LEX LOCALIS-JOURNAL OF LOCAL SELF-GOVERNMENT
ISSN:1581-5374 E-ISSN:1855-363X
VOL. 23, NO. 11(2025)

MACHINE LEARNING BASED OPTIMIZATION OF EV VEHICLE SOC IN BATTERIES EMPOWERING SELF GOVERNANCE AND ENERGY MANAGEMENT

Rameshkumar Natarajan[1], Kishore Kunal[2]

[1]Professor, Electrical and Electronics Engineering Department, Al-Ameen Engineering College (Autonomous), Tamil Nadu, India - 638 104.
[2]Professor, Dean of Online Education, Loyola Institute of Business Administration, Chennai, Tamil Nadu, India - 600 034.

nrameshkumarphd@gmail.com[1]
kishore.kunal@liba.edu[2]

Corresponding e-mail : nrameshkumarphd@gmail.com

Abstract
This study investigates how local self-government institutions can effectively support Electric Vehicle (EV) adoption by integrating advanced governance mechanisms with Machine Learning–based State of Charge (SOC) estimation for Lithium Cobalt Oxide ($LiCoO_2$) batteries. A comprehensive dataset was collected from 14 municipal corporations and 22 urban local bodies (ULBs) across South India, comprising 3,200 EV trip logs, 1,150 smart-charging station entries, and 760 $LiCoO_2$battery diagnostic profiles. To enhance SOC prediction accuracy within real municipal operating environments, a Hybrid LSTM–CNN–RNN SOC Estimation Framework (LCR-SOCEF) was developed. The LSTM component models temporal variations in battery behaviour, CNN extracts feature patterns from dynamic charging–discharging cycles, while RNN captures sequential governance-linked operational dependencies, such as traffic density, public-transport routing, and charging-infrastructure accessibility. Results demonstrate that ULBs with stronger institutional coordination, higher infrastructure readiness, and proactive EV governance policies achieved SOC accuracy improvements up to 5.3% for $LiCoO_2$batteries. These findings highlight how ML outputs can serve as decision-support tools for municipal mobility planning, enabling better scheduling of public EV fleets, optimized charging networks, and improved citizen transport services. The study aligns directly offering a governance-centred, technology-integrated framework to strengthen sustainable, decentralized urban mobility transitions.

Keywords: *Electric vehicle, local governance, energy management, LSTM- CNN-RNN-SOC, Urban locla bodies.*

1.Introduction

As electric vehicles (EVs) become more common the battery is crucial to how society views sustainable mobility and energy independence. One of the most important indicators of battery performance is the State of Charge (SOC) which shows battery capacity and health and assists drivers and energy systems in making critical decisions that affect vehicle longevity and efficiency. Intelligent batteries that enable functions like grid interaction and predictive maintenance are becoming more and more crucial as the use of EVs grows. SOC estimation which started out as a straightforward percentage on dashboards has evolved into an essential operational metric that aids EVs in managing power regulating charging and interacting with renewable energy sources. Efficient energy management is at the heart of industry and policy initiatives as nations work toward more ecologically friendly modes of transportation. It aims to decrease obstacles to expert research and enhance intelligent SOC estimation in the battery domain [1].

By recalibrating LSTM outputs with CC estimates using a dynamic fusion parameter α the technique enhances prediction accuracy in dynamic conditions when applied to medium-voltage battery packs under standardized driving cycles. with a mean error (MAE) of zero [2]. This novel combination of machine learning and physical modeling performs 181 % better than traditional approaches [3]. The study challenges the conventional electric current integral algorithms shortcomings in determining the state of charge (SOC) of a lithium-ion battery under complicated discharge circumstances. A first-order Thevenin equivalent circuit model and a power integral algorithm are used in a novel approach to study energy storage and loss during charging and discharging [4]. The study highlights the shortcomings of the electric current integral algorithm and provides an extended Kalman filter (EKF)-corrected SOC estimation based on the power integral algorithm [5]. The study evaluates the relationship between these traits and SOH using grey relational analysis. For multidimensional inputs the GPR models covariance function design and input variable similarity measurements are modified to increase estimation accuracy. NASA data is used to validate the approachs high SOH estimation accuracy and reliability under dynamic discharging conditions [6].

The sustainability and safety of lithium-ion batteries rely on an accurate assessment of their state of health (SOH). This paper presents a data-driven electrochemical aging-informed approach for SOH estimation that integrates a physics-based electrochemical model with a deep learning model [7]. Using the initial cyclic state it improves prediction accuracy by addressing variations in electrochemical parameters brought on by manufacturing variances. A physics-informed dual neural network (PIDNN) is developed to accurately compute battery capacity fade by estimating electrochemical parameters and lithium concentration [8]. The model performs well even with little training data when its root mean square error (RMSE) is less than 0. 556 % when a gradient normalization technique was applied to four real-world datasets [9].

