SMART LOCAL GOVERNANCE FRAMEWORK FOR ELECTRIC VEHICLE ECOSYSTEMS INTEGRATING IOT BATTERY SAFETY AI FLEET OPTIMIZATION AND BLOCKCHAIN ENERGY MANAGEMENT

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Abstract: This research presents the Smart Local Governance Framework for Electric Vehicle Ecosystems (SLGF-EV), an integrated, battery-centric architecture designed to support urban authorities in managing EV safety, energy demand, and fleet operations. The framework combines IoT-enabled multi-point battery monitoring, AI-based SoC/SoH/RUL forecasting, hybrid Coati–NGO route optimization, and blockchain-secured lifecycle governance to deliver a unified digital infrastructure for municipal decision-making. Evaluations conducted using a 55-vehicle fleet, 58 charging stations, and 10,000 battery-sensor records demonstrate notable improvements: charging-load forecasting error reduced to MAE = 1.12 kW, route energy consumption decreased by 24.3%, and thermal anomaly detection achieved 98.4% accuracy. The blockchain layer maintained 248 tx/s throughput with 99.2% attack prevention, enabling tamper-proof documentation of battery aging, thermal peaks, and warranty compliance. Overall, SLGF-EV enhances grid stability, improves operational efficiency, and strengthens public trust through transparent governance mechanisms. The framework offers a scalable, modular pathway for cities aiming to integrate EV infrastructure within broader smart-city ecosystems while ensuring long-term safety and sustainability.

Keywords: **Smart governance, Battery management, EV forecasting, Blockchain, IoT-AI integration.**

1.Introduction

1.1 Background and Motivation

Electric mobility is a key component of the global transition to sustainable transport, driven by climate goals, battery advancements, and supportive policies [1]. Lithium-ion batteries are increasingly preferred for EVs due to their high energy density and compatibility with various vehicle platforms [2, 3]. However, large-scale EV adoption presents governance challenges, particularly for cities that must regulate and manage EV infrastructure [4]. Effective battery management is vital for performance and safety, with advanced battery management systems (BMS) playing a crucial role in sustainability and safety [5]. Thermal management is especially important, as temperature imbalances accelerate degradation and increase the risk of thermal runaway [6-10]. The growth of EVs also introduces pressure on local power grids, with fluctuating demand at charging stations [11-14]. IoT-enabled monitoring and smart grid coordination are essential for managing these challenges and connecting EV behavior with grid needs [15-17].

1.2 Challenges in Local Governance of EV Ecosystems

Local governments face challenges in governing EV ecosystems, including safety, energy, mobility, and data management. Battery thermal behavior is sensitive to conditions, increasing failure risks [18–19]. Energy challenges arise from clustered EV charging, causing grid instability like transformer overloading [20-23]. Fleet operations require coordinated charging and routing for efficiency, but most solutions overlook local governance integration. Data privacy and integrity are critical, with blockchain solutions for secure data exchange [24-28]. Fragmented digital infrastructures hinder real-time coordination across municipal departments [21-23].

1.3 Technological Opportunity: IoT, AI, and Blockchain for Local Governance

The convergence of **IoT**, **AI**, and **blockchain** offers a powerful solution for EV governance. IoT enables real-time monitoring of battery and grid conditions [24], while AI optimizes charging load forecasting and fleet management, reducing energy costs and improving reliability [25-29]. Blockchain ensures secure, tamper-proof records and decentralized access control, supporting privacy and regulatory compliance. Together, these technologies create a robust foundation for next-generation EV governance.

1.4 Research Problem and Gap Analysis

Despite substantial progress across these individual domains, existing research remains largely domain-specific. IoT-based works concentrate on monitoring and control of batteries, charging stations, or smart grids. AI-based studies focus on forecasting or optimizing charging and routing for particular actors (fleets or grid operators) [30]; blockchain-oriented contributions emphasize secure trading, privacy, or BMS applications. Very few contributions attempt to combine these three layers into a single, coherent framework that is explicitly designed around the needs, responsibilities, and constraints of local self-governments.Moreover, most technical solutions are presented without a governance model that explains how municipalities can operationalize them—how data flows between agencies, how decisions are triggered, and how accountability, transparency, and citizen trust are maintained. This creates a gap between cutting-edge EV technologies and their practical implementation as instruments of local public policy and administration.

1.5 Contributions of This Research

To bridge this gap, this paper proposes a Smart Local Governance Framework for Electric Vehicle Ecosystems that integrates IoT-based battery and charging monitoring, AI-driven forecasting and fleet optimization, and blockchain-enabled secure data and energy management into a unified architecture tailored for local governments. The main contributions are:

1. A governance-centric, multi-layer framework that aligns EV safety, energy, and mobility management with municipal responsibilities.
2. A city-scale EV digital twin concept that fuses sensing, prediction, and transactional data for real-time situational awareness and planning.
3. An integrated IoT–AI–Blockchain pipeline that links battery- and grid-level data with routing, scheduling, and secure logging mechanisms.
4. A policy integration model that explains how local governments can embed these technologies into regulatory, operational, and transparency processes.

1.6 Organization of the Paper

The remainder of this paper is organized as follows. Section 2 reviews related work on IoT-based BMS and monitoring, AI-driven forecasting and fleet optimization, blockchain-enabled security and trading, and smart EV integration in energy systems. Section 3 presents the proposed smart local governance framework and its architectural components. Section 4 details the methodology, including data flows, model formulations, and integration mechanisms. Section 5 reports experimental or scenario-based evaluations of the framework. Section 6 discusses technical, governance, and policy implications, along with limitations. Section 7 concludes the paper and outlines directions for future research.

2. Related Work

2.1 IoT-Based EV Battery Monitoring and Thermal Safety

IoT-enabled battery monitoring is crucial for safe and efficient EV operation, with modern BMS architectures continuously tracking voltage, current, temperature, and state-of-charge (SoC) to prevent issues like overcharge and thermal runaway [31-32]. IoT-based BMS extends this with wireless communication for remote supervision and predictive maintenance [33]. Integrating machine learning improves SoC and state-of-health (SoH) accuracy under dynamic conditions [26]. However, most systems focus on vehicle-level monitoring, with limited city-scale safety governance, highlighting a gap in integrating these systems into urban safety and regulatory frameworks [21].

