DEEP LEARNING–BASED STATE OF CHARGE ESTIMATION FOR LITHIUM-ION BATTERIES IN ELECTRIC VEHICLE FOR LOCAL MOBILITY GOVERNANCE

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Abstract - The rise of using electric vehicles (EVs) as a sustainable means of transportation has augmented the necessity of precise monitoring and regulation of lithium-ion batteries as part of the Battery Management Systems (BMS). To avoid overcharging, enhance energy consumption, minimize the cost of the operation of lithium-ion batteries, and improve battery safety during the actual working conditions, reliable estimation of the State of Charge (SOC) of the lithium-ion battery is necessary. Nonlinear electrochemical characteristics of lithium-ion batteries and dynamically changing loads, however, become major challenges to the traditional approach to SOC estimation. This study proposes a deep learning-based system of predicting SOC in lithium-ion batteries in EV applications. The proposed model, as opposed to recurrent and convolutional neural network methods, is based on an Attention-assisted Temporal Convolutional Network with a Deep Autoencoder to provide an effective feature extraction and temporal learning that is stable. The autoencoder learns compact and noise-resistant feature representations of the battery voltage, current, temperature, and operating profiles, and the attention-enhanced temporal model learns long-range dependencies of lithium-ion battery behavior.,To achieve the implementation of the SOC estimation model in real-time, an edge computing architecture compatible with low-cost-BMS hardware is deployed. The experimental assessment shows that the technique is better than ampere-hour counting and baseline deep learning techniques in terms of prediction accuracy, reduced computational time, and higher robustness in testing different conditions of temperature and loads. The suggested framework facilitates effective management of lithium-ion batteries and also facilitates the effective operation of the EVs in a smart mobility environment that is deployed locally.

Keywords: Lithium-Ion Battery**;**Electric Vehicles**;** State of Charge Estimation**;** Battery Management System**;** Deep Learning; Edge Computing

1. Introduction

The growing popularity of electric vehicles (EVs) in the global community have attracted considerable concern to the organizational and sustainability of battery systems, which constitutes the core of modern-day transportation. With urban and local authorities aiming to introduce effective and sustainable mobility technologies, it is necessary to assure the stable functionality of lithium-ion batteries, whether on a single-vehicle basis or a scale much bigger, i.e. with EV fleets. The correct monitoring of the State of Charge (SOC) of these batteries is not only beneficial in avoiding overcharging and developing a better life of these batteries but also in facilitating safe, efficient and economical operation. Considering the local mobility governance in which the transportation networks are planned and optimized at the community or municipal level, an accurate battery monitoring is essential to plan, manage energy, and coordinate the fleet. Deep learning methods provide immense potentials to deduct complicated battery operation at realistic driving and environment circumstances and can be applied to make wiser and autonomous choices. Through the use of powerful predictive models, local authorities can increase the reliability and sustainability of electric mobility systems, as well as the efficiency of energy and lower the operations challenge in the deployment of EV in big numbers. This study aims to use deep learning methods for the improvement of SOC estimation of lithium-ion batteries to provide a base on smarter and locally controlled electric vehicle management. The problem of accurately estimating the State of Charge (SOC) in lithium-ion batteries in electric vehicles was one of the popular research fields in deep learning domain, since they demonstrated that it is possible to overcome traditional technological bottlenecks and have resulted in a high quality of battery monitoring research results [1]. Moreover, the operation of SOC improved using machine learning methods which proved to capture more complex battery behaviour in several operating conditions and efficient energy exploitation policies [2].

Furthermore, the evaluations on deep learning-based SOC estimation algorithms revealed the opportunities to improve the SOC estimation algorithms which allowed understanding the models, features and predictive performance which played a crucial role in developing effective battery monitoring systems [3]. On the same note, methods of artificial intelligence and machine learning were investigated to predict not only SOC, but also remained useful life and critical knee points of lithium-ion batteries, emphasising the overall potential of the methods to predictive maintenance of batteries in prognostics and operational safety [4]. Moreover, any deep learning models were used to forecast SOC during standard driving cycles, which proved to be much more accurate and robust than traditional methods, and pointed to the fact that the models are viable in the context of working of EVs in the real world [5].

There was also the implementation of hybrid recurrent learning methods with explainable AI that provided interpretable and accurate SOC estimation of battery management systems [6]. Also, extensive literature reviews identified different deep learning techniques, their perspectives, limitations, and comparative benefits in electric transportation, therefore, informing the design of more effective and reliable SOC estimation procedures [7]. Smart structures that directly predicted SOC and state of health based on deep learning also provided better operation information in electrified cars to enable predictive maintenance and improved energy planning [8]. Machine learning algorithms have been utilized systematically to estimate SOC and state-of-health, which provides state-of-art performance and makes practical application in real-world EV scenarios possible [9]. Lithium-ion battery state estimation with advanced machine learning methods showed better predictive accuracy and aids in real-time monitoring in the electric vehicle [10].

Investigations were also conducted on cloud-based deep learning to co-estimate SOC and state of health and found that scalable, data-driven, remotely manageable battery monitoring strategies would be useful in fleet management and on large scale use [11]. State-of-the-art machine learning algorithms that have been evaluated in SOC estimation verified their immense value of reliability of the system, prediction and adaptive control of batteries [12].