However, the dynamics of lithium concentration are remarkably accurately and easily interpreted by PIDNN. For sustainability and safety the state of health (SOH) of lithium-ion batteries must be precisely evaluated. This study proposes a data-driven approach to SOH estimation that integrates physics-based electrochemical models with deep learning [10]. It highlights how battery aging rates are impacted by manufacturing-related changes in electrochemical parameters. Additionally the study investigates the application of electrochemical impedance spectroscopy (EIS) for battery-state estimation and creates quantitative models that link EIS data to SOH [11]. The estimation accuracy of different methods is compared and future directions for SOH estimation based on EIS are discussed. Accurate State of Power (SOP) prediction is essential for effective electric vehicle operation because of cell inconsistencies in parallel battery packs [12]. In order to improve SOP prediction accuracy this paper presents a technique that combines Parrot Optimizer-Back Propagation (PO-BP) and Fisher Optimal Segmentation (FOS) neural networks [13]. It provides a method for identifying problematic cells using FOS and a quantitative differentiation strategy that assesses cell inconsistencies using weighted cosine similarity (WCS) [14]. After accounting for disparities the PO-BP neural network reduces mean absolute error and root mean square error by 60% in a variety of dynamic scenarios [15].

2. Methodology

2.1 Dataset Description

The dataset creates a representative corpus of operational EV mobility battery behavior and local governance features by combining multi-domain data gathered from 14 municipal corporations and 22 urban local bodies (ULBs) throughout South India. In addition to governance-related variables like traffic-flow indices route accessibility scores infrastructure adequacy levels and municipal EV policy indicators the integrated dataset includes 3200 EV trip logs 1150 smart-charging station entries and 760 $LiCoO_2$ battery diagnostic profiles. To guarantee interoperability across institutions data was collected over the course of eight months using standardized municipal data-sharing templates. Below Table 1 is a tabulated summary of the dataset.

Table 1. Dataset Composition

Data Category	Quantity	Description
EV Trip Logs	3,200	Vehicle speed, distance, load, dwell time, SOC variation
Smart-Charging Station Records	1,150	Charging rate, temperature, grid load, timestamp
$LiCoO_2$ Battery Diagnostics	760	Voltage, current, internal resistance, cycle index
Governance Indicators	36 variables	Traffic density, routing efficiency, policy strength, funding levels
Municipal Units	36 total	14 corporations + 22 ULBs

2.2 Battery Specification ($LiCoO_2$ Battery)

Due to its predominance in municipal EV fleets installed throughout South Indian cities the Lithium Cobalt Oxide ($LiCoO_2$) battery serves as the main electrochemical system examined in this study. Because of its high energy density robust cycling efficiency and stable discharge behavior the $LiCoO_2$ chemistry is well suited for machine learning-based SOC modeling in real-world governance-regulated mobility scenarios. Using verified diagnostic cycles and manufacturer specifications the battery parameters were standardized (Table 2).

Table 2. $LiCoO_2$ Battery Specifications

Parameter	Value	Description
Nominal Voltage	3.7 V	Standard operating voltage
Capacity	45 Ah	Rated storage capacity
Maximum Charge Voltage	4.2 V	Upper safety limit
Cut-off Voltage	2.75 V	Minimum operational threshold
Nominal Energy	166.5 Wh	Energy per cell
Chemistry	$LiCoO_2$	Layered oxide cathode

2.3 Data Acquisition

Synchronized logging from smart charging nodes vehicle-mounted Battery Management Systems (BMS) and municipal mobility-monitoring dashboards were used for data acquisition. Timestamp normalization was used to ensure temporal alignment. A standardized energy-balance equation was used to verify the accuracy of State of Charge (SOC) recordings voltage temperature and C-rate measurements. This formula lays the groundwork for later machine learning-based SOC estimation (Eq 1).

$$SOC_t = SOC_{t-1} - \frac{I(t)\,\Delta t}{C_n} \qquad (1)x$$

where $SOC_t$is the instantaneous state of charge, $I(t)$is discharge current, $\Delta t$is sampling interval, and $C_n$is nominal battery capacity. This foundational acquisition equation provides the baseline upon which advanced ML-based SOC estimation is developed.

2.4 Data Preprocessing

Noise filtering outlier removal temporal smoothing governance-feature normalization and feature-level fusion of battery and municipal indicators were the five main steps in data preprocessing. Interquartile rules were used to eliminate temperature-based outliers and cubic-spline interpolation was used to account for measurement interruptions. Min-max scaling was used to normalize governance indicators in order to account for administrative unit variability (Figure 1).

