oxide (LMO) provides excellent specific power. Nickel Cobalt Aluminium (NCA) and Nickel Manganese Cobalt (NMC) batteries are cost-effective and exhibit strong thermal stability. Lithium Iron Phosphate (LFP) batteries are characterised by a flat Open-Circuit Voltage (OCV) curve, but they typically have lower capacity and higher self-discharge rates. Meanwhile, Lithium Titanate (LTO) batteries excel in fast charging and long service life, though they have lower specific energy and come at a higher cost [5].

II. BATTERY MANAGEMENT SYSTEM:

BMS incorporate multiple functions that monitor and control battery performance across individual cells, modules, and entire battery packs. As batteries age, their energy storage capacity diminishes. This degradation is represented by the state of health, while the Remaining Useful Life (RUL) refers to the expected duration or number of charge-discharge cycles left before reaching End of Life (EoL). Fig. 1, a modern BMS also deliver precise estimates of key parameters such as the SoC, SoH, RUL, capacity, and available power. These estimations are derived from continuous monitoring of current, voltage, and temperature. Among these, SoC estimation is particularly vital, yet achieving accurate and real-time results is challenging due to the battery's complex and nonlinear electrochemical behaviour with the evolving characteristics associated with ageing [6]

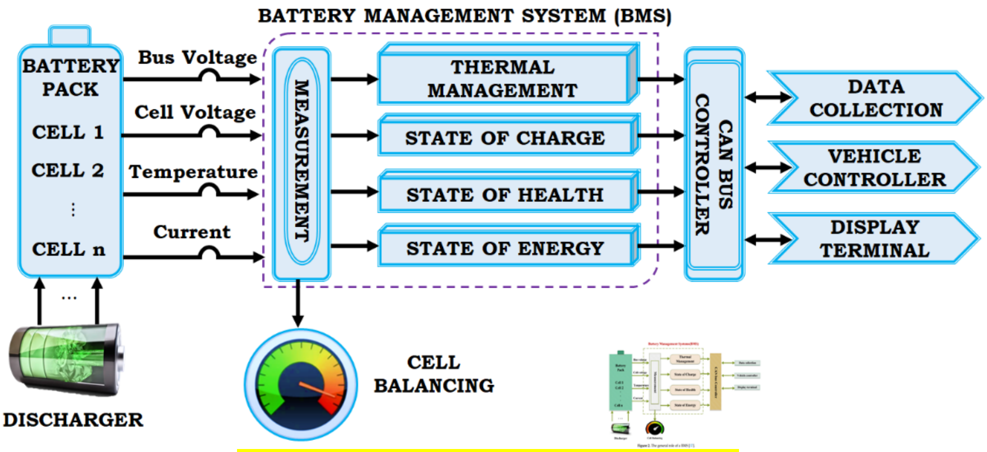

Fig. 1. Role of Battery Management System.

A battery management system integrates hardware and software to regulate battery operating conditions with the goal of extending battery lifespan, ensuring safety, and providing accurate assessments of various battery states for energy management purposes [7].

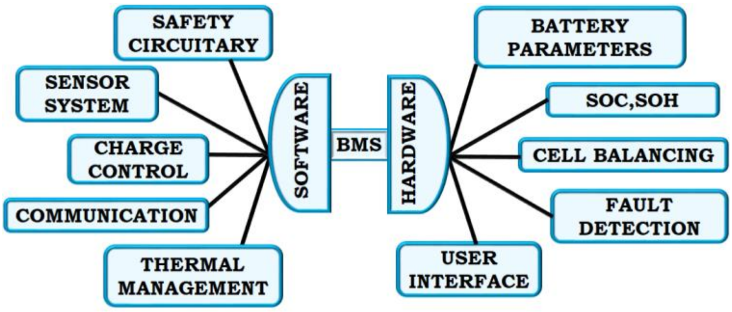

Fig. 2. Battery management in EV.

BMS incorporates various sensor networks to monitor and measure critical battery parameters, including current, voltage, and temperature, Fig. 2. However, acquiring highly accurate data outside of controlled laboratory settings is challenging due to equipment costs and spatial limitations. Temperature plays a crucial role in cell reliability and performance, and thermal imbalances lead to degradation. Once a BMS has acquired the necessary data, it operates autonomously. With advancements in smart battery technologies, it is now possible for the charger and battery to exchange detailed operational data, enhancing system coordination and efficiency [8].

State of charge estimation techniques are broadly categorised into five main types:

Coulomb Counting Methods (CCMs), Open-Circuit Voltage Methods (OCVMs), Impedance Spectroscopy-Based Methods (ISBMs), Model-Based Methods (MBMs), and those utilising Neural Networks (NNBMs) [9]. The coulomb counting method is among the simplest and most easily implemented techniques for estimating a battery's state of charge, requiring minimal computational power. It works by integrating the current over time during charging and discharging processes. However, its accuracy is compromised by external factors such as electrical noise, temperature fluctuations, and current measurement errors, which introduce uncertainty into the estimation [10]. The open-circuit voltage method is a highly accurate and simple approach for estimating the state of charge, making it easy to implement. Nevertheless, its primary limitation lies in the extended time required for the battery to reach a stable equilibrium state. Due to this delay, the OCV method is unsuitable for real-time SoC estimation and is therefore better suited for applications with low power demands where immediate response is not critical [11]. The impedance and internal resistance of lithium-ion batteries characterise their intrinsic electrical behaviour under various current stimuli, provided that temperature, SoC and SoH remain constant. Though measuring Electrical Impedance Spectroscopy (EIS) in real-time is challenging due to several factors, it often requires sinusoidal Alternating Current (AC), the correlation between impedance and SoC is not consistent, and the associated equipment is costly. Determining internal resistance involves applying Direct Current (DC) and capturing voltage and current over brief time intervals. Yet, internal resistance evolves gradually, making it difficult to track effectively for accurate SoC estimation. As a result, SoC estimation methods based on impedance and internal resistance are generally unsuitable for electric vehicle applications [12].

The model-based methods depend on accurate battery models to estimate the state of charge with precision. However, the internal parameters of a battery continuously change during charging and discharging cycles, making it challenging to develop a single model that reliably captures all external behaviours of the battery [13]. Various types of neural networks and related methodologies are widely used for capturing and modelling the nonlinear relationships between a system’s inputs and outputs [14]. A Deep Neural Network (DNN) model estimates the SOC of lithium-ion batteries used in electric vehicles. The DNN’s architecture, with adequately sized hidden layers, enables it to predict SOC for previously unseen drive cycles during training. A range of DNN configurations, varying in hidden layer count and training algorithms, leads to reduced prediction error and more accurate SOC estimation. Moreover, DNN is limited by validation, making its reliability and generalisation in battery systems not yet fully established [15]. The Feed-Forward Neural Network (FFNN) is used to estimate SoC prediction, the single-layer FFNN effectively modelled and predicts SOC across the dataset, with the exception of instances where the SOC approached the maximum value of 100% [16]. Bi-LSTM (Bidirectional Long Short-Term Memory) enhances SOC estimation accuracy by using two LSTM layers that process input sequences both forward and backwards, capturing comprehensive temporal dependencies. Though, Bi-LSTM offers high SOC estimation accuracy at room temperature, its performance significantly degrades under extremely low-temperature conditions [17]. To overcome these limitations, this research proposes a novel CARN integrated with transformer architecture, the RNN components enhance the model’s ability to retain and process sequential information over time, capturing short-term dependencies in SoC dynamics. The chaotic behaviour represents nonlinear patterns and the Transformer’s attention mechanism for long-range sequence learning, ensures improved robustness and accuracy across varying operational and environmental conditions.