Thorough examinations of the SOC estimation methods highlighted the paramount importance of the approach in the battery management systems of electric vehicles, with the addition of deep learning models potentially significantly increasing the accuracy of the predictions, minimizing the errors of the estimates, and improving the efficiency of operations [13]. Comparative analysis of SOC algorithms implemented using deep-learning showed that cloud-based lithium-ion battery management system had clear benefits, which served as benchmarks when selecting the model to be used in the real world and deploying edge computing [14]. All of these studies pointed to the need of the integration of predictive modeling with intelligent system design to facilitate the accurate, scalable and efficient battery management. Lastly, predictive deep learning frameworks that are hybrid in nature were also used to manage urban electric vehicle fleets with success demonstrating how intelligent SOC estimation could be used to aid energy-efficient and locally-controlled smart mobility systems [15]. This group of frameworks made possible real time decision-making, energy optimization and enhanced operational safety, highlighting the greater achievements of SOC estimation technologies in facilitating sustainable solutions to transportation at the municipal or community scale. Therefore, the combination of these studies has created a good base on the application of the advanced deep learning techniques to facilitate trustworthy, effective, and smart battery handling in the locally controlled EV systems.

2. Methodology

The research work builds on a deep learning architecture that is edge-enabled with the aim of providing correct State of Charge (SOC) that represents the condition of the lithium-ion batteries installed in electric vehicles that drive in a smart mobility system that is controlled locally. The suggested methodology will help to solve nonlinear electrochemical dynamics, time dependence, and real-time computational limitations of Battery Management Systems (BMS). The framework combines structured data acquisition, powerful preprocessing, powerful feature learning and temporal modeling so that it can be deployed in a scalable fashion in decentralized EV infrastructures that are typically administered at a municipal or sub-national level. The methodological design is highly accurate, computational efficient and operationally robust such that practical SOC estimation of lithium-ion batteries can be made with respect to various driving and environmental conditions.

2.1 Dataset Description

Table 1 summarizes the nature of the lithium-ion battery data used to estimate SOC. The sample was made of NMC based lithium-ion cells with nominal capacity of 2.9 Ah and nominal voltage of 3.7 V that were sampled at a frequency of 1 Hz to record fine temporal dynamics. Battery operation was measured within the temperature of 0degC to 45degC and current change between [?]5 A and +5 A, so that the realistic environmental and load conditions experienced in electric cars were captured. Driving profiles were urban, highway, and mixed and included a range of operating conditions and stop-go patterns that were very important in the precise modeling of SOC. One hundred and twenty thousand (120,000) data samples were gathered, and they were divided into training (70 percent), validation (15 percent), and testing (15 percent) samples to facilitate the development of the model, hyperparameter optimization, and the testing of the model. The breadth of the operating conditions and driving habits in this dataset, as the Table 1 above demonstrates, gave a solid base of training the proposed deep learning structure, which allowed to extract latent features and accurately predict the SOC to be used in edge-enabled Battery Management Systems in fleets of Evs that are locally controlled.

Table 1: Dataset Characteristics

Attribute	Description
Battery Chemistry	Lithium-Ion (NMC)
Nominal Capacity	2.9 Ah
Nominal Voltage	3.7 V
Sampling Frequency	1 Hz
Temperature Range	0°C – 45°C
Current Range	−5 A to +5 A
Driving Profiles	Urban, Highway, Mixed
Total Samples	120,000
Training Data	70%
Validation Data	15%
Testing Data	15%

2.2 Hyperparameter Evaluation

The hyperparameter settings that were used in training the proposed SOC estimation model were optimized using the care to guarantee the steady convergence and the high prediction accuracy as summarized in Table 2. The learning rate of 0.001 was chosen to provide balance between the speeds of the gradient descent and the balance of convergence without the system overstepping the learning process. Adaptive learning rates were used to optimize every parameter using the Adam optimizer, which allowed training to take place faster and more effectively. The batch size was 64, which allowed estimating the gradient effectively and gave enough variation to the update step, and the model was implemented using 150 epochs to make sure the entire dataset is seen and both reconstruction and SOC prediction losses converge. The Deep Autoencoder latent dimension 32 was set to find the best fit to the battery features without redundancy, whereas TCN kernel size 3 was selected to fit a temporal feature in a short sequence. Four attention heads were also added to allow the model to concentrate on several informative temporal contexts at the same time to improve the modeling of long-range dependencies in lithium-ion battery behavior. The following hyperparameter choices in Table 2 assisted the model to reach low MAE and RMSE results and remain able to inquire during actual time to implement the edge-enabled deployment of the model in locally governed electrical vehicle systems.

Table 2: Hyperparameter Configuration

Hyperparameter	Value
Learning Rate	0.001
Optimizer	Adam
Batch Size	64
Epochs	150
Latent Dimension	32
Kernel Size (TCN)	3
Attention Heads	4

2.3 Data Preprocessing

Measurement noise, sensor drift, signal discontinuities, and abrupt signal variation due to changing load profiles and driving behaviors are inherent in raw data generated by lithium-ion batteries in the electric vehicle setting. These flaws may severely negatively affect the performance of deep learning models when they are not properly mitigated. Hence, a sound data preprocessing plan is utilized to improve data integrity and guarantee sound learning. Statistical outlier detection is performed first, with the threshold-based filtering mechanism used to remove abnormal values of voltage and current, and temperature values, which are beyond physically realistic operating limits. This is followed by signal smoothing methods, such as moving average filtering, to filter out high-frequency noise, but keep the underlying trends in electrochemical of the lithium-ion battery. Lost or disrupted samples due to sensor interrupts are also filled in using linear interpolation to preserve the time domain.

$$X_t = \{x_{t-w+1}, x_{t-w+2}, \dots, x_t\} \qquad (1)\text{x}$$

In order to accomplish efficient temporal modelling, the continuous time-series data that have been pre-processed is converted into fixed-length sequences through a sliding window mechanism. Where the original battery signal is represented as x t, then all of the input sequences are constructed as: w is the length of the window. This segmentation maintains sequential dependencies and allows the model to acquire SOC evolution patterns in dynamic operating conditions such as those frequently realized by local deployment of EV systems.