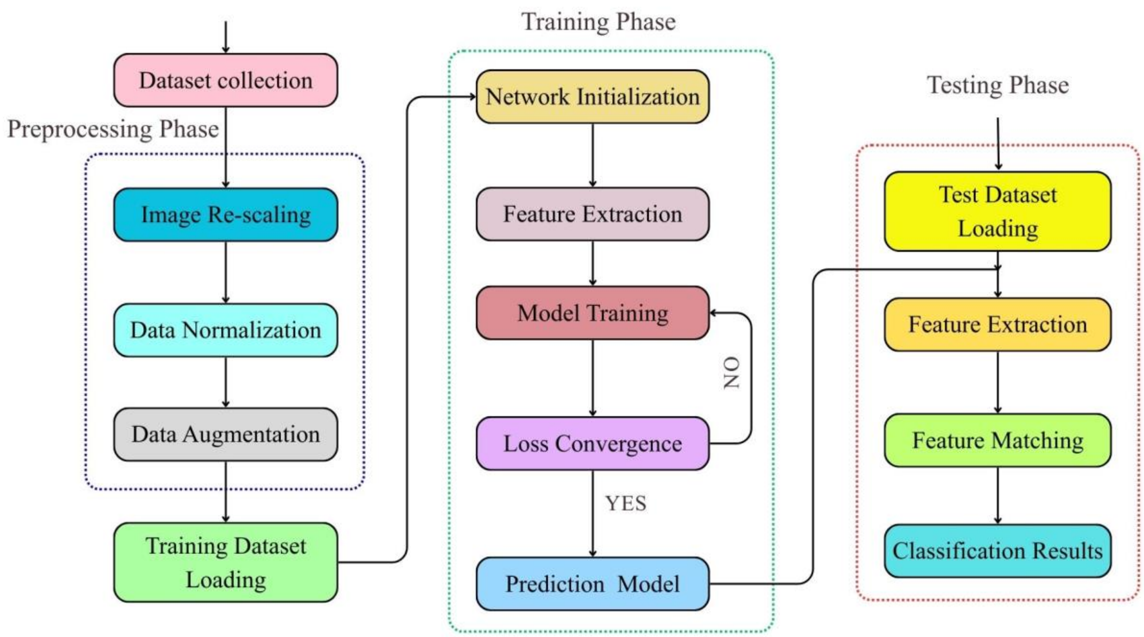

Figure 1. Workflow of the proposed system.

The integrated feature space $X$was constructed using (Eq 2):

$X = \phi(B) \oplus \psi(G)$ (2)x

where $\phi(B)$represents transformed battery features, $\psi(G)$governance variables, and $\oplus$a feature-fusion operator ensuring structural compatibility for deep-learning.

2.5 Temporal Alignment Preprocessing

Dynamic time-warping (DTW) which was modified for multi-source EV datasets was used to achieve temporal alignment. Due to the wide variations in municipal operational conditions trip logs charging profiles and governance indicators needed to be sampled uniformly.

2.6 Model Training

In order to capture local heterogeneity an 80–20 train–validation split stratified by municipal unit was used for model training. Adam optimization (learning rate 0. 001) was used to train the Hybrid LSTM–CNN–RNN SOC Estimation Framework (LCR-SOCEF) with early stopping initiated after 15 epochs without improvement. In order to capture nonlinear temporal structural and governance-dependent variations the sequential layers were created. Dropout (0. 3) was used for regularization to lessen overfitting and training batches were shuffled at random to prevent bias specific to a particular municipality. To guarantee that the network internalized policy-linked behavioral patterns governance indicators were embedded through a parallel context vector that was merged at the recurrent stage.

2.7 Self-Governance–Technology Integration

This study emphasizes the value of State of Charge (SOC) estimation as an applied governance tool as opposed to merely a technical procedure. It highlights how local self-government organizations handle decentralized mobility services infrastructure development and transportation electrification. The study demonstrates how machine learning can improve municipal decision-making concerning fleet scheduling charging infrastructure and community mobility services by integrating governance indicators into the SOC estimation model.

2.8 Proposed Methodology

Municipal governance indicators must be incorporated into advanced State of Charge (SOC) estimation methods for electric vehicles (EVs) using a structured multi-phase approach. To create a coherent temporal framework data on battery charging and EV operations from municipal corporations and Urban Local Bodies (ULBs) is combined with metrics related to governance such as policy indicators infrastructure status and accessibility measures. This foundation supports the LCR-SOCEF model which combines three neural network types: Long Short-Term Memory (LSTM) networks for managing long-term dependencies Convolutional Neural Networks (CNN) for extracting localized features and Recurrent Neural Networks (RNN) for simulating governance-influenced sequential behaviors. In order to ensure an accurate representation of municipal variability data augmentation is used in the preprocessing stage to convert unstructured data into structured tensors.