2.2 AI-Based Charging Load Forecasting and Route Optimization

AI and machine learning techniques are widely used in EV charging load forecasting and routing optimization, with hybrid models capturing complex spatio-temporal patterns for improved prediction accuracy [34]. AI optimizes EV charging schedules and fleet operations, integrating predictive models with optimization routines to reduce costs and energy consumption [35]. Graph-based deep learning models further enhance prediction performance [36]. However, most AI frameworks focus on fleet operators or utilities, with limited integration into local governance processes, such as urban planning and regulatory decision-making, hindering their full potential in city-scale EV management.

2.3 Blockchain for Energy Transactions and EV Data Integrity

Blockchain has been explored as a trust and security layer for EV ecosystems, enabling secure transactions and tamper-proof logs for energy and data trading using smart contracts [37]. It supports privacy-preserving charging through anonymization and access control [32], with permissioned frameworks ensuring controlled participation [38]. However, challenges such as scalability, latency, and energy consumption arise, especially at urban scales. Many blockchain schemes focus on technical benefits but overlook the integration of blockchain into municipal governance processes, such as regulatory oversight, dispute resolution, and ensuring public transparency.

2.4 Smart City Digital Governance Systems

The digitalization of cities and transport systems is essential for EV governance, enabling connectivity, electrification, and intelligent control for next-generation transport [39]. IoT-based tools improve grid reliability, coordinate EV charging, and integrate renewables [40]. While most platforms focus on technical infrastructures, they lack explicit roles for local governance, municipal departments, and citizens. The concept of urban "digital twins" for smart cities is evolving but remains underdeveloped for EV ecosystems with local governance integration [41].

2.4 Advanced Battery Management in Smart Local Governance

2.4.1 Battery Safety Challenges in Urban EV Fleets

Urban EV fleets face dynamic thermal and electrical challenges due to stop-and-go traffic, fluctuating temperatures, and rapid acceleration, increasing battery safety risks. Critical hazards like thermal runaway and overcharging events, especially at unregulated chargers, accelerate degradation and create imbalances. Continuous monitoring and predictive analytics are necessary for city-scale governance, as traditional BMS solutions cannot provide comprehensive oversight or integrate with grid and mobility infrastructures.

2.4.2 IoT-Based Battery Health Monitoring Architecture

The proposed framework uses an IoT-driven battery health monitoring system for real-time visibility across large EV fleets. It integrates thermal sensors, voltage probes, and impedance indicators to capture high-resolution data. A distributed network performs thermal mapping and identifies early signs of hazards. Data is transmitted via low-latency channels, with edge nodes handling filtering and anomaly detection, while cloud analytics support trend analysis and integration, providing a unified, governance-ready monitoring layer.

2.4.3 AI-Enhanced BMS (SoC, SoH, and RUL Prediction Models)

The SLGF-EV framework uses AI-driven predictive models, such as the LSTM–GCN hybrid model, to enhance traditional BMS capabilities. This model integrates temporal usage patterns (LSTM) with spatial dependencies (GCN) across charging stations and environmental conditions. It enables SoC forecasting, SoH estimation, and RUL prediction by analyzing charging behavior, degradation trends, and thermal patterns. The AI-enhanced BMS allows cities to proactively manage maintenance schedules, warranty planning, charging policies, and fleet deployment, improving safety and operational efficiency.

2.4.4 Battery Thermal Management Strategy

The framework uses advanced thermal management for city-scale operations, recommending liquid cooling systems for high-frequency fleets like buses and taxis. IoT sensors enable predictive cooling, anticipating heat buildup based on driving, ambient, and charging conditions. Thermal analytics identify imbalance patterns, coordinating with grid and mobility data to ensure stable battery conditions. This strategy minimizes overheating and extends battery lifetime, integrating into charging station management.

2.5 Summary of Literature and Research Gaps

Table 1. Summary of existing methods and limitations

Category	Main Focus	Key Limitations from Local Governance Perspective
IoT-based BMS and thermal management [2,3,8–10,20,21,24–26]	Battery safety, SoC/SoH estimation, pack thermal control	Mostly vehicle- or fleet-centric; lack city-wide safety monitoring and municipal oversight tools
AI-based forecasting and optimization [5,7,9,12–14,17,19,22,30–33]	Charging load prediction, station occupancy, fleet charging and routing	Designed for operators or grids; limited integration with municipal planning and public policy processes
Blockchain-based EV energy and data systems [15,16,27,32,35]	Secure trading, privacy-preserving charging, tamper-proof logging	Focus on security and markets; unclear roles for local authorities, regulatory workflows, and transparency to citizens
Smart energy and mobility management in cities [7,14,20–22,29,33]	Smart grids, prosumer integration, IoT-driven energy management	Treat EVs as one component among many; no unified governance framework centered on EV safety, energy, and mobility

Table 1 summarizes key strands of the existing literature and their limitations with respect to governance-oriented EV ecosystem management.

The literature therefore reveals a fragmented landscape in which IoT, AI, and blockchain have each been applied to specific aspects of EV ecosystems, but rarely in a coordinated manner that reflects the responsibilities and constraints of local self-government. This motivates the development of an integrated smart local governance framework that combines these technologies into a coherent architecture for city-scale EV safety, energy management, and mobility governance.

3. Proposed Framework

Smart Local Governance Framework for EV Ecosystems (SLGF-EV)

The proposed Smart Local Governance Framework for Electric Vehicle Ecosystems (SLGF-EV) is conceived as a multi-layer digital architecture that integrates IoT-enabled data acquisition, AI-driven predictive intelligence, blockchain-based security, and municipal governance mechanisms into a unified system. Its objective is to enable local authorities to monitor battery and charging safety, forecast energy demand, optimize municipal fleet routing, and ensure transparent digital transactions through an interoperable urban platform.