The contributions of proposed SoC estimation model are listed below:

- The collected raw sensor data is cleaned, normalised, and balanced to ensure robust model performance across various operating conditions.
- Exploratory data analysis performed in-depth analyse to understand patterns, detect anomalies, and assess feature relevance, guiding subsequent modelling steps.
- Feature engineering derives meaningful input variables from raw data to enhance the predictive capability of the model, including temporal dynamics and interaction terms.
- Data Splitting segregates the dataset into training and testing subsets to validate the model’s generalisation ability, using structured trip-based partitioning.

- CARN-Transformer is integrated, which combines a convolutional attention residual network and transformer mechanisms for accurate SOC estimation.

Table 1

Related works of SoC estimation in LiB for EV systems.

Ref.No	Author & Title	Methodology used	Operations	Limitations
[18]	Eymen İPEK *et al* "A novel method for SOC estimation of Li-ion batteries using a hybrid machine learning technique"	XGBoost (Extreme Gradient Boosting) is used to estimate SOC under dynamic operating conditions	XGBoost estimates SOC by training on labelled battery data using the \`XGBRegressor\`, learning patterns through supervised learning, and then validating its prediction accuracy with similar test data to model SOC as a regression problem.	Its effectiveness in SOC estimation is limited by the availability and quality of training data, requiring well-characterised operational profiles to perform reliably even with minimal data.
[19]	Obuli Pranav D. *et al* "Enhanced SOC estimation of lithium-ion batteries with RealTime data using machine learning algorithms"	Gaussian Process Regression (GPR) is designed for modelling the complex relationship between real-time driving data and battery SOC.	GPR estimates SOC by using a kernel function to model the correlation between data points while optimising noise and complexity trade-offs to ensure accurate and flexible predictions.	However, it is computationally intensive and less scalable for large datasets.
[20]	J. Harinarayanan *et al* "SOC estimation for a lithium-ion pouch cell using machine learning under different load profiles"	Machine learning technology, based random forest method, is presented for estimating SoC.	RF estimates SoC by using an ensemble of decision trees to capture complex patterns in battery data, delivering more accurate, reliable predictions under real-world driving conditions.	Yet, its performance declines when faced with unfamiliar load profiles or insufficient training models.
[21]	Sadiqa Jafari *et al* "Efficient state of charge estimation in electric vehicles batteries based on the extra tree regressor: A data-driven approach"	Extra Tree Regressor (ETR) is presented for effectively predicting the SoC of EVs.	It employs ensemble learning by aggregating multiple decision trees to reduce overfitting and improve robustness.	It is highly dependent on data quality, and its predictive accuracy and generalizability are influenced.
[22]	Muhammad Adib Kamali *et al* "ANN-based State of Charge Estimation of Li-ion Batteries for Embedded Applications	This study utilises data-driven SOC estimation based on an artificial neural network (ANN).	ANNs, known for their strong adaptability to nonlinear systems, are increasingly used to model the relationship between measured battery data and SOC, demonstrating reliable	It requires manual parameter tuning.

			performance across different battery ageing levels.	

PROPOSED SYSTEM DESCRIPTION

The accuracy of the SoC estimation is crucial for ensuring the reliable and efficient operation of LiB in EV systems. The proposed work introduces a hybrid architecture leveraging the chaotic attractor recurrent network with a transformer, which is depicted in Fig. 3

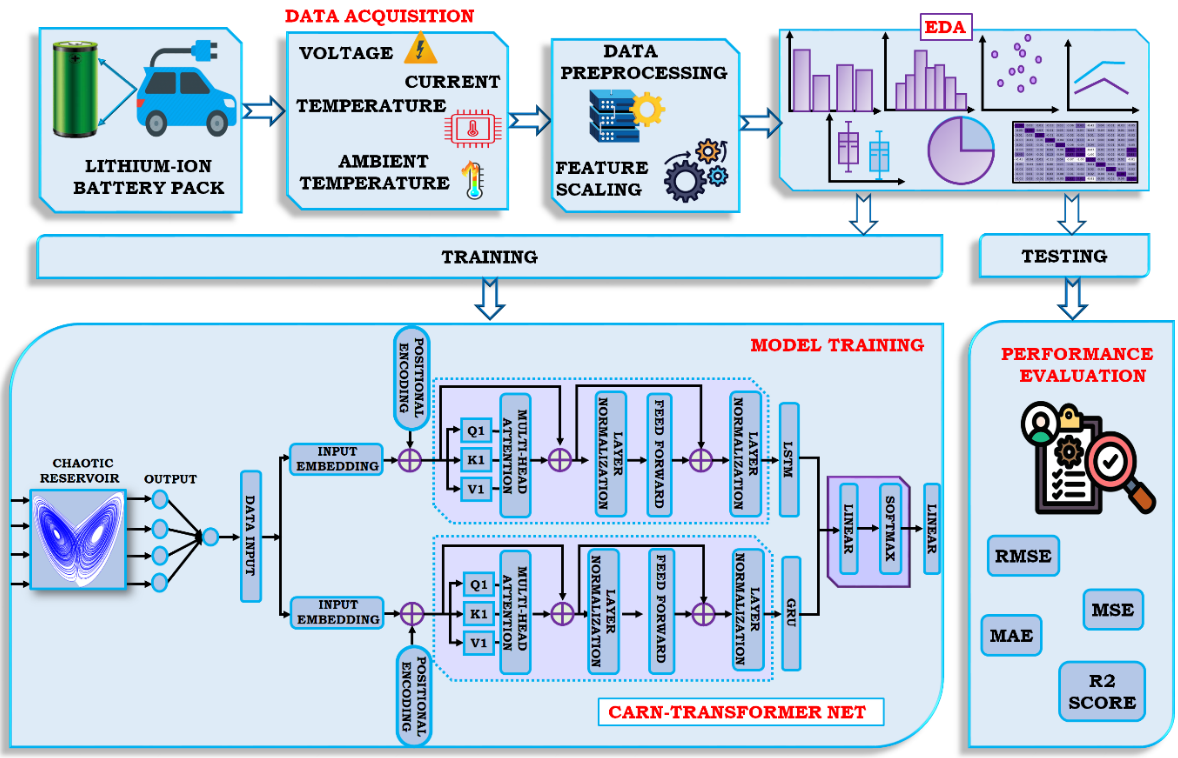

Fig. 3. Proposed SoC estimation of LiB model.

The real-time battery parameters such as voltage, current, temperature and ambient temperature data are collected from the battery management system. The raw data collected is pre-processed by handling missing values, enhancing the quality of the data. The pre-processed data is rescaled to a specific range, to ensure faster convergence throughout the system. The feature-scaled data are visually analysed through EDA tools, able to explore the patterns, correlations and trends among the variables. After feature scaling, the data are then passed to the CARN Transformer model, the chaotic attractor component dynamically assigns the weight to feature inputs, enabling the system to prioritise the abrupt fluctuations in voltage or current, when predicting SOC. The recurrent network integrates the gated memory units the capturing long-range dependencies in the time-series data. The Transformer's multi-head attention mechanism is adept at modelling temporal dependencies, which is particularly important in battery systems where past charge/discharge events significantly influence current behaviour. The Transformer captures both short- and long-term patterns effectively, this hybrid approach effectively enhances the accuracy of SoC estimation in LiB.