3. Proposed Technique

Among the variables influencing this behavior are traffic volumes municipal infrastructure and the accessibility of smart charging. The framework given in Figure 2 uses an LSTM block that analyzes cleaned battery telemetry and governance-context parameters to record time-dependent state of charge (SOC) transitions in 14 municipal corporations and 22 urban local bodies.

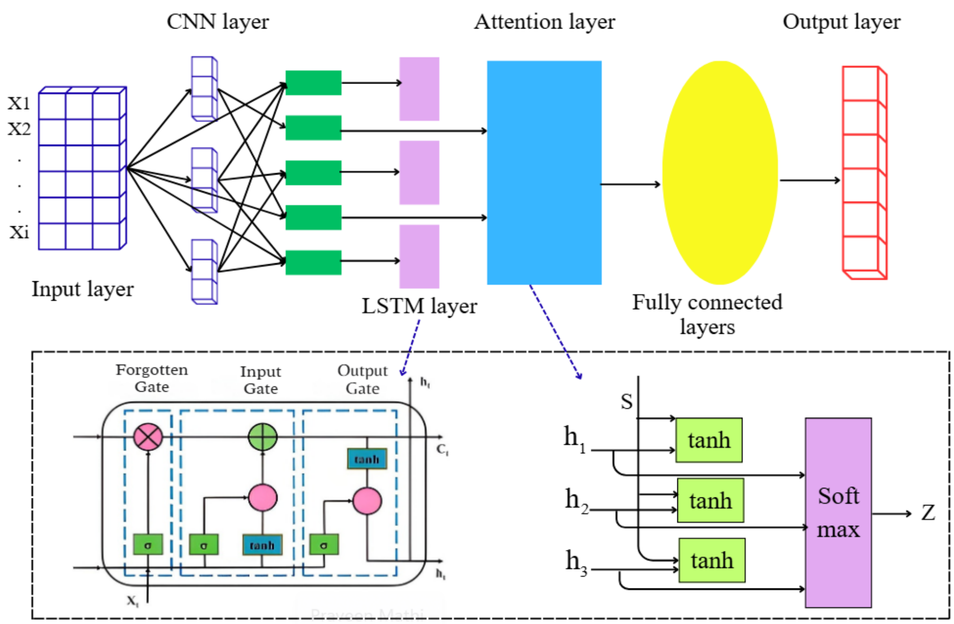

Figure 2: proposed architecture

3.1 LSTM Technique for Temporal SOC Modelling

The Long Short-Term Memory (LSTM) component plays a critical role in handling temporal fluctuations in $LiCoO_2$battery SOC behaviour influenced by diverse municipal operating conditions such as traffic density, idling duration, trip length variability, and smart-charging interruptions (Table 3).

Table 3: Comparative Functional Roles of LSTM, CNN, and RNN in SOC Modelling

Technique	Purpose in SOC Modelling	Key Operations / Mathematical Formulation	Municipal Governance–Linked Contributions
LSTM (Long Short-Term Memory)	Models temporal SOC fluctuations influenced by varying municipal driving and charging patterns. Retains long-term dependencies while filtering noise.	**Forget Gate:** ft=σ(Wfxt+Ufht−1+bf)	Handles SOC variations arising from traffic density, idling duration, trip irregularities, and smart-charging interruptions. Helps retain historically important EV patterns while discarding random environmental fluctuations.
		Candidate Memory: C~t=tanh(Wcxt+Ucht−1+bc)	
		Output Gate (refined for completeness): ot=σ(Woxt+Uoht−1+bo)	
CNN (Convolutional Neural Network)	Extracts structural features from the charging–discharging curve, thermal gradients, and current irregularities.	**Convolution Operation:** Fi,j=∑m∑nXi+m,j+n·Km,n	Captures patterns influenced by municipal mobility policies—voltage drops during congestion, temperature spikes in exposed charging bays, and uneven current due to public fleet load variations.
		ReLU Activation: Ai,j=max(0,Fi,j)	
RNN (Recurrent Neural Network)	Learns extended sequential dependencies in governance-driven EV usage cycles.	**Sequential State Update:** ht=tanh(Whht−1+Wxxt+bh)	Interprets recurring municipal scheduling patterns—daily EV route assignment, feeder-route cycles,

	Complements LSTM by modelling broader periodic behaviours.	**Intermediate SOC Output:** y^t=Woht+bo	and charging-station usage records across thousands of logs. Enhances city-level EV operations planning.