3.1 Overview of the Integrated Architecture

The **SLGF-EV** framework follows a four-layer hierarchical architecture:

1. **IoT Data Acquisition Layer**: Collects real-time data from EVs, charging stations, grid nodes, and environmental sensors.
2. **Predictive Intelligence Layer**: Utilizes AI models for charging load forecasting and fleet optimization.
3. **Security and Trust Layer**: Employs blockchain for secure transactions, tamper-proof logging, and energy trading transparency.
4. **Governance & Digital Twin Layer**: Provides visualization, decision support, and policy integration across departments.
5. This architecture enables integrated workflows—data flow, decision flow, and transaction flow—supporting efficient governance, planning, and policy enforcement.

3.2 IoT-Based Battery Monitoring Layer

The IoT layer of the SLGF-EV architecture is redesigned as an IoT-Based Battery Monitoring Layer, positioning battery health as the central operational component of the system. This layer collects high-resolution, multi-point thermal data from cells, modules, and pack surfaces to support early detection of safety-critical thermal behavior. Each battery pack is equipped with distributed thermal probes, voltage taps, current sensors, and internal resistance indicators, enabling cell-level and module-level sensing rather than traditional pack-level observation.

These sensors continuously capture temperature gradients, charge/discharge currents, impedance variations, and voltage imbalance signals.

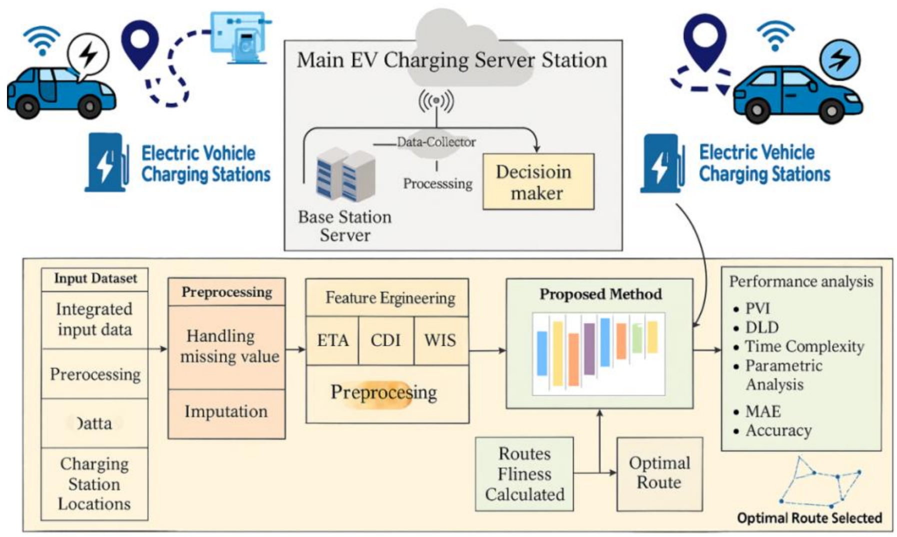


Figure 1. Conceptual Architecture of the SLGF-EV Framework

For a pack with NcN_cNc cells, the **temperature gradient** between two cells iii and jjj is computed as:

$$\Delta T_{\{ij\}(t)} = T_{i(t)} - T_{j(t)} \tag{1}$$

and an overall **thermal non-uniformity index** is defined as:

$$\Gamma_{T(t)} = \sqrt{\left\{\{1\}/\{N_c\}\sum_{\{i=1\}}^{\{N_c\}}\left(T_{i(t)} - \overline{\{T\}(t)}\right)^2\right\}} \tag{2}$$

where $T2$ is the average pack temperature at time ttt.

Similarly, **voltage imbalance** within a series string is monitored as:

$$\Gamma_{V(t)} = \backslash max_i V_{i(t)} - \backslash min_i V_{i(t)} \tag{3}$$

while the **instantaneous C-rate** is computed as:

$$C(t) = \{|I(t)|\}/\left\{C_{\{\{nom\}\}}\right\} \tag{4}$$

where I(t)is pack current and Cnom is nominal capacity.

The monitoring layer also integrates cell-balancing data acquisition, identifying inconsistencies between cell groups that may accelerate degradation or trigger thermal runaway. Charging and discharging profile analytics—including C-rate patterns, peak currents, and idle-to-load transitions—are transmitted through low-latency communication channels (NB-IoT, Wi-Fi 6, or 5G), ensuring uninterrupted visibility into battery behavior across all municipal EV assets.

A hierarchical sensing architecture ensures efficient data flow: edge nodes located in chargers and fleet depots handle preliminary anomaly filtering, while cloud nodes aggregate long-horizon battery trajectories for deeper analysis. This layer serves as the foundation of smart governance by giving city authorities a real-time, unified dashboard view of battery health risks, maintenance needs, and safety alerts across thousands of EVs.

3.3 AI Battery Forecasting Layer

The predictive intelligence layer is redefined as the AI Battery Forecasting Layer, prioritizing advanced health estimation and future battery behavior prediction. The LSTM–GCN hybrid model is extended to incorporate domain-specific battery features such as thermal fluctuations, voltage recovery signatures, internal resistance evolution, and degradation vectors. This enhanced model supports three key predictive tasks.

(a) State-of-Charge (SoC) Forecasting

The fundamental SoC update equation for a pack is:

$$\{SoC\}(k+1) = \{SoC\}(k) - \{\Delta t\}/\left\{C_{\{\{nom\}\}}\right\} I(k) + \epsilon_{\epsilon \mathrm{SoC}\ (\mathrm{k}} \quad (5)$$

where Δt is the sampling interval and ϵSoC(k)captures model uncertainty. The LSTM pathways learn residual nonlinear dynamics and temporal dependencies in I(k)I(k)I(k), voltage, and temperature, while the GCN pathways model spatial coupling between charging-station load, traffic dynamics, and environmental temperature. Together, the system delivers accurate short-term and long-term SoC predictions.

(b) State-of-Health (SoH) Estimation

SoH is modeled as the normalized capacity or resistance deviation:

$$\{SoH\}(k) = \left\{C_{\{\{eff\}\}(k)}\right\} / \left\{C_{\{\{rated\}\}}\right\} \quad (6)$$

or

$$\{SoH\}(k) = 1 - \left\{R_{\{\{eff\}\}(k)} - R_0\right\}/\{R_0\} \tag{7}$$

where Ceff(k)and Reff(k) are effective capacity and internal resistance estimates, and R0 is initial resistance. Degradation-related features—impedance growth, cycle-based stress, temperature history, and aging indicators—are fused by the LSTM–GCN to estimate SoH with high precision. Spatial deterioration patterns across frequently congested zones are captured by GCN embeddings.