PROPOSED SYSTEM MODELLING

I. DATA PREPROCESSING

A. Data Collection

In designing SOC estimation model, voltage, current, temperature, and ambient temperature is intentionally selected as a key input variable. This decision reflects the well-established influence of temperature on the behaviour and performance of lithium-ion batteries, which are extensively used in electric vehicles. Temperature directly affects battery capacity, charge and discharge rates, and overall battery health. Since electric vehicles operate across diverse environmental conditions, it is essential to account for temperature fluctuations. Incorporating ambient temperature into the model enhances adaptability and ensures reliability across varying climates and usage scenarios. Moreover, ambient temperature is a practical choice, as it is easily measurable or estimable in real-world vehicle systems. Ultimately, this inclusion enhances the model's precision and robustness, supporting more accurate SOC estimation in diverse operating environments typical of electric mobility.

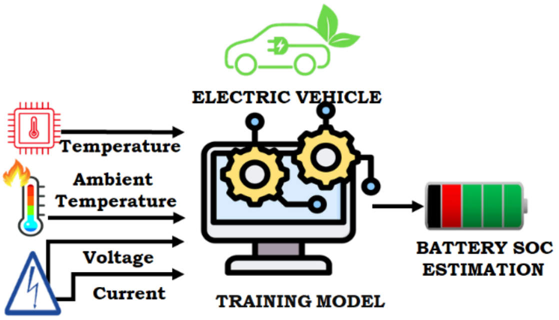

Fig. 4. SoC estimation model.

From Fig.4, the collected real-world driving trip data, includes key parameters such as voltage (V), current (A), battery temperature (ºC), and ambient temperature (ºC). Merging all recorded values into a unified dataset, ensuring the accurate synchronisation of corresponding sensor readings.

Data Pre-processing

The pre-processing ensures the development of accurate and reliable SoC estimation models. Datasets used for SoC prediction often suffer from incomplete entries, which arise from a variety of factors, including human input errors, sensor malfunctions, limitations in data availability, or intentional omission of certain measurements. Additionally, inconsistencies or outdated entries lead to data removal during quality checks. Moreover, instances of anomalous data values that deviate significantly from expected patterns are also treated as missing, as they are typically discarded to maintain dataset integrity. These values are commonly addressed through data imputation techniques or repair mechanisms, which substitute missing or invalid values with contextually appropriate estimates. Thus, properly managing such incomplete or corrupted data is essential for improving model convergence and enhancing the accuracy of SoC predictions in real-world operating environments.

B. Feature Scaling

Feature scaling is performed on the variables such as battery voltage, current, ambient and internal temperatures, transforming their values into a standardized range of [0–1] while preserving their original context. This normalization process was essential for optimizing the performance and convergence of the learning algorithm.

C. Exploratory Data Analysis

Exploratory data analysis serves a critical foundational role in estimating SoC levels. EDA primarily involves statistical summarisation, visualisation through graphs and plots, understanding distribution patterns, uncovering inter-variable relationships, cultivating intuition about the dataset, and distilling meaningful insights from raw observations. EDA focuses on the intrinsic structure of the data itself, without imposing rigid distributional constraints. It emphasises data visualisation as a tool for revealing hidden patterns and anomalies, offering analysts immediate insights into the underlying system dynamics. EDA is inherently exploratory, helps to investigate the data further, and fosters a more nuanced understanding. This iterative, insight-driven process is crucial for discovering models that genuinely fit the behaviour of battery systems during charge/discharge cycles.

Viewing data through visual representations such as graphs, charts, histograms, and plots greatly enhances the ability to identify patterns and trends at a glance, fig.5. These tools make complex datasets more approachable and intuitive, especially for individuals without a technical background, enabling them to grasp insights that might otherwise be hidden in raw numbers. SOC estimation relies heavily on continuous features like voltage, temperature, current, and degradation indices. These data are visualized with:

- **Bar charts**: Illustrate the frequency of occurrences, such as the number of cycles performed under each operating mode.
- **Pie charts**: Represent the percentage breakdown of different charge protocols or usage classifications.
- **Histograms**: Revealing the distribution of SOC over charge/discharge cycles or showing how voltage levels vary across time.
- **Box plots**: Summarize voltage range, highlight charging extremes, and flag temperature outliers affecting battery health.
- **Scatter plots**: Uncovering correlations between features, such as SOC vs. voltage or temperature vs. capacity fade.
- **Heat maps**: Displaying grid-like visualizations of sensor measurements across cycles to expose thermal runaway patterns or aging hotspots.

- **Line plots**: Tracing SOC trajectories over time or usage cycles, essential for detecting nonlinearities, drifts, and charge efficiency loss.

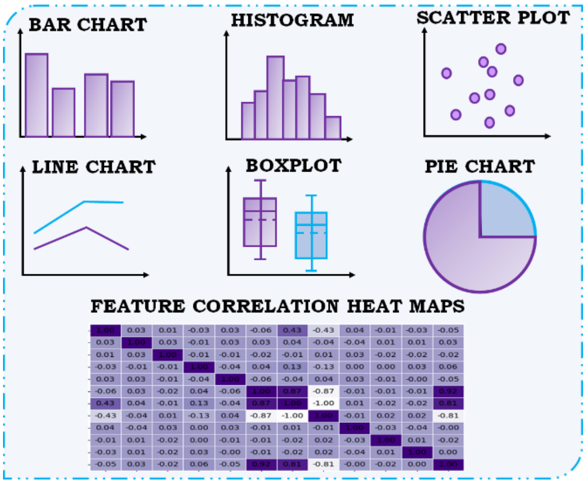

Fig. 5. Techniques in EDA.

The relations between battery data are visually explored through EDA, revealing key patterns and correlations among voltage, current, temperature, and ambient temperature, which is crucial for accurate SOC estimation. For training and evaluation purposes, the dataset was split according to the 70/30 ratio, with 70% allocated for training and 30% for testing, in effective estimation of SoC levels in LiB for EV systems.

D. Carn-Transformer Net

The CARN approach starts by representing lithium-ion Battery SoC as a nonlinear dynamic process through employing chaotic temporal dynamics in battery data to enable predictive learning with a recurrent neural architecture. The chaotic systems are characterized by the interaction of multiple non-linear processes, resulting in sensitive dependence on initial conditions and complex dynamics. To model such systems, consider the deterministic dynamical process:

$$F : M \to M \qquad (1)$$

Evolving on a geometric structure known as an attractor A located within a manifold M, which is locally C^N (N-times continuously differentiable). When this system is observed through time series data $\{z_i\} \subset R$, these observations are interpreted as being produced by an unknown measurement function h. To reconstruct the underlying dynamics of this hidden system, Phase Space Reconstruction (PSR) is utilized, a method that allows us to approximate the original dynamics via a reconstructed map

$$K : R^m \to R^m \qquad (2)$$

Where the system's behaviour unfolds on a topologically equivalent attractor $\tilde{A}$ embedded in Euclidean space of dimension m. This reconstructed attractor forms a differentiable homomorphism of the original attractor A, preserving its essential geometric and topological features. The entire flow of transformation is modelled where, $\{z_i\}$ and $\{u_i\}$ represent sampled sequences originating from two dynamic systems. The chaotic attractor structure,

$$\tilde{A} = \left\{\tilde{A}_i\right\} \qquad (3)$$

which resides in the phase space R^m. During the forecasting phase, a local prediction strategy is employed. This involves estimating future states using the rule:

$$u_{i+1} = K^{(i)}(u_i) \qquad (4)$$

Here, the local mapping $K^{(i)}$ is either a linear or a nonlinear neural network function, where in parameters are shared across nearby states u_i or among states located in the same neighbourhood of the reconstructed attractor. This approach assumes that points lying within close proximity on the manifold tend to exhibit similar evolution behaviour. From the universal approximation properties of polynomials, which enable them to closely mimic a wide range of dynamical behaviours, polynomial functions are exploited to model these intricate chaotic structures with high fidelity. The transformation pipeline is abstracted as follows:

The system's first-order linear time-invariant dynamics,

$$x'(t) = Ax(t) + Bu(t) \qquad (5)$$

Convolution of the system response with input $u(t)$ is indicated as,

$$x(t) = (K * u)(t) \qquad (6)$$

The system kernel using the exponential of the product of matrices A and Brepresented as,

$$K(t) = e^{tAB} \qquad (7)$$

Chaotic attractor recurrent network-transformer have shown exceptional proficiency in modelling time-series data, making them highly applicable to state of charge estimation for LIBs, Fig. 6. In recent developments, these architectures have been successfully implemented in research fields such as epilepsy detection and classification. This work adopts an integrated modelling strategy that combines transformer encoders with LSTM and GRU networks.