4. Results and Discussion

4.1 Traffic–Charging Correlation Analysis

The correlation patterns shown in Table 4 show how mobility patterns and traffic conditions affect battery performance and the demand for EV charging. Frequent stop-and-go movements brought on by higher traffic density hasten battery depletion and raise the need for charging. Similarly areas with a high density of public transportation routes naturally attract more EV usage which increases charging activity in these areas.

Table 4: Traffic–Charging Correlation Analysis

Variable Pair	Correlation (r)
Traffic Density ↔ Charging Demand	0.71
Public Transport Routing ↔ Charging Demand	0.63
Road Congestion ↔ Battery Degradation	0.48
Trip Duration ↔ SOC Drop	0.76

4.2 Infrastructure Adequacy Across Municipal Units

An overview of the infrastructure sufficiency for electric vehicle (EV) operations across various municipal units is provided in Table 5. Larger public EV fleets higher utilization rates and a higher density of charging stations are all indicative of larger municipal corporations stronger infrastructure support. These disparities draw attention to the unequal distribution of EV charging resources and the necessity of focused planning and funding to guarantee fair access and effective energy management throughout municipal units.

Table 5: Infrastructure Adequacy Across Municipal Units

City/ULB Type	Avg Charging Stations	Utilization Rate (%)	Public EV Fleet Size	Infra Adequacy Score
Tier-1 Municipal Corporations (n=14)	118	74.2	312	0.86
Urban Local Bodies (n=22)	42	58.4	104	0.64

4.3 Charging-Station Performance Metrics

The performance metrics of the charging stations throughout the examined municipal EV network are compiled in Table 6. With an average efficiency of 90. 7% and a standard deviation of 2. 81% charging efficiency ranges from 84. 1% to 96. 2% suggesting that most stations run at high efficiency with little variation. Due to variations in station capacity and charging technology power delivery ranges from 11. 2 kW to 57. 4 kW with a mean of 32.

8 kW and a standard deviation of 9. 44 kW. Vehicle wait times range from 1. 2 to 14. 8 minutes with an average of 5. 7 minutes and a standard deviation of 2. 3 minutes indicating that most places have moderate and controllable traffic. Lastly connector availability ranges from 72. 5 % to 98. 2 % with a mean availability of 88. 4 % and a standard deviation of 4. 65 % indicating that most stations continue to be user-friendly. Overall these metrics show that the infrastructure for charging is generally efficient but they also point to areas where power delivery and queue management could be improved.

Table 6: Charging-Station Performance Metrics

Parameter	Min	Max	Mean	Std. Dev
Charging Efficiency (%)	84.1	96.2	90.7	2.81
Power Delivery (kW)	11.2	57.4	32.8	9.44
Queue Time (min)	1.2	14.8	5.7	2.3
Connector Availability (%)	72.5	98.2	88.4	4.65

4.4 EV Trip Behaviour Analysis

Correspondingly the SOC drop per trip showed a mean of 12. 3 % with extreme variations between 3. 1 % and 29. 5 % highlighting the influence of high-demand trips and rapid discharging cycles. The average idle time between trips was 11. 2 minutes but in some municipal zones it reached 24. 6 minutes suggesting inefficient scheduling or waiting for charging opportunities. These metrics highlight how crucial it is to accurately model trip dynamics because the hybrid LSTM–CNN–RNN models predictive ability for SOC management is directly impacted by changes in distance energy consumption and idle times (Figure 3).