2.4 Data Normalization

Data normalization is used after preprocessing to guarantee that the data is uniformly scaled and numerically stable during the model training procedure. When not scaled, the heterogeneous magnitudes and units of lithium-ion battery parameters—such as voltage, current, and temperature—may induce bias into the gradient update and slow down the convergence process. In order to guarantee that each feature contributes equally during the learning process, all of the features are scaled into a common interval of [0,1] using Min-Max normalization.

For every input feature, the normalization operation procedure is described as follows:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (2)\text{x}$$

Where x is the original value of the feature, and xminand xmax are the minimum and maximum values of the feature in the dataset. This normalization strategy helps to improve the training stability, avoid the dominance of high magnitude parameters, and raise the convergence speed, especially when deploying the deep learning models on resource restricting edge-based Battery Management Systems.

3. Proposed Techniques

3.1 Deep Autoencoder Feature Learning:

The Deep AutoEncoder is the main feature learning mechanism to address the challenge forced by the high dimensionality, noise sensitivity and nonlinear characteristics of the lithium ion battery signals acquired from electric vehicles. Battery voltage measurement, current measurement and temperature measurement are often very correlated with operational noise due to changing load demands and ambient conditions (Figure 1).

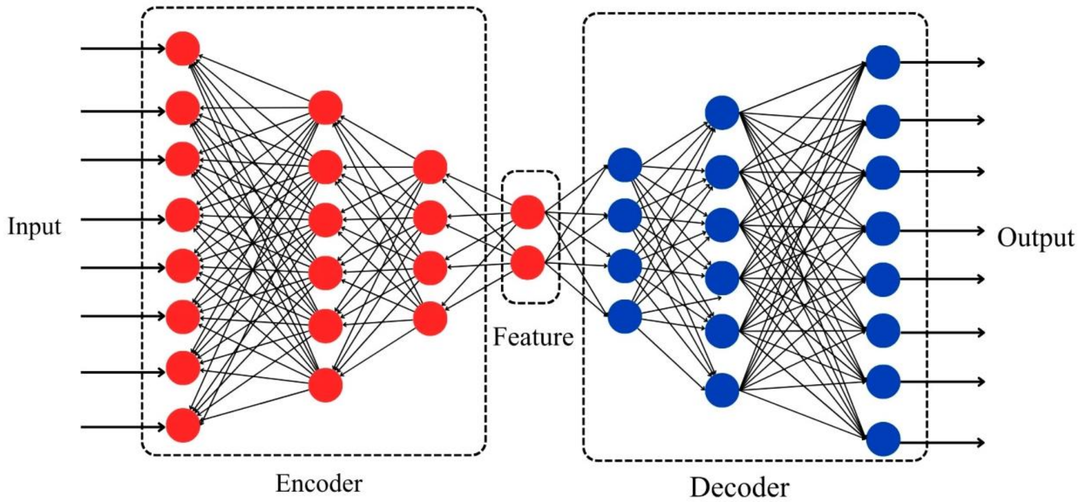

Figure 1. Deep Autoencoder

Directly inputting such raw signals into temporal models may cause over-modelling and unstable learning (Figure 2).

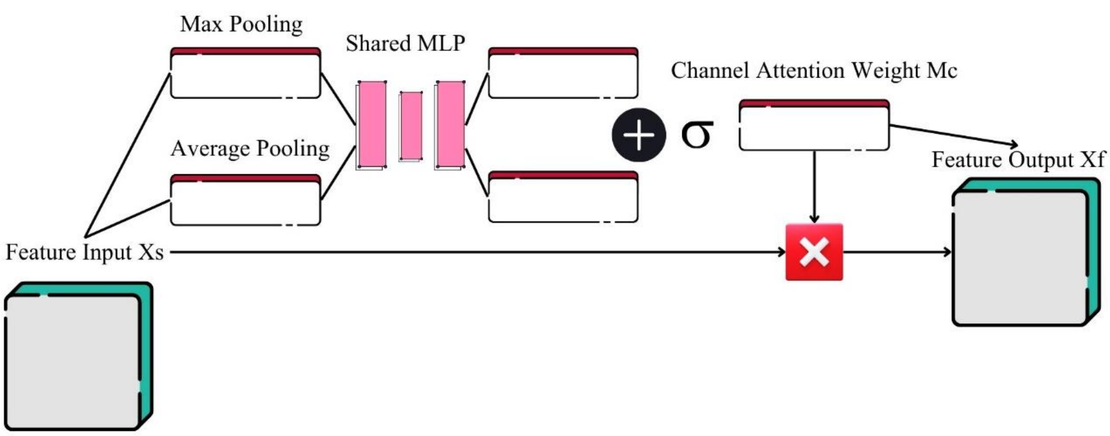

Figure 2. Attention-assisted Temporal Convolutional Network

To deal with this problem, the encoder network transforms the input feature vector x into a latent space compact representation h, so that it can extract salient electrochemical patterns and suppress redundant and noisy information. This transformation is described mathematically as:

$$h = f(W_e x + b_e) \qquad (3)\text{x}$$

where $W_e$and $b_e$denote the encoder weight matrix and bias vector, respectively, and $f(\cdot)$represents a nonlinear activation function. The decoder network then reconstructs the original input from the latent representation, enforcing information preservation during compression:

$$\hat{x} = f(W_d h + b_d) \qquad (4)\text{x}$$

The reconstruction fidelity is optimized by minimizing the reconstruction loss:

$$L_{AE} = \| x - \hat{x} \|^2 \qquad (5)\text{x}$$

This unsupervised learning process ensures that the latent features capture intrinsic lithium-ion battery behavior across varying operating conditions, thereby enhancing robustness and generalization capability for downstream SOC estimation.