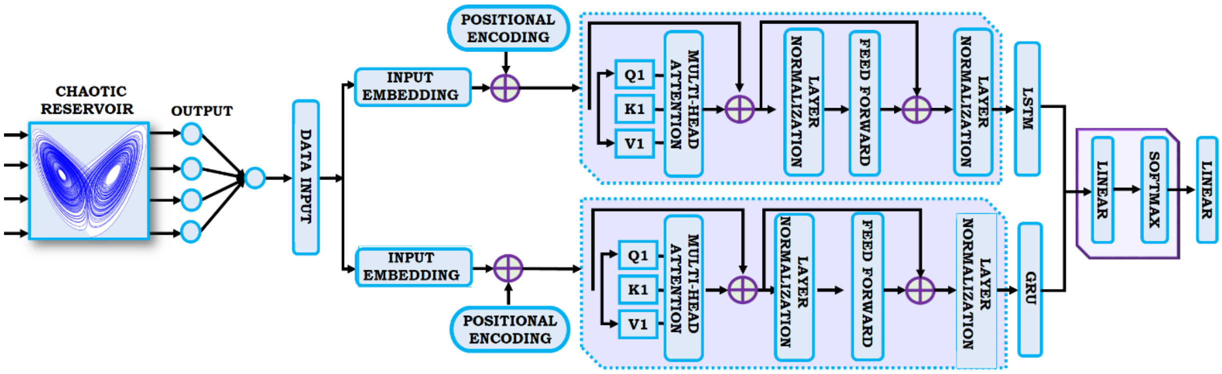

Fig. 6. CARN-Transformer Net.

To begin with, the input tensor $\delta \in R^{S \times T \times F}$, which represents spatial, temporal, and frequency data, is reshaped to emphasize different dimensions:

- The temporal-frequency dimension is flattened into $\delta_S \in R^{S \times T \times F}$
- The spatial-temporal dimension is flattened into $\delta_F \in R^{F \times (S \cdot T)}$

These transformed matrices are then fed separately into the model as dual input channels. Positional encodings are added to both time and frequency inputs to retain ordering information. To thoroughly extract serial dependencies, the framework employs two specialized encoder streams**,** each tailored to capture either time-based or frequency-based relationships. Each encoder shares the same structure, composed of:

- A multi-head self-attention mechanism.
- A Feedforward Neural Network (FFN) block.

In the multi-head attention module, each attention head generates output as defined in Equation (8), where:

$$Attention(Q,K,V) = soft\,max\left(\frac{QK^T}{\sqrt{d_k}}\right)V. \quad (8)$$

Where Q, K, and V represent the query, key, and value matrices respectively.

This attention process allows the Transformer to focus on various subspaces of input representations simultaneously, thereby enhancing the diversity and granularity of learned features. As shown in Equation (9), multiple heads (denoted by m) contribute independently to produce outputs:

$$MultiHead(Q,K,V) = Concat(h_1,\ldots,h_m) \quad (9)$$

Here, W_i^Q, W_i^K and W_i^V are the learnable projection matrices, $h_i = Attention(QW_i^Q, KW_i^K, VW_i^V)$. These outputs then pass through a feed-forward network that processes each input position independently and in parallel, accelerating the training process. The Transformer encoder's ability to manage long-range dependencies is further enhanced by introducing recurrent neural networks, namely Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), after the encoding stage. At each time step t, given the current observation o_t the recurrent model aims to predict the next observation $\hat{o}_{t+1}$. The models also leverage historical data denoted by $H_t <\in R^{n \times d}$, which supplements the current input. The general predictive model is represented as:

$$\hat{o}_{t+1}, H_t = f_\theta(o_t, H_t) \quad (10)$$

Where f_θ is a learned function parameterised by θ. While all models adhere to this overarching framework, they differ in the structure of f_θ and how their parameters are optimised to forecast the evolution of the observable vector. Three variants of Recurrent Neural Networks (RNNs) used in this study: long short-term memory, gated recurrent unit, and these architectures are illustrated in Fig. 7.

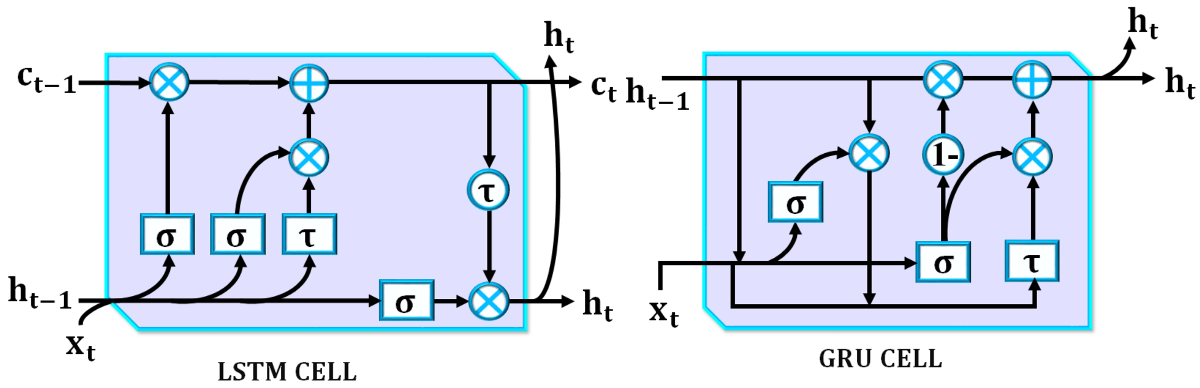

Fig. 7. Structure of LSTM and GRU cell.

.Long Short-Term Memory (LSTM)

The LSTM architecture effectively addresses the Vanishing Gradient Problem (VGP) commonly observed in RNNs by introducing gating mechanisms. Let $z_t = (h_{t-1}, o_t)$. The LSTM updates the hidden state h_t over time using the following equations:

$$h_t = g_t^0 \odot tanh(c_t) \quad (11)$$

$$c_t = g_t^f \odot c_{t-1} + g_t^i \odot c_t \quad (12)$$

$$g_t^k = \sigma(W_k z_t + b_k), k \in \{f, i, o\} \quad (13)$$

$$c_t = tanh(W_c z_t + b_c) \quad (14)$$

Here, g_t^f , g_t^i, and $g_t^0 \in R^{d_h}$ denote the forget, input, and output gates, respectively, and $c_t \in R^{d_h}$ is the internal cell state propagated through time. The model's learnable parameters include weight matrices $W_k \in R^{d_h \times (d_h + d_0)}$ and bias vectors $b_k \in R^{d_h}$, for $k \in \{f, i, o\}$. The operator $\odot$ signifies the Hadamard (element-wise) product, and σ represents the sigmoid activation function.