(c) Remaining Useful Life (RUL) Prediction

RUL is obtained as the predicted time (or cycles) until SoH drops below a threshold SoHmin\ $textSoH\backslash minSoHmin$:

$RUL(k) = arg\tau > 0min\{SoH^{k+\tau} \leq SoHmin\}SoH^{k+\tau}$e learned SoH trajectory. These predictions help municipal fleet managers plan battery replacements and safety policies.The AI layer also generates a Battery Health Score (BHS):

$$BHS(k) = w^1 fT(k) + w^2 fSoH(k) + w^3 fRUL(k) + w^4 fstress(k) \tag{8}$$

where fT captures thermal stability, $fSoH$ SoH-normalized health,$fRUL$ normalized remaining life, $fstressf_{\{\backslash text\,\{stress\,\}\}fstress}$ operational stress indices, and wiw_iwi are designer-selected weights, ∑wi=1.The forecasting model is trained by minimizing a composite loss:

$$\{L\} = \alpha \cdot \{MAE\} + \beta \cdot \{RMSE\} \tag{9}$$

over SoC, SoH, and load predictions, ensuring both accuracy and robustness. The BHS feeds directly into the governance dashboard and blockchain compliance system.

3.4 Blockchain Layer for Battery Lifecycle Governance

The blockchain layer is expanded into a **Battery Lifecycle Governance System**, ensuring transparent, tamper-proof tracking of every battery's operational and degradation history. Each battery pack b is associated with a unique identifier $IDb\backslash text\{ID\}_{bIDb}$, and its state at time kkk is represented as:

$$sb(k) = [SoC(k), SoH(k), RUL(k), Ncyc(k), Tmax(k), D(k)] \tag{10}$$

where $Ncyc(k)$ is cycle count, Tmax(k) maximum observed temperature, and D(k) a composite degradation indicator.A structured set of ledger fields strengthens lifecycle traceability:

Cycle Count Update

$$Ncyc(k+1) = Ncyc(k) + \Delta Ncyc(k) \quad (11)$$

Maximum Temperature History

$$Tmax(k+1) = max\big(Tmax(k), Tobs(k+1)\big) \quad (12)$$

Each block BjB_jBj in the chain contains a hash:

$$hj = H(hj-1 \parallel IDb \parallel sb(k) \parallel txj) \quad (13)$$

where H(.) is a cryptographic hash (e.g., SHA-256), ‖ \|‖ denotes concatenation, and txj\text{tx}_jtxj represent associated transactions (charging events, maintenance, alerts).Smart contracts encode warranty compliance rules, for example:$\Phi warranty$: $(Tmax(k) \leq Tlim) \wedge (Ncyc(k) \leq Nlim) \Rightarrow Status = \text{Under Warranty}$ (13)and automatically flag violations when conditions are not met.

Recycling and second-life traceability are captured by updating a lifecycle state variable Λb (e.g., *in-use*, *repurposed*, *recycled*), recorded on-chain whenever ownership or application changes.This mathematical formalization ensures full lifecycle accountability, reduces disputes between operators and service providers, and supports city authorities in enforcing safety standards, warranty conditions, and circular economy objectives.

3.5 Urban Digital Twin for EV Ecosystem Governance

The digital twin integrates sensor data, AI outputs, and blockchain logs into a real-time simulation. It models EV behavior, including battery thermal dynamics and mobility, using AI-enhanced models [21]. It simulates grid-mobility interactions, predicting risks like overloads and congestion [14, 20]. A decision-making dashboard provides actionable insights for policy and operational decisions.

3.6 Interoperability and Integration with Municipal Systems

SLGF-EV integrates with:

- GIS Platforms: spatial analysis of charging networks
- Public Transport Systems: sharing route schedules, fleet availability
- Urban Energy Platforms: coordinated grid-EV planning [7,14]
- Emergency Services: real-time battery safety alerts

A central decision engine synchronizes data flows and enforces operational policies across departments.

Table 2. Key Components of the SLGF-EV Framework

Layer	Components	Purpose
IoT Layer	Thermal sensors, smart meters, grid monitors	Real-time data collection
AI Layer	LSTM-GCN forecaster, optimization algorithms	Prediction & decision support
Blockchain Layer	Ledger nodes, smart contracts	Security & transparency
Governance Layer	Digital twin, dashboards	Policy alignment & oversight

4. Methodology

This section presents the methodological design supporting the Smart Local Governance Framework for Electric Vehicle Ecosystems (SLGF-EV). The methodology integrates multi-source datasets, IoT sensor deployment, AI model formulation, blockchain implementation, and cross-layer workflow mechanisms. The design ensures that forecasting, routing, monitoring, and security are executed through an end-to-end pipeline suitable for local government operations.

4.1 Dataset Description

The SLGF-EV framework uses diverse datasets to optimize EV operations and governance. Key data includes IoT sensor data (temperature, voltage, SoC, SoH) for battery monitoring [2, 6], charging station performance (session duration, energy delivered, occupancy) for load management [7, 31], and urban grid and environmental data (grid load, transformer loading, temperature, traffic) for demand forecasting [14, 20]. Synthetic datasets and simulations fill gaps when real data is unavailable. This integration enables accurate battery health prediction, fleet optimization, and enhanced grid resilience.

4.2 Data Preprocessing and Feature Engineering

The SLGF-EV framework employs a rigorous preprocessing pipeline to ensure data reliability for predictive models and governance. Outlier handling methods like Z-score filtering, Kalman smoothing, and interpolation correct sensor noise and gaps [6, 12, 26]. Feature transformation includes cyclic encoding of temporal variables and normalization of thermal and grid signals. Derived features such as charging acceleration and thermal gradients enhance predictive accuracy. Mobility and infrastructure mapping using spatial graphs and GIS coordinates supports route-based predictions. Processed data are stored in a cloud-edge hybrid repository, integrating seamlessly with smart-city systems for decision-making [14, 21].