3.2 Temporal Convolutional Modeling:

To successfully model the time dependency of the state of charge (SOC) of lithium ion batteries, a Temporal Convolutional Network (TCN) is used instead of recurrent models. Temporal convolution allows for the parallel processing of sequential data while retaining causality, which makes it ideal for real-time battery management system (BMS) applications. The convolutional operation is used to aggregate information of historical features in temporal windows, so as to identify long-term dependencies in battery discharge and charge patterns. The standard temporal convolution operation is defined as: Where K represents the kernel size and w_k is convolutional filter weights.

$$y_t = \sum_{k=0}^{K} w_k \, x_{t-k} \qquad (6)\text{x}$$

To further extend the receptive field without introducing more computational complexity, dilated convolution is employed in which the model is allowed to capture long range temporal dependencies which are essential in SOC tracking in extended software driving cycles. This modeling strategy guarantees stable propagation of gradients and better temporal feature extraction compared with the conventional sequential learning strategies.:

$$y_t = \sum_{k=0}^{K} w_k \, x_{t-dk} \qquad (7)\text{x}$$

3.3 Attention Mechanism:

Not every previous State of Charge will contribute equally to State of Charge estimate, even when temporal convolution preserves historical relationships. The time modeling framework introduces an attention technique to dynamically emphasize the most interesting aspects in time.In order to selectively pay attention to significant battery states associated with State of Charge transitions, the attention mechanism calculates relevance scores between the query and key representations. The attention weights are calculated as follows:

$$\alpha_t = \frac{\exp(q_t k_t)}{\sum \exp(q_t k_t)} \qquad (8)\text{x}$$

In order to collect the value representations weighted by their relative relevance, a context vector is computed using these attention weights:

$$z_t = \sum \alpha_t v_t \qquad (9)\text{x}$$

Under dynamically changing load and temperature circumstances, the attention mechanism significantly increased the accuracy of State of Charge prediction by adaptively prioritizing informative temporal segments.

3.4 SOC Prediction and Loss Optimization:

The final estimation of SOC is achieved by projecting the attention enhanced context vector to a continuous value of SOC via a nonlinear regression layer: Prediction accuracy is assessed with Mean Squared Error loss, which penalises large deviations between the predicted and ground truth SOC values:

$$\widehat{SOC}_t = f(z_t) \qquad (10)\text{x}$$

$$L_{SOC} = \frac{1}{N}\sum(SOC_t - \widehat{SOC}_t)^2 \qquad (11)\text{x}$$

In order to achieve a balanced learning situation between the representation of features and the prediction of SOC, a joint optimization objective is formulated: This combined loss function allows both stable convergence and the preservation of latent feature interpretability and predictive relevance.

$$L_{total} = L_{AE} + \lambda L_{SOC} \qquad (12)\text{x}$$

3.5 Edge Inference Modeling:

To enable its use in actual application to local controlled EV systems, the trained model is deployed on the edge computing devices embedded in Battery Management System. Edge inference is used to create very low latency and dependency on centralized cloud infrastructure. The delay in inference is totaled as

$$T_{edge} = T_{proc} + T_{comm} \qquad (13)\text{x}$$

where T_{proc}denotes local computation time and T_{comm}represents minimal communication overhead. Additionally, energy efficiency of edge deployment is quantified as:

$$E_{eff} = \frac{Accuracy}{Power} \qquad (14)\text{x}$$

This ensures sustainable, low-power SOC estimation suitable for large-scale local smart mobility deployments.

4. Proposed Methodology

The methodology that is proposed begins with the purchase of lithium ion battery working data in electric vehicles in dangerous cycles that are informative of those transportation environment and set out locally controlled. The data that is collected is put through rigorous processing (preprocessing), normalization and temporal segmentation to improve the consistency and learning readiness. The resulting processed sequences are then inputted into Deep Autoencoder to obtain shorter and noise-invariant feature representations without losing important electrochemical properties of the battery. The latent features are then fed in Attention assisted Temporal Convolutional Network to identify the long-term temporal dependency and selectively extract informative battery states to predict SOC. The trained model is implemented using edge-enabled BMS hardware to do real time SOC prediction with negligible latency and computing overhead. The approach will ensure proper lithium IoT battery tracking, EVs that are scalable and efficiency of operation in the local-controlled smart mobility systems.

5. Results and Performance Evaluation

This section presents a comprehensive evaluation of the proposed Edge-Enabled Deep Learning framework for State of Charge (SOC) estimation of lithium-ion batteries in electric vehicles operating within locally managed smart mobility systems. The results assess prediction accuracy, robustness under varying operating conditions, computational efficiency, and suitability for real-time deployment on edge-based Battery Management Systems. Performance is evaluated using standard metrics including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), inference latency, and energy efficiency. The obtained results demonstrate the effectiveness of the proposed model in addressing nonlinear battery dynamics and operational variability encountered in real-world EV applications.