Gated Recurrent Units (GRU)

The GRU is a streamlined variation of the LSTM architecture that reduces the number of parameters by combining the input and forget gates into a single update gate. Let $z_t = (h_{t-1}, o_t)$. The GRU updates its memory as follows:

$$h_t = g_t^0 \odot \bar{h}_t + (1 - g_t^z) \odot h_{t-1} \quad (15)$$

$$\bar{h}_t = tanh\left(W_h\left(g_t^r \odot h_{t-1}\right) + b_h\right) \quad (16)$$

$$g_t^k = \sigma(W_k z_t + b_k) \;\; k \in \{z, r\} \quad (17)$$

In the GRU architecture, the vectors g_t^z and $g_t^r \in R^{d_h}$ represent the update and reset gates, respectively. The model includes learnable parameters in the form of weight matrices $W_k \in R^{d_h \times (d_h + d_0)}$ and bias vectors $b_k \in R^{d_h}$, where $k \in \{z, r, h\}$ corresponds to the update, reset, and candidate activation components. Functionally, the update gate g_t^z regulates how much of the previous hidden state should be retained, analogous to a combination of the input and forget gates found in LSTMs. To streamline the model, GRU enforces a constraint that the outputs of certain gates sum to one element-wise this helps reduce the total number of parameters. GRUs omit the output gate entirely. Instead, they introduce a reset gate g_t^r which serves to directly clear portions of the memory before updating it with new information. Following the GRU and LSTM layers, the resulting features denoted as matrices M (from LSTM) and N (from GRU) are merged using a gated fusion strategy. Specifically, the outputs M and N are concatenated into a single feature vector. This concatenated vector is linearly projected into a common space H. A SoftMax-based gating mechanism assigns importance scores to each output. μ_1 is assigned to the LSTM output and μ_2 is assigned to the GRU output. Through this weighted combination, the fused feature τ is generated, incorporating both temporal and frequency characteristics effectively. This fusion process is formally described using Equations (18), (19), and (20).

$$H = W \cdot Concat(M, N) + b, \quad (18)$$

$$\mu_1, \mu_2 = Softmax(H) \quad (19)$$

$$\tau = Concat(M \cdot \mu_1, N \cdot \mu_2) \quad (20)$$

Finally, the τ is passed through a fully connected layer, which reduces it to a 2-

dimensional vector representing the final classification output, providing the SOC estimation results.

RESULT AND DISCUSSION

This study presents a Python-based implementation that integrates a chaotic attractor with a transformer recurrent network framework for estimating SoC in LiB for EV systems. The workflow initiates with a data preprocessing phase focused on dataset processing and balanced distribution, ensuring robust input for subsequent analysis and estimation. The EV-Battery: Charging-Data" dataset is employed in this research, in which 70% is utilized for training and the remaining 30% for testing the CARN-TransNet Architecture in estimating SOC of LiB.

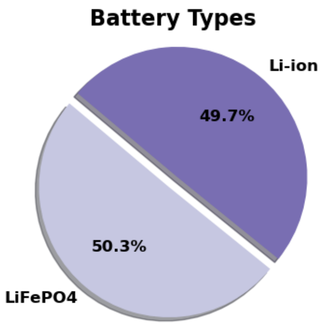

Fig. 8. Battery types.

Fig. 8 presents the distribution of battery types, highlighting the dominance of Li-ion and LiFePO4 battery utilization in electric vehicle applications that play a pivotal role in SoC estimation in a Hybrid CARN-TransNet Architecture. It indicates that the percentage of LiFePO4 batteries is slightly higher at 50.3% compared to Li-ion batteries at 49.7% of given battery types, this allocation highlighting the need for precise SOC estimation techniques for both battery chemistries, especially Li-ion, since they form a substantial proportion of EV system energy storage solutions.

Fig. 11 illustrates the correlation between the Degradation Rate (%) of Li-ion batteries and their Charging Duration (min) in electric vehicle applications. It exhibits a general trend of higher degradation rate with increased charging duration, effectively quantifies charging behaviour impact on battery health and optimization of charging policies for minimising degradation and maximising the life of Li-ion batteries, thereby making it possible for accurate CARN-TransNet SoC estimation models to consider degradation effects.

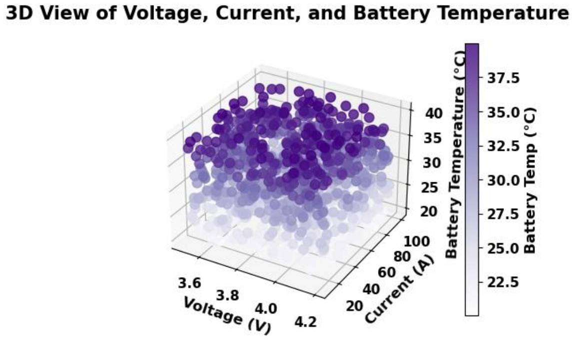

Fig. 9. 3D view of voltage, current and battery temperature.

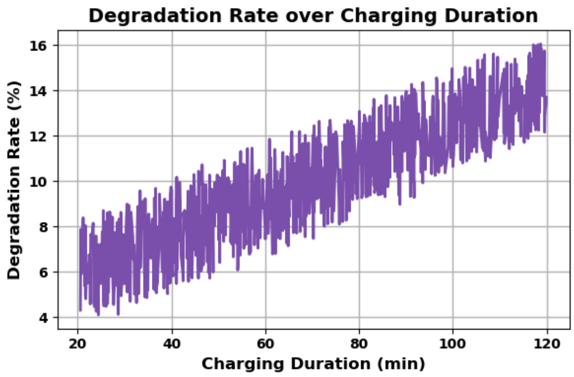

Fig. 10. Degradation rate over charging duration.

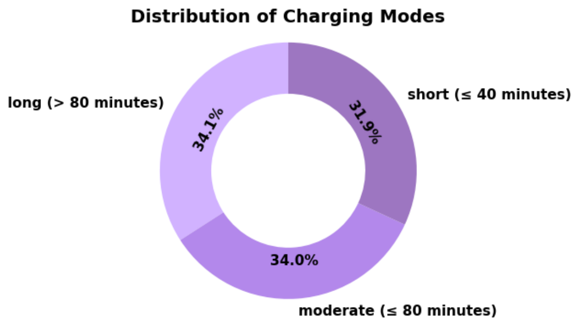

Fig. 11. Distribution of charging modes.

Fig. 12 visualizes the distribution of charging modes, indicating the frequency distribution of different charging times for electric vehicle Li-ion batteries, usable for examining real-world charging behaviour in a hybrid CARN-TransNet approach for accurate SOC estimation. The distribution "short" (≤ 40 minutes) for 31.9% of events, "moderate" (≤ 80 minutes) for 34.0%, and "long" (> 80 minutes) for the largest proportion at 34.1%, providing the varied demands the battery face in different charging circumstances.

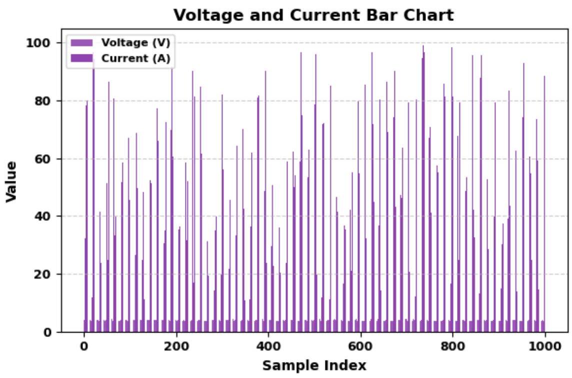

Fig. 12. Voltage and current bar chart.