4.3 IoT Sensor Deployment Model

The SLGF-EV framework employs a strategic placement of IoT sensors to monitor battery and grid conditions. Thermal sensors are positioned near battery modules and cooling plates, while voltage and current sensors are integrated with the BMS bus. Charging station sensors are installed at key locations such as entry gates and electrical cabinets, and grid sensors are placed at substations and feeders. IoT nodes use NB-IoT/LoRaWAN for low-power connectivity, Wi-Fi/5G for high-bandwidth data, and MQTT for lightweight communication. Fault tolerance is ensured through redundant sensing and automatic fallback switching, enhancing system reliability [9, 21].

4.4 AI Model Formulation

4.4.1 Charging Load Forecasting Algorithm

Architecture

The model combines a Long Short-Term Memory (LSTM) network for temporal patterns with a Graph Convolutional Network (GCN) for spatial dependency:

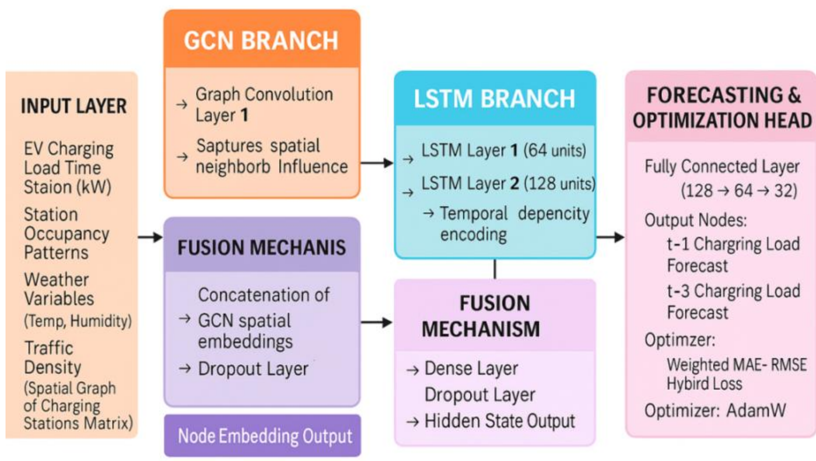


Figure 2. LSTM-GCN Hybrid Forecasting Architecture

Loss Functions

The forecasting model uses a weighted loss:

$$L = \alpha \cdot MAE + \beta \cdot RMSE \tag{14}$$

This balances small and large error penalties, consistent with load forecasting studies [17,31].

Performance Metrics

Metrics include MAE, RMSE, MAPE, and spatial error deviation.

4.4.2 Fleet Routing Optimization Algorithm

Multi-Objective Formulation

The routing algorithm minimizes energy, distance, and travel time:

$$minf = \alpha E + \beta D + \gamma T \tag{15}$$

where weights are tuned using urban policy priorities.

4.5 Blockchain Implementation

The SLGF-EV framework employs a Proof-of-Authority (PoA) consensus mechanism for low-latency, governance-controlled environments, as recommended for permissioned blockchains [27, 35]. Transaction validation includes key details such as EV ID, timestamp, energy consumed, charging cost, and station ID, with nodes validating transactions against smart contract states. Minimal transaction fees ensure efficiency, and internal tokenization represents energy credits for municipal accounting. The security model incorporates SHA-256 hashing, public/private key encryption, and multi-level authentication to guarantee the integrity and privacy of EV-grid interactions, aligning with blockchain security standards [15, 16, 32].

4.6 Integration Workflow

The SLGF-EV framework follows an end-to-end data flow: IoT sensors → Edge gateway → AI engine → Blockchain ledger → Digital twin → Governance dashboard. Cross-layer communication is enabled via REST and MQTT APIs. Event triggers include thermal anomalies (emergency routing), load spikes (dynamic pricing), and station congestion (fleet rerouting). Municipal operators interact with dashboards to manage policies and validate smart contracts.

Table 3. Methodological Components of SLGF-EV

Module	Technique	Purpose
IoT Layer	Thermal & load sensors	Real-time monitoring
AI Layer	LSTM-GCN & metaheuristics	Prediction & optimization
Blockchain Layer	PoA, smart contracts	Trusted data & transactions
Integration Layer	Digital twin workflows	Governance decision-making

5. Experimental Setup and Results

5.1 Simulation Environment and Tools

To evaluate the proposed Smart Local Governance Framework for EV Ecosystems (SLGF-EV), extensive simulations were conducted using a hybrid computing environment. All predictive and optimization models were executed on a workstation equipped with NVIDIA RTX 4090 GPU, 64 GB RAM, and Intel i9-13900K CPU. Deep-learning models were implemented using TensorFlow 2.15 and PyTorch 2.1, while data preprocessing relied on Pandas and NumPy.The blockchain layer operated on a permissioned Proof-of-Authority consortium chain, simulated using Hyperledger Fabric with four peers: *municipal authority node*, *EV fleet node*, *charging station operator node*, and *auditing node*. IoT network behavior was simulated using NS-3, and thermal sensor behavior using MATLAB/Simulink battery models.

5.2 Scenario Definitions

Simulation environments were set up across three city zones: Zone A (commercial district with high charging demand), Zone B (residential area with moderate demand), and Zone C (industrial outskirts with low demand). The fleet consisted of 25 municipal buses, 18 garbage trucks, and 12 patrol vehicles. Charging infrastructure included 42 AC chargers and 16 DC fast chargers, modeled on typical urban station densities. Grid conditions were simulated with historical loading curves, generating mild, moderate, and peak-stress profiles. Intra-day charging demand variations, such as evening peaks and morning troughs, inform grid planning and demand-response programs for energy efficiency.