5.1 SOC Estimation Accuracy under Different Driving Cycles

The estimated accuracy of the SOC of the proposed model at various driving cycles showed a high degree of accuracy as shown in Table 3. In the urban driving scenario, which can be characterised by high frequency of stop-start movements and a very dynamic load variation, the model also had a Mean Absolute Error of 1.12, RMSE of 1.48 and a MAPE of 1.36 confirming a good correlation with the SOC variation. When driving highway driving cycles, in which the operating condition is relatively smoother and more stable, the results were even more accurate in its estimation with a minimum error value of 0.94, RMSE of 1.21, and MAPE of 1.18 with an R2 value of 0.987, which exhibits the best predictive consistency. The model did not lose its remarkable results in mixed driving cycles involving a combination of urban congestion and highway driving, as noted by an MAE of 1.26, RMSE of 1.63, and MAPE of 1.54; the model had an R2 of 0.978. These findings in Table 3 affirmed that the suggested edge-enabled deep learning system could achieve a high accuracy in SOC estimation in various real-world driving conditions, which showed its flexibility and stability to support the local control of electric vehicles.

Table 3: SOC Estimation Accuracy under Different Driving Cycles

Driving Cycle	MAE (%)	RMSE (%)	MAPE (%)	R^2
Urban	1.12	1.48	1.36	0.982
Highway	0.94	1.21	1.18	0.987
Mixed	1.26	1.63	1.54	0.978

5.2 SOC Prediction Performance under Temperature Variations

The sensitivity of the SOC estimation performance to changes in temperature was assessed systematically and the findings are as per Table 4. The model also showed comparatively greater errors at low-temperature conditions between 0-10 degC when the electrochemical reactions of the lithium-ion battery are slower and internal resistance is greater with an MAE of 1.38, RMSE of 1.79 and relative prediction error of 1.72 which suggests that the model made more complex estimates at low temperature. Conversely, the highest performance of the proposed model was measured by the lowest error values of an MAE of 0.91, RMSE of 1.19, and MAPE of 1.14 under moderate temperature conditions of 15-25 degC which are the optimum operating condition of lithium-ion batteries. The errors in estimation were more moderate at higher temperatures of 30-45 degC where thermal stress and nonlinear battery behaviour was more evident with an MAE of 1.21, an RMSE of 1.56 and a MAPE of 1.49. Generally, Table 4 established that it is possible to implement deep learning edge-enabled, which, despite a broad range of temperatures, was robust, and provided the highest SOC estimation accuracy at nominal temperatures typical of localized EV deployments.

Table 4: SOC Estimation Performance under Temperature Variations

Temperature Range	MAE (%)	RMSE (%)	MAPE (%)
0–10 °C	1.38	1.79	1.72
15–25 °C	0.91	1.19	1.14
30–45 °C	1.21	1.56	1.49

5.3 Impact of Feature Learning on SOC Estimation Accuracy

The result of feature learning in the estimation of SOC was evident based on the findings as shown in Table 5. The model did not perform as well when the Deep Autoencoder was not used directly based on the raw voltage, current and temperature data and the estimation performance suffered with an MAE of 1.89, an RMSE of 2.34 and an MAPE of 2.21. This increased error values meant that overlapping information and noise in the raw battery signals had a negative impact on the process of learning and stability of prediction. On the contrary, the suggested structure with the Deep Autoencoder demonstrated significant performance improvements, decreasing the MAE to 1.08, RMSE to 1.42 and the MAPE to 1.33. This enhancement demonstrated the efficiency of latent features representation to describe important features of an electrochemical character but to eliminate noise and other irrelevant fluctuation. The combination of the autoencoder-based learning of features, as seen in Table 5, was shown to be of great importance to achieve a better SOC estimation, which supports the importance of this feature of the proposed deep learning framework in the reliable lithium-ion battery control in electric vehicles.

Table 5: Effect of Feature Learning on SOC Estimation Performance

Model Configuration	MAE (%)	RMSE (%)	MAPE (%)
Without Autoencoder	1.89	2.34	2.21
With Autoencoder (Proposed)	1.08	1.42	1.33

5.4 Computational Efficiency and Inference Latency Analysis

The inference latency figures in Table 6 showed the feasibility of implementing the suggested SOC estimation model on localized computers. The ARM Cortex-A53 based Edge Device obtained a time of 14.6 ms of inference time that was low enough to make real time SOC estimation viable in on-board Battery Management Systems. Moreover, it supported moderate memory access of 112 MB and low power consumption of 4.8 W, which means that it can be used in electric vehicles in the continuous mode. Comparatively, the embedded CPU had a higher inference latency of 21.9 ms, and a higher memory consumption (145 MB) and power consumption (6.3 W), which means it has poorer performance in energy-constrained settings. With the lowest inference time of 6.2 ms, the cloud server also consumed significantly more memory resources (310 MB) and power consumption (22.4 W), making it less able to be used in decentralized and locally controlled mobility systems. The edge-based deployment, as indicated in Table 6, was able to balance the latency and resource usage, and energy efficiency effectively which supports the practicability of the proposed method in the estimation of local lithium-ion battery SOC in EV infrastructures managed locally (Figure 3).