Fig.12 reveals the oscillating voltage and current values with respect to time, plotted on the x-axis by "Sample Index" and on the y-axis by "Value" (Voltage in V, Current in A). It helps to easily identifies voltage and current values at each sample point, indicating the dynamic electrical behaviour of a Li-ion battery when exposed to real-world operating conditions in an EV. For over 1000 sample indices, CARN-TransNet accurately recognize these complex patterns and make precise State of Charge SoC estimations in the presence of natural noise and real-time battery variability.

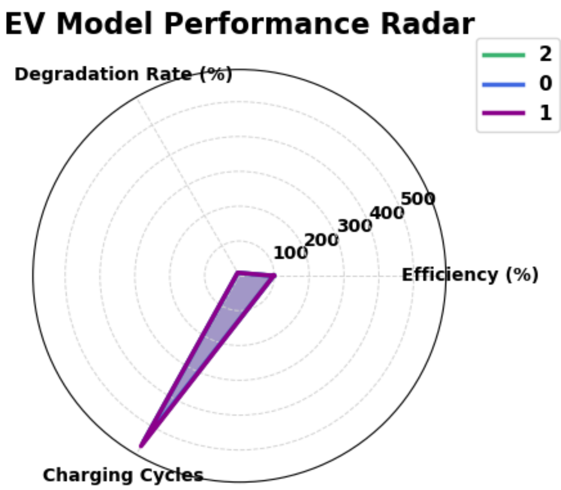

Fig. 13. EV model performance radar.

Fig.13 shows the radar chart of electric vehicle model key performance measures of the proposed architecture for optimal performance of the battery and SOC estimation. The "Degradation Rate (%)" and "Efficiency (%)", and "Charging Cycles", axes of radar charts, are influenced by the CARN-TransNet architecture as key parameters. It facilitates a brief comparison of the model's performance revealing the trade-offs and advantages achieved based on the accurate SOC estimation provided by the hybrid architecture.

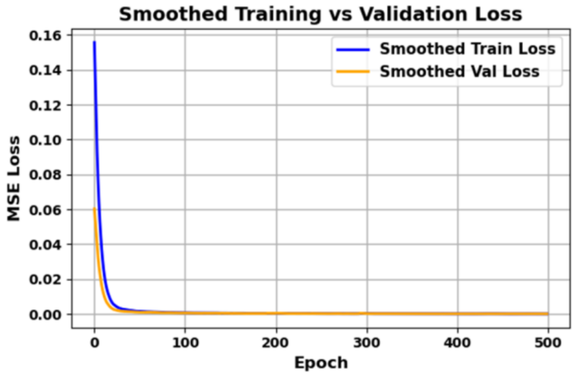

Fig. 14. Smoothed training Vs validation loss.

Fig. 14 presents the smoothed training vs validation loss depicting the trend of convergence of the hybrid CARN-TransNet structure, estimating SOC of Li-ion batteries in the EV systems. After initial drop in training and validation loss, and then their levelling off at values of near zero, to successful convergence indicating to its suitability to accurately estimate the SOC of Li-ion batteries for electric vehicle applications.

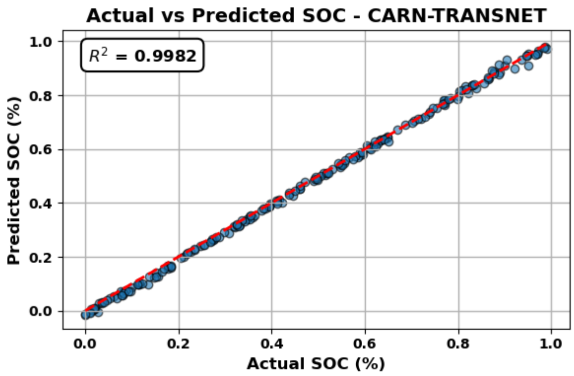

Fig. 15. Scatter Plot of Actual Vs Predicted SoC (%).

Fig. 15 represents the time-varying voltage and current measurements that distinguishes four sample points, showing the dynamic electrical behaviour of a Li-ion battery in use in an EV. Over the 1000 sample indices indicate the necessity of a robust architecture such as CARN-TransNet to efficiently identify such complicated patterns and make accurate SoC estimates in spite of the inherent noise and variability in real-world battery data.

Table 2 SoC estimation model Comparison

Model	RMSE	MSE	MAE	R2-Score

0	**CNN**	14.9700	224.1000	8.030	0.9200
1	**DNN**	9.3200	86.8600	6.810	0.9500
2	**ANN**	1.7160	2.9400	1.210	0.9700
3	**RBFN**	1.4900	1.7500	9.210	0.9600
4	**Proposed**	0.9671	0.9352	0.793	0.9986

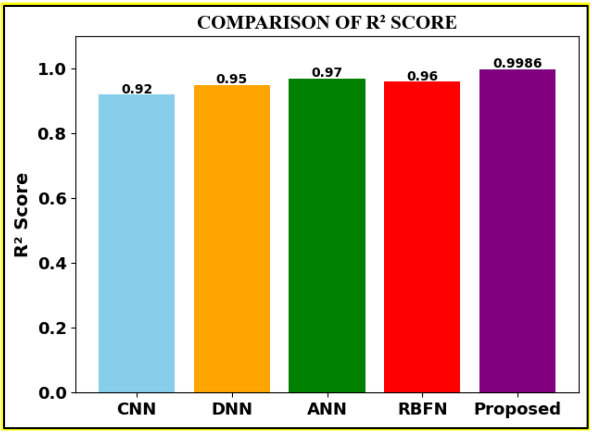

Fig.16. Comparison of R^2-score.

The comparative performance of five models such as CNN, DNN, ANN, RBFN, and the proposed hybrid CARN, Transformer architecture is assessed through their key regression metrics: RMSE, MSE, MAE, and R, score. From the table.2 and the corresponding fig.16, it is evident that the proposed model outperforms other models by a significant margin in all metrics. Proposed model is able to keep to its minimum the RMSE and MSE with values of 0.9671 and 0.9352, respectively, and also the MAE, which equals 0.793, therefore indicating the lowest prediction error and the highest estimation accuracy. Particularly, the proposed model leads to an R, score of 0.9986, thus strongly signifying a very high correlation between the predicted and the true SoC values.Fig.17 shows actual versus predicted SoC values with CNN, DNN, ANN, and RBFN models. ANN (R = 0.97) and RBFN (R = 0.96) exhibit closer trends than CNN (R = 0.92) and DNN (R = 0.95), however, all models are still outperformed by the CARN-Trans Net model, which yields an R, score of 0.9986 along with very low error metrics, thus, it is stated that this model is accurate and also robust in real, time SoC estimation.

Table 2 Comparison of RMSE.

SoC Estimation Models	RMSE
CNN [26]	**14.97**
DNN [25]	**9.32**
Bi-LSTM [24]	**1.716**
ANN [22]	**1.49**
RBFN [23]	**1.32**
Proposed	**0.9671**

Table 2 demonstrates the comparative analysis of RMSE values for various SoC estimation models in LiB for EV systems. The Convolutional Neural Network (CNN) [26] and DNN [25] exhibited relatively high RMSE values, indicating lower accuracy followed by Bi-LSTM [24], ANN [22] and Radial Basis Function Network (RBFN) [23]. The proposed CARN with Transformer model achieves lowest RMSE value of 0.9671, ensuring its superior performance in SoC prediction.