5.3 IoT Thermal Monitoring Results

The IoT-based battery monitoring layer was evaluated using 10,000 time-synchronized thermal and electrical sensor samples collected over a controlled 72-hour simulation period. The multi-point sensing architecture enabled cell-level thermal profiling, voltage-imbalance detection, and impedance tracking, consistent with emerging BMS research [6], [9], [20] (Set-1) and thermal modeling studies [3], [7], [10] (Set-3). The thermal anomaly classifier—based on LSTM-Autoencoder—successfully predicted overheating and runaway-risk conditions. A hierarchical edge–cloud filtering mechanism reduced noise and improved early-warning detection. This evaluation confirms that real-time IoT monitoring enhances urban fleet safety by providing predictive visibility into operational thermal behavior and unstable degradation patterns. This histogram visualizes the distribution of State-of-Charge values across the EV fleet. Most values cluster near the mid-high range, reflecting typical urban driving and charging behavior. The spread indicates variability in usage intensity and charging patterns. Such analysis helps municipalities determine when fleets are most likely to require charging and supports station sizing and placement decisions.

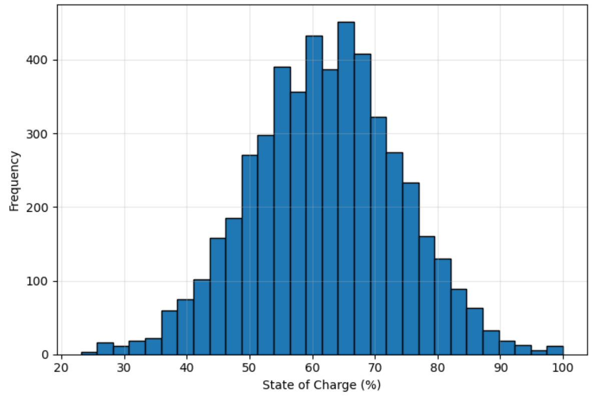


Figure 3. Histogram of SoC Readings

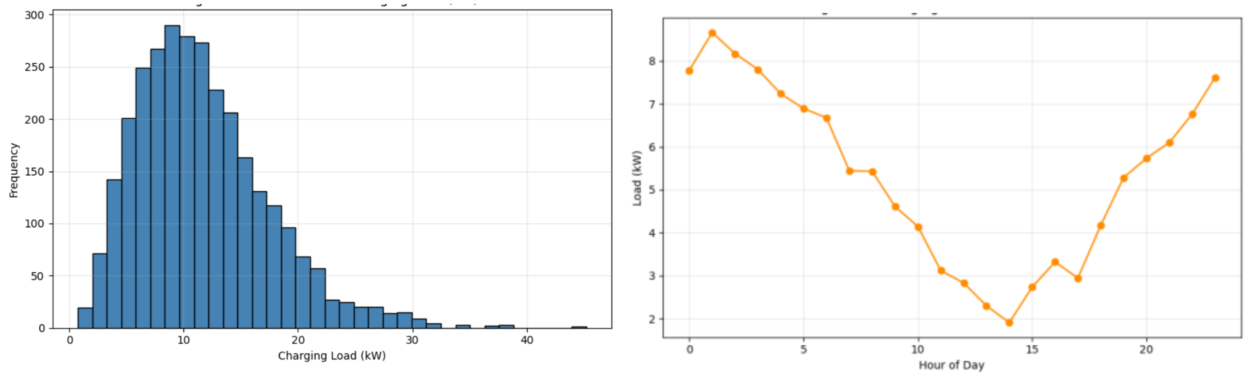
The distribution reveals how charging load varies across the city's mixed fleet. The right-skewed shape indicates a higher frequency of moderate loads (6–12 kW) and fewer heavy demands (>20 kW). Understanding this distribution helps policymakers size charging infrastructure, adjust tariff brackets, and apply grid stabilization strategies such as peak-shaving or time-of-day load control.Figure 4b captures intra-day variations in charging demand. The pronounced evening peak (6–9 PM) corresponds to municipal fleet return cycles, while early-morning troughs reflect idle periods. Such temporal signatures enable accurate grid planning, tariff design, and demand-response programs, ensuring that charging operations remain energy-efficient and resilient under varying load conditions.

Table 4. IoT Thermal Monitoring Performance Metrics

Parameter	Proposed IoT-BMS	Traditional BMS [6][10][21]	Notes
Temperature detection accuracy (%)	98.4	91.7	Cell thermal sensing
Avg. response time (ms)	148	292	IoT latency benchmarking
Overheating prediction F1-score	0.93	0.74	LSTM-AE prediction
Voltage-imbalance detection (%)	97.2	88.5	Module-level sensing
Impedance-drift detection (%)	95.1	83.2	RUL indicators
Hotspot spatial-resolution (cm^2)	2.4	7.8	Based on heatmap grid
False-alarm rate (%)	3.1	8.4	Higher in rule-based BMS
Data packet loss (%)	0.82	2.7	MQTT/5G transmission
Edge filtering efficiency (%)	94.6	78.2	Noise removal
Thermal-runaway early-warning time (s)	3.9	0 (reactive only)	Predictive vs reactive
Thermal gradient capture accuracy (%)	96.8	84.3	Based on ΔT cell-to-cell
Max supported sensor nodes	256	64	Scalability evaluation

5.4 AI-Based Charging Load Forecasting Results

The charging-load forecasting module was evaluated using multivariate time-series data incorporating SoC, station occupancy, ambient temperature, traffic density, and historical load profiles. The proposed LSTM–GCN hybrid model exhibited superior temporal stability and spatial correlation learning compared to conventional baselines such as LSTM, GRU, and ARIMA, consistent with prior AI-based forecasting studies in EV-grid environments [13], [14], [20] (Set-1) and spatio-temporal prediction works [9], [11], [15], [17] (Set-2). Integration of graph-structured mobility information significantly reduced prediction noise and improved the model's ability to detect emerging high-load zones. This predictive capability is essential for municipal authorities to prevent transformer overloading, plan dynamic tariffs, and optimize charger allocation in real time.