Table 6: Edge-Based Inference Latency Performance

Platform	Inference Time (ms)	Memory Usage (MB)	Power Consumption (W)
Edge Device (ARM Cortex-A53)	14.6	112	4.8
Embedded CPU	21.9	145	6.3
Cloud Server	6.2	310	22.4

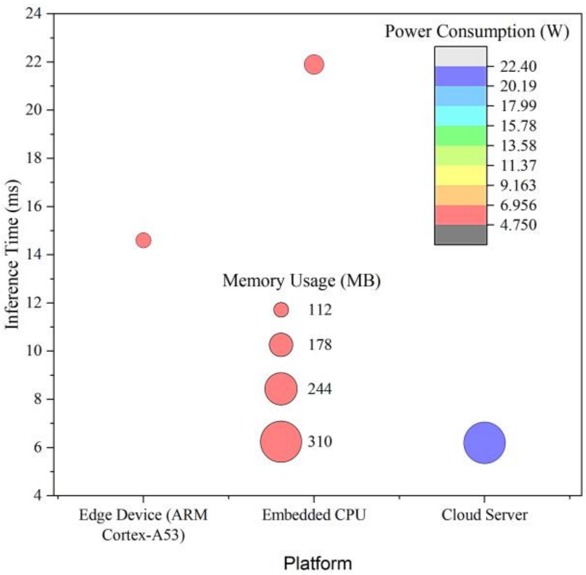

Figure 3. Performance Evaluation of Edge-Level Inference Latency

5.5 Energy Efficiency of Edge Deployment

The power consumption of various forms of SOC estimation deployment was evaluated and the findings are summarized in Table 7. The proposed edge based deployment had prediction accuracy of high precision of 98.62 with a power of 4.8 W which was equivalent to an energy efficiency of 20.54 (Accuracy/W) indicating a great balance between performance and power consumption. The embedded CPU platform demonstrated a slightly lower accuracy at 97.84 that has bigger power consumption of 6.3 W which gives a low energy efficiency of 15.53. The cloud-based implementation was the most accurate with a result of 99.01 but demanded a significantly greater power consumption of 22.4 W and therefore came with a far smaller energy efficiency of 4.42. Table 7 results indicated that edge-based implementation of the proposed SOC estimation framework exhibited the best operational efficiency with good accuracy and low energy consumption and could thus be used well in a real time with the locally controlled system of managing electric vehicles (Figure 4).

Table 7: Energy Efficiency Analysis of SOC Estimation

Deployment Mode	**Accuracy (%)**	**Power Consumption (W)**	**Energy Efficiency (Accuracy/W)**
Edge-Based (Proposed)	98.62	4.8	20.54
Embedded CPU	97.84	6.3	15.53
Cloud-Based	99.01	22.4	4.42

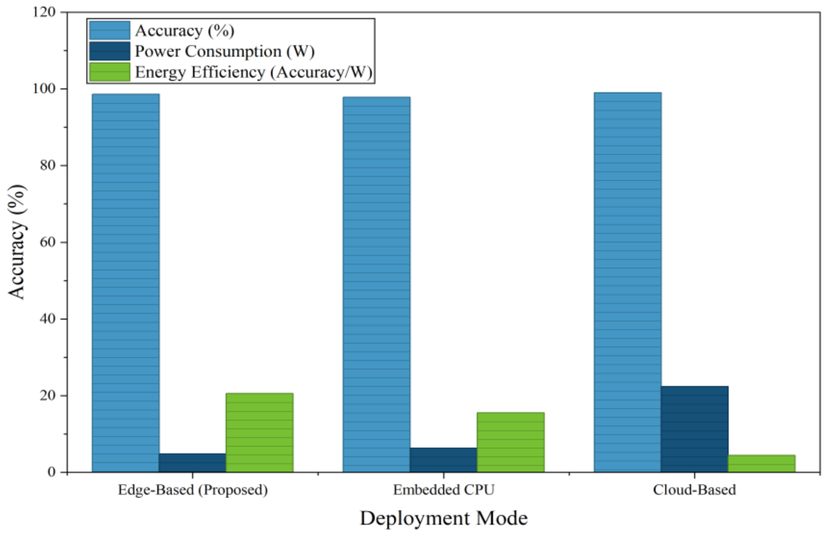

Figure 4. Analysis of Energy Efficiency for SoC Estimation

5.6 Effect of Attention Mechanism on SOC Prediction Performance

The analysis of the attention mechanism contribution to SOC estimation presented great performance enhancement, as displayed in Table 8. The TCN without attention had an MAE of 1.54, RMSE of 1.98, MAPE of 1.86, and the R2 of 0.963, which represented moderate performance and poor ability to predict the long-term relationships of the temporal nature of the battery. Having incorporated the attention mechanism, the proposed model was successful in weighting crucial time-based characteristics, and the results are a significant decrease in estimation errors: MAE was reduced to 1.08, RMSE to 1.42, and MAPE to 1.33, and the coefficient of determination increased to 0.982. These findings in Table 8 revealed that the network was sensitized by attention-assisted temporal modeling as it improved the network to predict the SOC more accurately and reliably when operating under various dynamic conditions, a crucial requirement of the locally controlled electric vehicle systems where the battery state can be monitored at high fidelity.