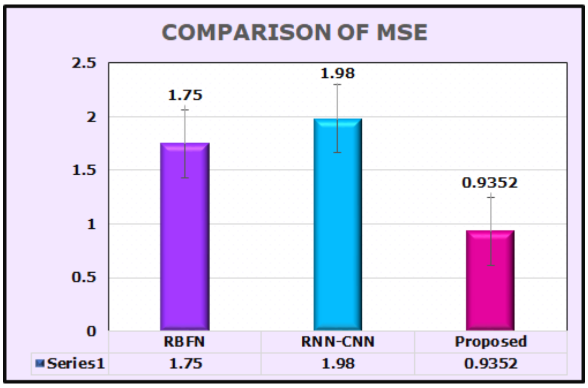

Fig. 17. Comparison of MSE.

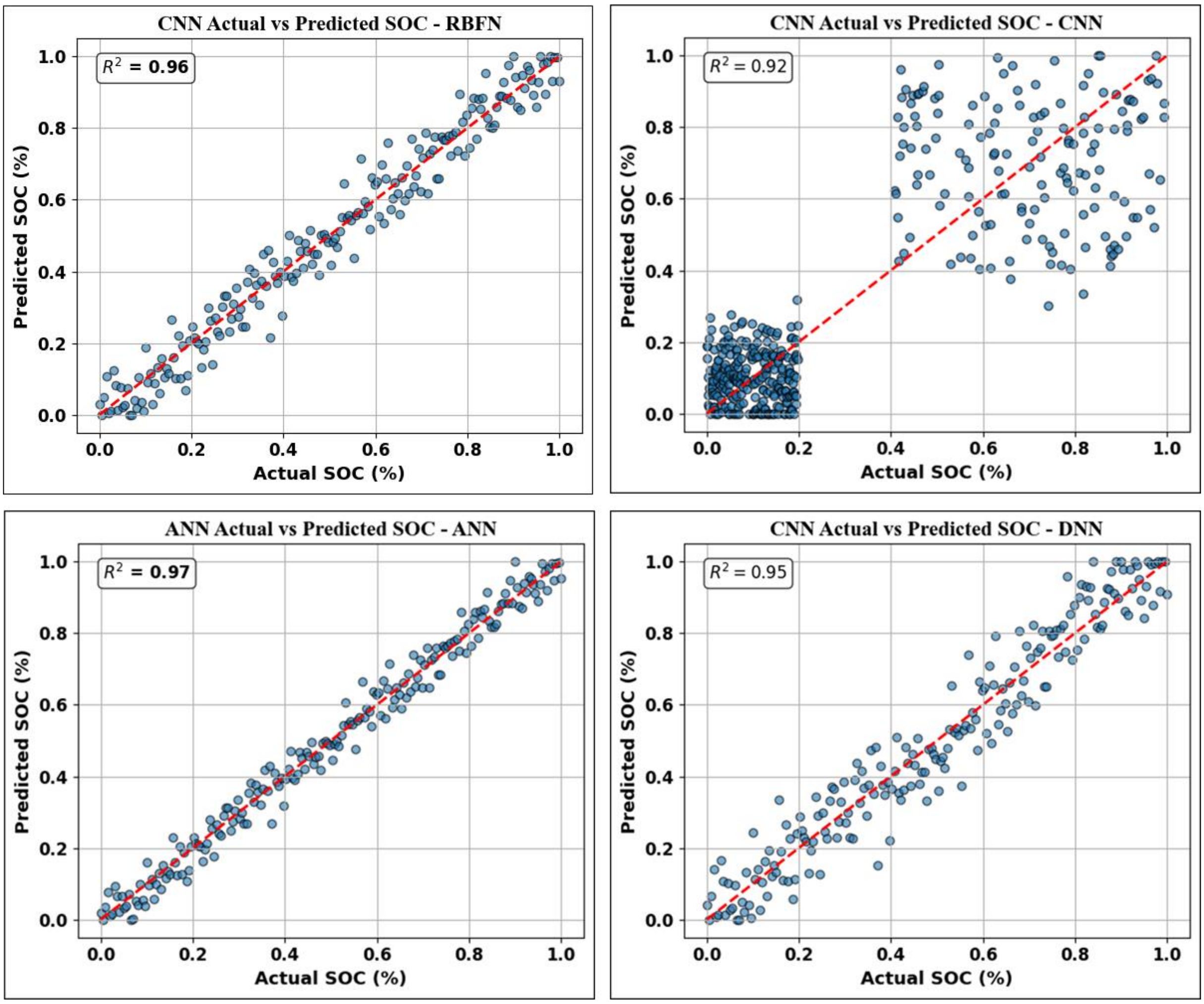

Fig.18. Comparison of Actual and Predicted values.

Fig. 18 displays the performance of MSE of different techniques used for estimating SoC of LiB in EV applications. The proposed hybrid CARN with transformer model demonstrates the lowest MSE of 0.9352, indicating its enhanced efficiency in SoC prediction, outperforming conventional algorithms.

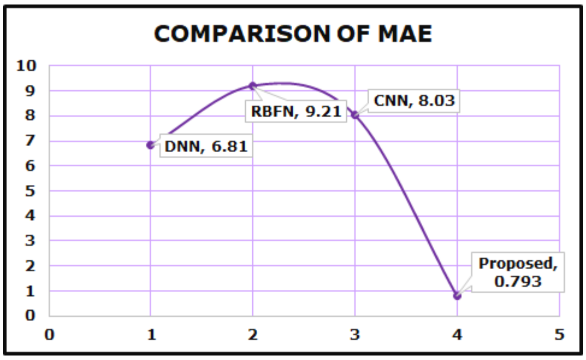

Fig. 29. Comparison of MAE.

Fig.29 represents the performance of comparative analysis of MAE for RBFN [23], CNN [26] approach, and the proposed SoC estimation model. The proposed CARN with transformer model has a MAE of 0.793, outperforms the conventional methods.

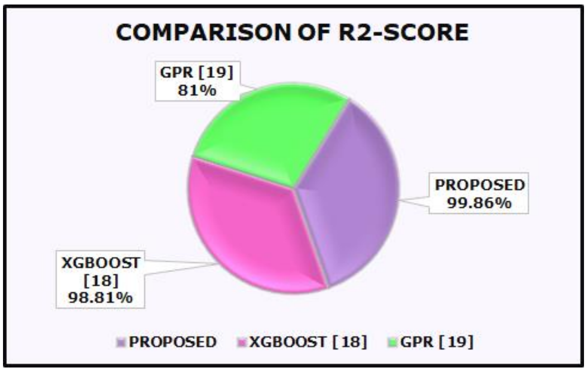

Fig. 20. Comparison of R2-score.

In Fig. 20, a comparative graph of R^2- Score of previous methods and the performance of the proposed CARN with transformer model are displayed. The proposed method outperforms conventional methods in terms of R^2- Score of 99.86% respectively.

CONCLUSION

This research proposes a robust framework that integrates a hybrid chaotic attractor-based recurrent neural network with transformer modules, tailored for SOC estimation in LiB for enhanced EV systems. The integration of chaotic attractor mechanisms with recurrent network transformer architecture significantly improves the model's ability to handle complex, nonlinear datasets by emphasizing critical patterns and temporal dependencies. This work is implemented through Python software, the proposed solution demonstrates superior SoC estimation performance, achieving reduced RMSE of 0.9671, MSE of 0.9352, MAE of 0.793 and exhibiting enhanced R^2-score of 99.86%. The model satisfies operational constraints for field development, thereby optimizing decision-making processes in EV system diagnostics and battery optimization scenarios.