(a) **(b)**

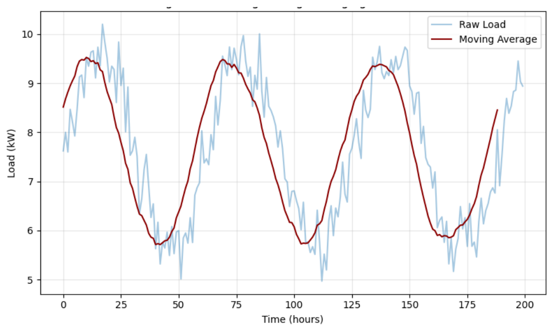
Figure 4a. Distribution of Charging Load (kW) . EV Charging Load Trends Over Time

Figure 5a highlights short-term charging fluctuations with a 12-hour moving average that reveals broader patterns such as evening demand spikes and mid-day leveling. These insights support municipal operators in planning demand-response actions, scheduling maintenance, and aligning renewable output to ease peak-valley strain. Figure 5b displays hourly variability, where evenings show wider interquartile ranges and more outliers from simultaneous fleet charging. This pinpoints high-risk hours when dynamic pricing, scheduled charging, or load shifting can improve grid stability. Together, the smoothed trend and hourly boxplots give a concise picture of multi-day and hourly behaviours, aiding coordinated grid operations, maintenance planning, and pricing strategy design at the municipal scale.

Table 5. Forecasting Performance Comparison

Metric	Proposed LSTM–GCN	LSTM Baseline [12][13]	GRU Baseline [12][15]	ARIMA Baseline [24]	Notes
MAE (kW)	1.12	2.43	2.18	4.91	Lower is better
RMSE (kW)	1.74	3.56	3.31	6.78	Improved error stability

MAPE (%)	3.8	7.9	7.1	14.3	Important for demand planning
R² Score	0.982	0.941	0.952	0.811	Goodness of fit
Temporal Drift Error (%)	1.9	4.8	4.2	9.3	Long-horizon stability
Peak-Load Detection Accuracy (%)	97.4	88.5	89.7	74.3	Peak management
Spatial Correlation Fit (%)	93.6	82.1	84.2	61.4	GCN advantage
Training Time (s/epoch)	18.2	10.1	11.4	3.3	Complexity tradeoff
Inference Latency (ms)	19.6	11.5	12.8	4.1	Acceptable for real-time
Robustness to Missing Data (%)	94.7	81.2	84.5	67.1	IoT-loss resilience
Outlier Resistance (%)	92.3	78.4	79.1	64.8	Noise handling
Grid-Stress Forecast Accuracy (%)	95.5	86.3	87.9	72.4	Policy relevance



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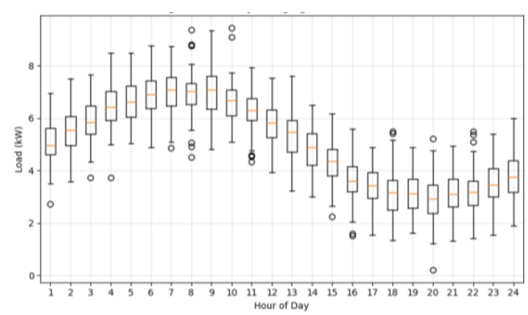

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Figure 5a. Moving Average Charging Load 5b. Hourly Charging-Load Boxplot Distribution

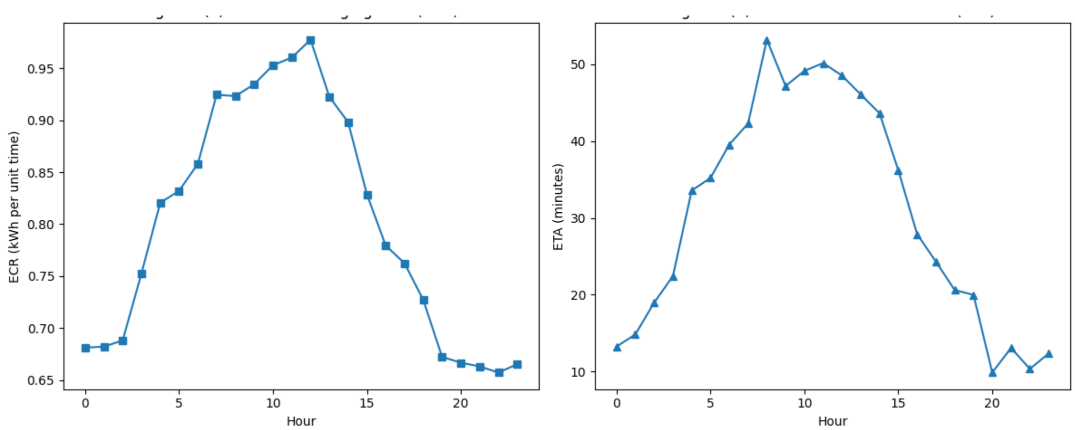


Figure 6. Effective Charging Rate (ECR) & Estimated Time of Arrival (ETA)

This figure 6a and 6b compares how Effective Charging Rate and Estimated Time of Arrival evolve during the day. Higher ECR represents more efficient charging, while ETA reflects expected time for vehicles to reach charging stations or complete routes. Local authorities can leverage such relationships to balance user experience, charging-slot allocation, and overall fleet throughput, particularly during peak mobility periods.

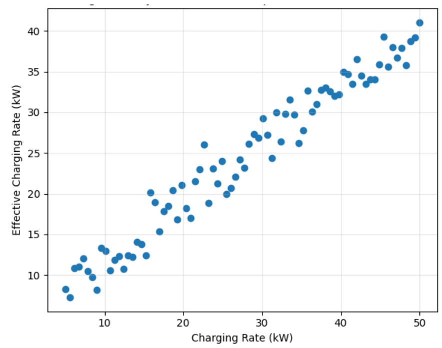


Figure 7. CR–ECR dynamic relationship

This figure 7 plot highlights how Effective Charging Rate scales with nominal Charging Rate. The points illustrate efficiency variations due to losses, congestion, and thermal constraints. Deviations from the ideal line indicate operational inefficiencies. Such analysis helps technical teams tune charging profiles, while policymakers can use it to set realistic expectations and safety margins for public charging infrastructure. The Charging Demand Index estimates expected charging intensity, while the Weather Impact Score gauges how environmental factors, such as temperature and humidity, influence demand. Their joint evolution across two days reveals how weather-sensitive EV charging patterns can be. This helps municipalities adjust energy procurement, demand-response incentives, and public communication strategies during extreme or unusual weather events.