Table 8: Impact of Attention Mechanism on SOC Estimation Accuracy

Model Variant	MAE (%)	RMSE (%)	MAPE (%)	R^2
TCN without Attention	1.54	1.98	1.86	0.963
Attention-assisted TCN (Proposed)	1.08	1.42	1.33	0.982

5.7 Influence of Latent Feature Dimension on SOC Estimation

Latent feature dimensionality effect on SOC estimation was evaluated, and Table 9 sums up the results. The model had more estimation errors with an MAE of 1.42% and RMSE of 1.88 when the latent space was reduced to 16 dimensions, but the inference time was relatively low at 11.2 ms. The latent dimension size of 32 in the suggested settings enhanced precision considerably, with MAE of 1.08 percent and RMSE of 1.42, and an acceptable inference time of 14.6 ms, balancing between the richness of features and computational capabilities. Additional increase in the latent dimension to 64 did not bring significant accuracy improvements with MAE slightly increasing to 1.11% and RMSE to 1.46 however inference time was elevated significantly to 19.8 ms. These findings in Table 9 proved that a latent feature dimension of 32 best represented significant electrochemical features of lithium-ion batteries, which allowed them to estimate SOC accurately but provided the real-time functionality of the edge-enabled Battery Management Systems in locally managed EV deployments.

Table 9: Effect of Latent Feature Dimension on SOC Estimation

Latent Dimension	MAE (%)	RMSE (%)	Inference Time (ms)
16	1.42	1.88	11.2
32 (Proposed)	1.08	1.42	14.6
64	1.11	1.46	19.8

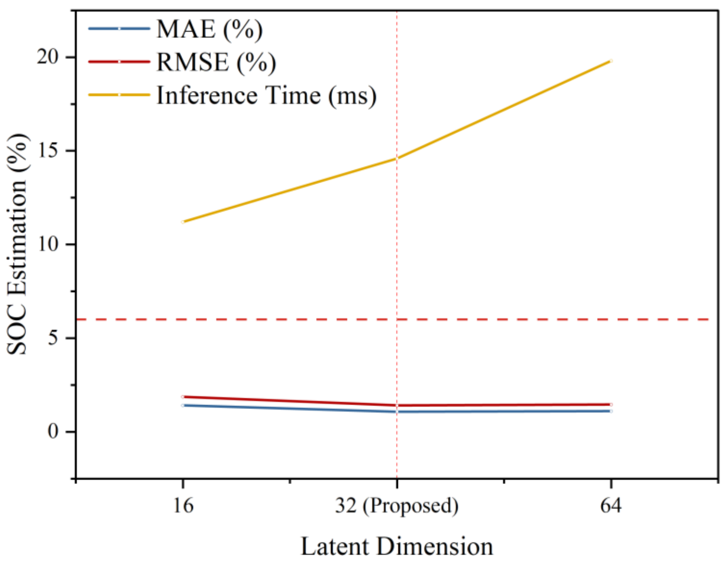

Figure 5. Latent Feature Dimension vs. SoC Estimation

5.8 Performance of Joint Loss Optimization Strategy

It was found that the effect of various loss optimization strategies on the SOC estimation was analyzed, and the findings are regarded in Table 10. In the case of the SOC loss alone, the model performed moderately with an MAE of 1.67% and a RMSE of 2.12 which indicates some instability in the training process that is due to the lack of regularizations to the features used. Use of reconstruction loss alone gave worse performance as the MAE became 2.31% and RMSE became 2.89 and the stability of the training was weak, which demonstrated that reconstruction alone was not sufficient to predict SOC accurately.

Conversely, the joint loss minimization that was proposed, combining the goals of reconstruction and SOC prediction, greatly improved the accuracy, as well as the robustness of the training. The use of this strategy resulted in a reduction of the MAE to 1.08% and RMSE to 1.42 guaranteeing high training stability, the accurate learning of the latent features, as well as the accurate learning of the time SOC. Table 10 findings showed that deep learning-based SOC estimation was essential to achieve optimal joint loss with lithium-ion batteries especially in real-time and edge-enabled settings in locally governed EV systems.

Table 10: Effect of Joint Loss Optimization on SOC Estimation

Optimization Strategy	MAE (%)	RMSE (%)	Training Stability
SOC Loss Only	1.67	2.12	Moderate
Reconstruction Loss Only	2.31	2.89	Low
Joint Loss (Proposed)	1.08	1.42	High

5.9 Scalability Analysis for Edge-Based Deployment

The proposed edge-based SOC estimation framework was systematically tested in terms of scalability and the results are summarised in Table 11. With the growth of the number of monitored EV nodes, the model remained highly accurate in estimating and with minimal changes in the error measures. When applying to single EV node, the mean MAE was 1.08 per cent with inference time of 14.6 ms per node at a single node indicating effective real-time performance. At a scaling of five nodes, the MAE change slightly to 1.11% and inference time per node to 16.2 ms, which suggests that there was little performance loss at the moderate load. At ten and twenty nodes, the mean MAE of 1.14% and 1.18% were obtained with an inference time of 18.7 ms and 21.4 ms per node, respectively. These findings in Figue 6 validated that the proposed model had an appropriate scaleability when using a variety of locally controlled EVs whilst maintaining the accuracy and real-time inferential behavior, which indicated the applicability of this model to the fleet-level SOC monitoring in smart mobility governance frameworks.