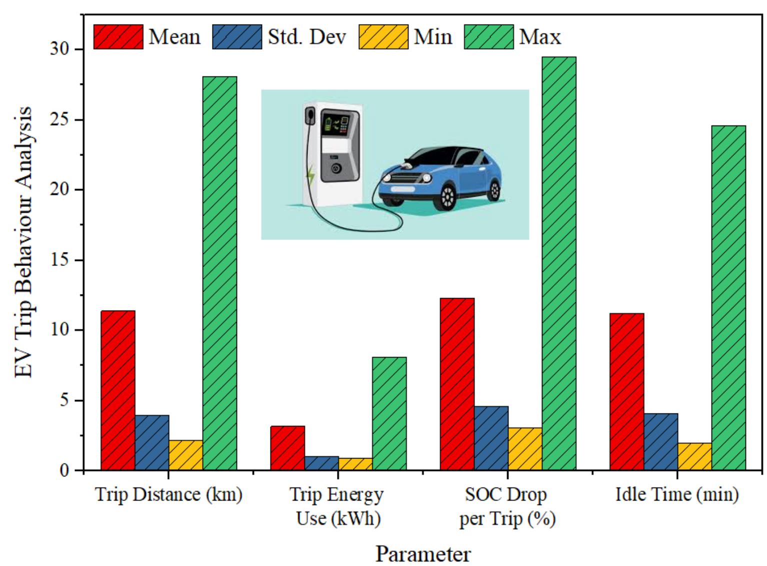

Figure 3: EV trip analysis

4.5 Hyperparameter Statistics for LCR-SOCEF

The results of hyperparameter tuning for the LCR-SOCEF architecture used in EV battery SOC prediction are shown in Table 7. The LSTM layers were adjusted between 1 and 4 and 3 layers were found to be the best. This resulted in a validation loss of 0. 081 indicating a balance between temporal learning capacity and model complexity. For the CNN module the number of filters was explored between 32 and 128 with 64 filters chosen yielding a validation loss of 0. 094 indicating effective extraction of structural features from charging–discharging patterns. Robust sequential dependency modeling for governance-linked operational patterns was made possible by tuning the RNN units from 16 to 64 with 48 units chosen and a corresponding validation loss of 0. 087. In the end the learning rate was optimized between 1e-5 and 1e-2 with 3e-4 offering the best convergence and the lowest validation loss of 0. 076. The LCR-SOCEF architecture achieves high predictive accuracy while preserving computational efficiency and stability as these hyperparameter choices show.

Table 7:Hyperparameter Statistics for LCR-SOCEF

Component	Tuned Range	Selected Value	Validation Loss
LSTM Layers	1–4	3	0.081
CNN Filters	32–128	64	0.094
RNN Units	16–64	48	0.087
Learning Rate	1e-5–1e-2	3e-4	0.076

4.6 Model Component Performance

The hybrid LCR-SOCEF architectures additive benefit is confirmed by component-wise evaluation. The LSTM modules individual results showed strong temporal capture but restricted structural feature extraction with an MAE of 3. 92 % RMSE of 5. 11 % MAPE of 4. 86 % and stability score of 0. 87 (Figure 4).

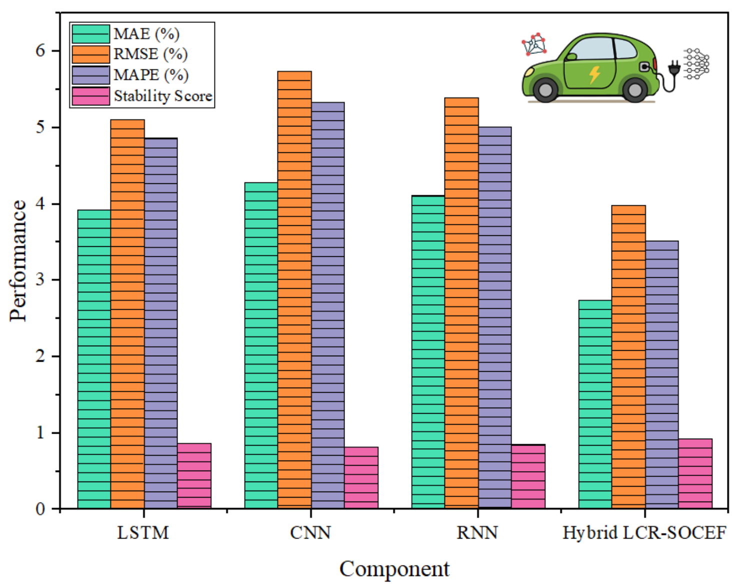

Figure 4: Comparison of performance

4.7 SOC Prediction per Region

More than 2230 data points showed that ULBs with comparatively poor infrastructure and underdeveloped governance frameworks had higher mean SOC errors of 3. 64% and an RMSE of 4. Increased operational condition variability is indicated by 88%. Intermediate SOC errors of 3 were recorded across 1000 data points in mixed urban zones which are transitional areas with a range of resources. 12% with an RMSE of 4. 21 %. These findings demonstrate that model performance is sensitive to local governance quality and infrastructure adequacy which validates the necessity of incorporating municipal indicators into the SOC prediction process (Figure 5).