REFERENCE

[1] Tabine A., Elachhab A., Bouzaid S., Hajjaji A. Innovative method to precise SOC estimation for lithium-ion batteries under diverse temperature and current conditions. *International Journal of Hydrogen Energy,* 2024, no. 96, pp. 1299-1309.

[2] Yao, J., Kowal, J. A multi-scale data-driven framework for online state of charge estimation of lithium-ion batteries with a novel public drive cycle dataset. *Journal of Energy Storage,* 2025, no. 107, pp. 114888.

[3] Al-Alawi, M.K., Jaddoa, A., Cugley, J., Hassanin, H. A novel enhanced SOC estimation method for lithium-ion battery cells using cluster-based LSTM models and centroid proximity selection. *Journal of Energy Storage*, 2024, no. 97, pp. 112866.

[4] Abinaya I., Prabha U., Kathirvel C., Veerapandiyan V., Kumar S. V., Artificial intelligence and Internet of things for renewable energy systems. *Artificial Intelligence and Internet of Things for Renewable Energy Systems*, 2021, no. 12, Walter de Gruyter GmbH & Co KG.

[5] Veerasamy V., Abdul Wahab N.I., Vinayagam A., Othman M.L., Ramachandran R., Inbamani A., Hizam, H. A novel discrete wavelet transforms based graphical language classifier for identification of high impedance fault in distribution power system. *International Transactions on Electrical Energy Systems*, 2020, vol. 30, no. 6, pp. e12378. Wiley Online Library.

[6] kumar Soma A. Hybrid RNN-GRU-LSTM Model for Accurate Detection of DDoS Attackson IDS Dataset. *Journal of Modern Technology,* 2025, vol. 2, no. 01, pp. 283-291.

[7] Kumar R.R., Bharatiraja C., Udhayakumar K., Devakirubakaran S., Sekar K.S., Mihet-Popa L. Advances in batteries, battery modeling, battery management system, battery thermal management, SOC, SOH, and charge/discharge characteristics in EV applications. *IEEE Access,* 2023, no. 11, pp. 105761-105809.

[8] Bose B., Soni R., Garg A. Analysis of SoC estimation for Master-Slave BMS configuration. *In 2022 4th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N)*, 2022, pp. 1317-1322. IEEE.

[9] Naguib M., Kollmeyer P., Emadi A. Lithium-ion battery pack robust state of charge estimation, cell inconsistency, and balancing. *IEEE Access*, 2021, no. 9, pp. 50570-50582.

[10] Lee J., Won J. Enhanced coulomb counting method for SoC and SoH estimation based on coulombic efficiency. *IEEE Access,* 2023, no. 11, pp. 15449-15459.

[11] Kadem O., Kim, J Real-time state of charge-open circuit voltage curve construction for battery state of charge estimation. *IEEE Transactions on Vehicular Technology,* 2023, vol. 72, no. 7, pp. 8613-8622.

[12] Bourelly C., Vitelli M., Milano F., Molinara M., Fontanella F., Ferrigno, L. Eis-based soc estimation: A novel measurement method for optimizing accuracy and measurement time. *IEEE Access,* 2023, no. 11, pp. 91472-91484.

[13] Naseri F., Schaltz E., Stroe D.I., Gismero A., Farjah E. An enhanced equivalent circuit model with real-time parameter identification for battery state-of-charge estimation. *IEEE Transactions on Industrial Electronics,* 2021, vol. 69, no. 4, PP. 3743-3751.

[14] Zhong Z., Lam H.K., Basin M.V., Zeng X.J. Fuzzy neural network-based adaptive sliding-mode descriptor observer. *IEEE Transactions on Fuzzy Systems,* 2024, vol. 32, no. 6, pp. 3342-3354.

[15] How D.N., Hannan M.A., Lipu M.S.H., Sahari K.S., Ker P.J., Muttaqi, K.M. State-of-charge estimation of li-ion battery in electric vehicles: A deep neural network approach. *IEEE Transactions on Industry Applications,* 2020, vol. 56, no. 5, pp. 5565-5574.

[16] Ofoegbu E.O. State of charge (SOC) estimation in electric vehicle (EV) battery management systems using ensemble methods and neural networks. *Journal of Energy Storage,* 2025, no. 114, pp. 115833.

[17] Vedhanayaki S., Indragandhi, V. A Bayesian optimized deep learning approach for accurate state of charge estimation of lithium-ion batteries used for electric vehicle application. *IEEE Access,* 2024, no. 12, pp. 43308-43327.

[18] Ipek E., Yilmaz, M. A novel method for SOC estimation of Li-ion batteries using a hybrid machinelearning technique. *Turkish Journal of Electrical Engineering and Computer Sciences*, 2021, vol. 29, no. 1, pp. 18-31.
[19] Babu P.S., V. I. B. A. S V., C. K. Enhanced SOC estimation of lithium ion batteries with RealTime data using machine learning algorithms. *Scientific Reports*, 2024, vol. 14, no. 1, pp. 16036.
[20] Harinarayanan J., Balamurugan, P. SOC estimation for a lithium-ion pouch cell using machine learning under different load profiles. *Scientific Reports*, 2025, vol. 15, no. 1, pp. 1-15.
[21] Jafari S., Byun Y.C. Efficient state of charge estimation in electric vehicles batteries based on the extra tree regressor: A data-driven approach. *Heliyon*, 2024, vol. 10, no. 4.
[22] Kamali M.A., Lim W. ANN-based state of charge estimation of li-ion batteries for embedded applications. *Jurnal Nasional Teknik Elektro dan Teknologi Informasi*, 2023, Vol. 12, no. 2, pp. 85-92.
[23] Zhou Z., Ryan Z.J., Sharma U., Tran T.A., Mehrotra S., Greco A., West J., Prasad M. Deep learning approaches for battery capacity and state of charge estimation with the NASA B0005 dataset. 2025.
[24] Yılmaz M., Çinar E., Yazıcı A. A Transformer-Based Model for State of Charge Estimation of Electrical Vehicle Batteries. *IEEE Access*, 2025.
[25] Hasib S.A., Gulzar M.M., Shakoor A., Habib S., Murtaza, A.F. Optimizing electric vehicle driving range prediction using deep learning: A deep neural network (DNN) approach. *Results in Engineering*, 2024, no. 24, pp. 103630.
[26] Alwabli, A."From data to durability: Evaluating conventional and optimized machine learning techniques for battery health assessment." Results in Engineering 23 (2024): 102445.
[27] Nazim M.S., Rahman M.M., Joha M.I., Jang Y.M. A Hybrid Rnn-Cnn Based Approach for Battery State of Charge (SOC) Estimation Under Various Temperatures and Discharging Cycle. *Available at SSRN 4855442*.

Information about authors

Dr. Ch. Leela Kumari c Her main area of interest includes Power Systems, Electric Vehicles, and Renewable Energy Systems, and she is working on MSME project currently. Email: leesmileschalla2021@gmail.com . ORCID: https://orcid.org/0009-0007-2332-2351

Dondapati Ravi Kishore Ph.D. in Energy systems, His main area of interest includes power systems, renewable energy systems, and energy auditing. Email: hod.eee@ggu.edu.in ORCID: https://orcid.org/0000-0002-2567-2888

Muthum Pavan Kalyan UG strudent. His main area of interest includes power systems. Email:pavankalyan231702@gmail.com

Kodati Bhavani Shankar UG student. His main area of interest includes renewable energy systems, and energy auditing. Email: shankarbhavani9505@gmail.com

Katta Saikrishna UG student. His main area of interest includes power systems, renewable energy systems, and energy auditing. Email: srisaikrishnakatta@gmail.com