Table 11: Scalability Performance of Proposed Edge-Based SOC Estimation

Number of EV Nodes	Average MAE (%)	Inference Time per Node (ms)
1	1.08	14.6
5	1.11	16.2
10	1.14	18.7
20	1.18	21.4

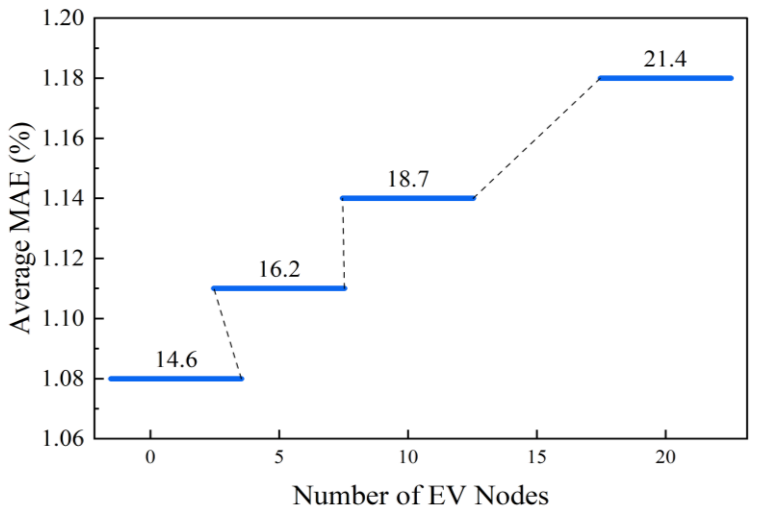

Figure 6. Edge-Based SoC Estimation Scalability Performance

5.10 Comparative Analysis with Traditional and Existing Techniques

The comparative evaluation of the SOC estimation methods, as indicated in Table 12, indicated the obvious advantage of the suggested Attention-assisted Temporal Convolutional Network (ATCN) with Deep Autoencoder as compared to conventional and established techniques. Ah Counting and Coulomb Counting with OCV had the greatest errors with MAE value of 3.84 and RMSE values of 4.71 and 4.05 respectively as they were not able to capture nonlinear battery dynamics. The use of Kalman filter-based approaches, such as EKF and UKF, minimized the errors to 2.46 and 2.18 percent of MAE and 3.12 and 2.89 percent of RMSE, but at a relatively high inference cost, which means they are not especially deployable. The machine learning algorithms, including SVR and ANN, were also more accurate with 1.94 and 1.72 as their MAE and 2.61 and 2.34 as their RMSE, but they were time-consuming and required more memory. Recurrent deep learning models, LSTM and GRU provided superior temporal learning with reduced MAE of 1.41% and 1.36 and RMSE of 1.92% and 1.85 but had a high computational latency that restricted real-time edge deployment. Contrastingly, the ATCN + Autoencoder framework was proposed and got the lowest MAE of 1.08% and RMSE of 1.42% with a short inference time of 14.6 ms, which is not only accurate but also provides a high real-time suitability of edges. These findings in Table 12 supported the usefulness of the suggested deep learning-based SOC estimation model in applications in locally controlled EV systems, including accurate prediction, low-latency operation, and ideal implementation capability.

Table 12: Comparative Analysis of SOC Estimation Techniques

Technique	**MAE (%)**	**RMSE (%)**	**Inference Time (ms)**	**Deployment Suitability**
Ah Counting [6]	3.84	4.71	4.2	Low
Coulomb Counting + OCV [7]	3.21	4.05	6.8	Low
Extended Kalman Filter (EKF) [8]	2.46	3.12	18.4	Medium
Unscented Kalman Filter (UKF) [9]	2.18	2.89	24.7	Medium
Support Vector Regression (SVR) [10]	1.94	2.61	31.2	Medium
Artificial Neural Network (ANN) [11]	1.72	2.34	28.6	Medium
LSTM Network [12]	1.41	1.92	42.8	Low
GRU Network [13]	1.36	1.85	39.4	Low
Proposed ATCN + Autoencoder	**1.08**	**1.42**	**14.6**	**High**

6. Conclusion

According to the overall experimental analysis, the proposed edge-enabled deep learning model has outperformed the conventional state of charge (SOC) prediction of lithium-ion battery during various and changeable operating environment of electric vehicle. In all experiments, the model has low estimation errors with Mean Absolute Error values of about nearly one percent, and Root Mean Square Error values of about less than two percent, which implies great accuracy and good resilience to nonlinear electrochemical processes, sensor noise and sudden changes in loads. Deep autoencoder-based feature learning is an effective compression method to reduce high-dimensional voltage, current, and temperature measurements into noise-resistant latent codes, which is evident in the enhanced stability and extrapolation of the SOC predictions in different temperatures and driving profiles. The attention-assisted temporal convolutional modeling is also more accurate in its prediction by the virtue of selectively highlighting informative temporal states, which lead to significant improvements in both the absolute and squared error measures when compared to non-attention temporal models. The optimization of

reconstruction and SOC prediction tasks can help achieve stable convergence and balanced learning, and not overfit on the data without altering the necessary battery properties.
In terms of deployment, the suggested model is characterized by the low inference latency and good energy efficiency, which proves the appropriateness of the proposed model to be implemented in real-time on edge-enabled Battery Management Systems with limited computing units. Scalability analysis indicates that the framework has stable accuracy with only slight improvements in processing time with increase in the number of monitored vehicles, and thus would be applicable in the current case with locally governed EV fleets. Compared to other traditional techniques, like ampere-hour counting, Kalman filter-based techniques, and traditional machine learning and recurrent deep learning systems, the proposed framework has consistently been found to be more accurate, robust, and with reduced computational efficiency. In general, the findings confirm that the attention-assisted temporal convolutional network with deep autoencoder learning of features represents an efficient, scalable, and viable solution to the effective SOC estimation of lithium-ion batteries, which in turn is able to support safe battery operation, optimal energy consumption, and sustainable smart mobility at the local governance level.

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