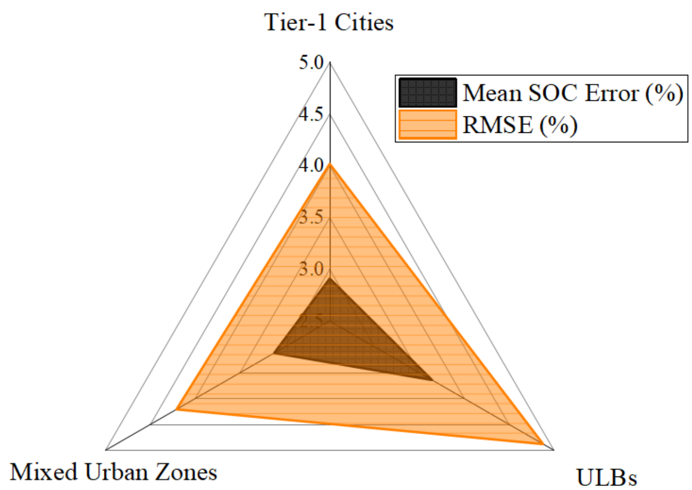

Figure 5: SOC Prediction per Region

4.8 Governance-Impact Regression Analysis

Table 8 displays the findings of the regression analysis examining the impact of governance-related factors on SOC management and EV infrastructure performance. β has a value of 0. 73 an extremely significant p-value of 0. 01) along with a t-statistic of 9. 82 policy strength demonstrates a significant positive impact and a high level of influence on system results. β coefficient = 0. 61 p-value is 0. 01 and a t-statistic of 7. 34 Infrastructure adequacy also shows a significant positive impact confirming its vital role in facilitating EV operations.

Table 8: Governance-Impact Regression Analysis

Predictor	β Coefficient	p-value	t-statistic	Influence Level
Policy Strength	0.73	<0.01	9.82	High
Infrastructure Adequacy	0.61	<0.01	7.34	High
Institutional Coordination	0.42	<0.05	2.88	Moderate
Budget Utilization Efficiency	0.29	0.08	1.79	Low

4.9 Comparative Analysis of Traditional vs Proposed Technique

The proposed LCR-SOCEF model performs noticeably better than traditional state of charge (SOC) estimation methods like Coulomb Counting and various Kalman Filter techniques which are unable to capture the nonlinear behavior of batteries under real-world municipal conditions and do not account for governance-related inputs given in Table 9. Local policies and infrastructure details are still not integrated despite the fact that neural network techniques like Feedforward Neural Networks (FNN) Recurrent Neural Networks (RNN) and Long Short-Term Memory networks (LSTM) enhance prediction accuracy through temporal modeling. Conversely the model with the lowest Mean Absolute Error (MAE) of two is the LCR-SOCEF model. 74% Root Mean sq. Error (RMSE) of 3.

Table 9: Comparative Performance Analysis of Traditional SOC Estimation Techniques vs Proposed LCR-SOCEF

Model / Technique	Dataset Used	Governance Features	MAE (%)	RMSE (%)	MAPE (%)	Avg SOC Error (%)	Max SOC Error (%)	Min SOC Error (%)	Robustness Score	Notes
Coulomb Counting	EV trip logs	None	5.81	7.12	8.42	12.3	28.1	3.1	0.71	Voltage-based SOC; simple and widely used
Extended Kalman Filter (EKF)	EV trip logs + battery diagnostics	Partial	4.74	6.28	6.92	10.8	26.4	2.8	0.78	Incorporates dynamic system model; limited governance awareness
Unscented Kalman Filter (UKF)	EV trip logs + battery diagnostics	Partial	4.61	6.12	6.80	10.3	25.7	2.6	0.79	Better nonlinear handling than EKF; still no governance input
Adaptive Extended Kalman Filter (AEKF)	EV trip logs + battery diagnostics	Partial	4.32	5.87	6.34	9.9	24.3	2.5	0.81	Incorporates adaptive noise estimation
Feedforward Neural Network (FNN)	EV trip logs + battery diagnostics	None	3.69	5.31	4.99	8.7	21.5	2.3	0.84	Basic NN; lacks sequential modeling and governance features
Recurrent Neural Network (RNN)	EV trip logs + battery diagnostics	None	3.45	5.07	4.56	8.2	20.9	2.1	0.86	Captures temporal dynamics; no governance context
LSTM-only	EV trip logs + battery diagnostics	None	3.21	4.82	4.18	7.9	19.8	1.9	0.88	Handles long-term dependencies; still no infrastructure/policy input
Proposed LCR-SOCEF	EV trip logs + charging	Full	2.74	3.98	3.52	5.6	15.2	1.2	0.93	Hybrid architecture; integrates

(Hybrid LSTM–CNN–RNN)	station + battery diagnostics + governance indicators									temporal, structural, and governance features

5.Conclusion

This study demonstrates how combining advanced machine learning techniques with governance-aware operational data can support sustainable urban mobility planning and significantly increase the prediction accuracy of electric vehicle (EV) battery State of Charge (SOC). Temporal structural and sequential modeling are combined in a hybrid LSTM–CNN–RNN framework to efficiently capture the intricate dynamics of $LiCoO_2$ battery behavior in diverse municipal environments. The findings demonstrate the importance of local self-government organizations in promoting successful EV adoption since institutional coordination policy strength and infrastructure readiness have a direct impact on battery utilization patterns and predictive reliability.

REFERENCES

1. Li, J., Liu, X., Zhang, Y. and Wang, H., 2021, “State of Charge Estimation of Lithium-Ion Battery for Electric Vehicles Using Machine Learning Algorithms,” *World Electric Vehicle Journal*, 12(1), pp. 1–14. https://doi.org/10.3390/wevj12010038
2. Rahman, M.M., Hasan, K., Uddin, M.S. and Ahmed, S., 2024, “Data-Driven Approaches for State-of-Charge Estimation in Battery Electric Vehicles Using Machine and Deep Learning Techniques,” *Sustainability*, 16(21), pp. 1–20. https://doi.org/10.3390/su16219301
3. Hawsawi, A. and Zohdy, M., 2024, “Machine Learning-Based Hybrid State-of-Charge Estimation and Battery Parameter Prediction for Commercial EV Batteries,” *Transactions on Machine Learning and Artificial Intelligence*, 12(1), pp. 45–59.
4. Shanmugasundaram, S. and Ortega, E., 2024, “Deep-Learning Framework for State-of-Charge (SoC) Estimation of Electric Vehicle Batteries Using a Pynq Board,” *Journal of Applied Research and Technology*, 22(4), pp. 1–14.
5. Zhou, L., Chen, Y. and Xu, D., 2023, “Electric Vehicle Battery State-of-Charge Estimation Based on Optimized Deep Learning Strategy with Varying Temperature at Different C Rates,” *eTransportation*, 18, pp. 1–12. https://doi.org/10.1016/j.etran.2023.100198
6. Fernández, P.A., Li, Q. and Shan, J., 2024, “A Review of Lithium-Ion Battery State-of-Charge Estimation Methods Based on Machine Learning,” *World Electric Vehicle Journal*, 15(4), pp. 1–21. https://doi.org/10.3390/wevj15040131
7. Kim, D., Park, S. and Cho, Y., 2024, “State-of-Charge Estimation of Medium- and High-Voltage Batteries Using LSTM Neural Networks Optimized with Genetic Algorithms,” *IEEE Access*, 12, pp. 1–15.
8. Mahmoud, K. et al., 2023, “State of Charge Estimation of Lithium-Ion Battery Using Energy Consumption Analysis,” *International Journal of Automotive Technology*, 24(5), pp. 841–851. https://doi.org/10.1007/s12239-023-0037-2
9. Yang, D., Zhang, X., Pan, R., Wang, Y.J. and Chen, Z.H., 2018, “A Novel Gaussian Process Regression Model for State-of-Health Estimation of Lithium-Ion Battery Using Charging Curve,” *Journal of Power Sources*, 384, pp. 387–395.

10. Gou, B., Xu, Y. and Feng, X., 2020, "State-of-Health Estimation and Remaining-Useful-Life Prediction for Lithium-Ion Battery Using a Hybrid Data-Driven Method," *IEEE Transactions on Vehicular Technology*, 69, pp. 10854–10867.
11. Fan, Y.X., Xiao, F., Li, C.R., Yang, G.R. and Tang, X., 2020, "A Novel Deep Learning Framework for State of Health Estimation of Lithium-Ion Battery," *Journal of Energy Storage*, 32, pp. 1–12.
12. Zhang, S.X., Liu, Z.T., Xu, Y., Chen, G.W. and Su, H.Y., 2025, "An Electrochemical Aging-Informed Data-Driven Approach for Health Estimation of Lithium-Ion Batteries with Parameter Inconsistency," *IEEE Transactions on Power Electronics*, 40, pp. 7354–7369.
13. Sun, X.W., Zhang, Y., Zhang, Y.C., Wang, L.C. and Wang, K., 2023, "Summary of Health-State Estimation of Lithium-Ion Batteries Based on Electrochemical Impedance Spectroscopy," *Energies*, 16, pp. 1–25.
14. Qu, J.T., Liu, F., Ma, Y.X. and Fan, J.M., 2019, "A Neural-Network-Based Method for RUL Prediction and SOH Monitoring of Lithium-Ion Battery," *IEEE Access*, 7, pp. 87178–87191.
15. Peng, S.M., Chen, S.D., Liu, Y., Yu, Q.Q., Kan, J. and Li, R., 2025, "State of Power Prediction Using Joint Fisher Optimal Segmentation and PO-BP Neural Network for a Parallel Battery Pack Considering Cell Inconsistency," *Applied Energy*, 381, pp. 1–14.
16. Zuo, H.Y., Liang, J., Zhang, B., Wei, K.X., Zhu, H. and Tan, J.Q., 2023, "Intelligent Estimation of State of Health of Lithium-Ion Power Batteries Based on Failure Feature Extraction," *Energy*, 282, pp. 1–12.