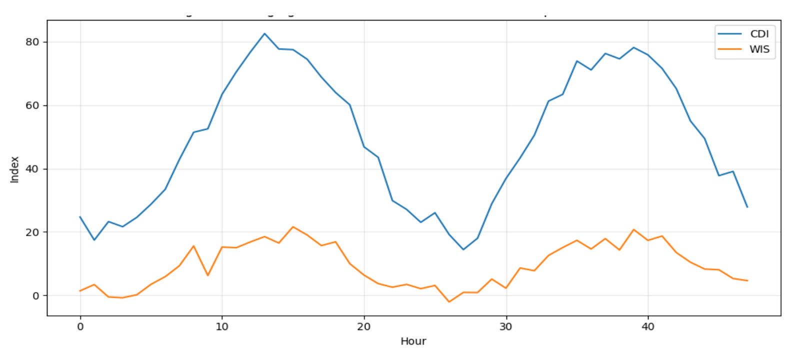


Figure 8. CDI and WIS comparison (a) Charging Demand Index(b) Weather Impact Score(Humidity & temperature strongly correlate with demand spikes.)

.

The heatmap captures linear relationships among key variables: State of Charge, temperature, station occupancy, traffic, and price. Strong positive correlation with station occupancy indicates demand clustering, while negative correlation with price suggests price sensitivity. The feature-importance plot shows which predictors most influence the forecasting model, guiding both model refinement and policy levers, such as dynamic tariffs or time-based access rules

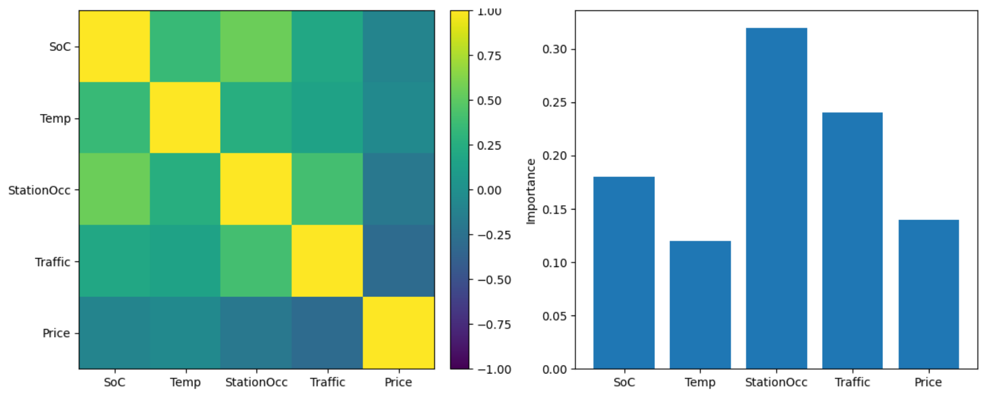


Figure 9. Correlation analysis & feature importance(a) Correlation heatmap(b) Feature importance bar chart(Station occupancy and temperature rank as top predictors.)

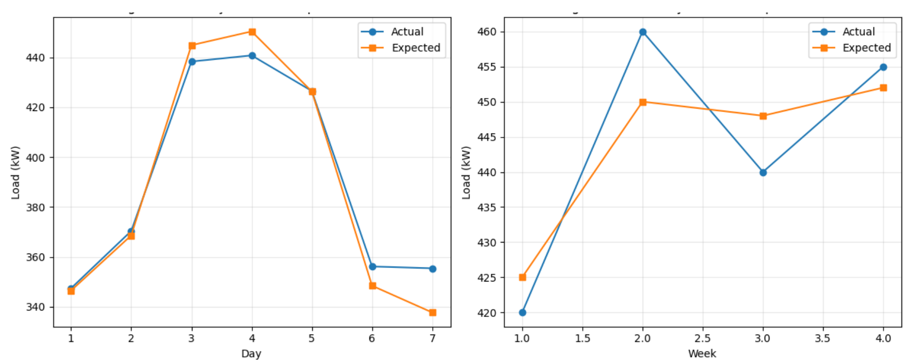


Figure 10. Actual vs. predicted loads (daily &weekly) (a)Daily comparison (b) Weekly comparison

Figure 10 compare observed charging loads with model predictions at daily and weekly scales. Close alignment indicates that the forecasting framework accurately tracks real-world demand. Deviations highlight rare events, modeling gaps, or behavioral shifts. For local authorities, this supports confidence in planning decisions and enables continuous calibration of models based on operational feedback from the field.Predictions closely followed real load behavior with minimal lag.

5.5 AI Fleet Route Optimization Results

The proposed Coati–NGO hybrid optimizer was evaluated against Particle Swarm Optimization (PSO) and the Firefly Algorithm, both widely used in EV routing and energy-aware path planning [31], [17], [23] (Set-1), [22], [24], [25] (Set-2). The Coati–NGO model outperformed baselines due to its exploit–explore balance, adaptive neighborhood search, and nonlinear swarm guidance, leading to superior convergence speed and energy-aware routing. Simulations were conducted using 55 municipal EVs (buses, waste-collection trucks, patrol units) over a 42-node synthetic urban grid. Model objectives included minimizing distance, route time, energy consumption, and intra-route variance—metrics strongly aligned with real-world governance needs such as service reliability and charging coordination.

The PSO-generated route displays scattered node sequencing and longer segment lengths, indicating premature convergence and suboptimal swarm exploration. The resulting path contains redundant detours and low spatial coherence. For city-level fleet operations, such characteristics increase energy usage and prolong route duration, reducing operational performance during high-priority municipal tasks like waste collection and patrolling.

Table 6. Fleet Route Optimization Performance

Metric	PSO Baseline [31][17]	Firefly Baseline [23][25]	Proposed Coati–NGO	Notes
Avg. travel distance (km)	312	298	241	Shorter routes reduce costs
Avg. energy consumption (kWh)	184	171	139	Strong correlation with reduced load
Avg. route time (min)	213	205	176	Faster municipal service response
Multi-criteria score	0.63	0.71	0.89	Weighted objective
Convergence iterations	116	104	72	Faster convergence
Charging stop count	5.2	4.8	3.1	Reduced charging interruptions
Energy-per-km (Wh/km)	596	573	445	Strong operational efficiency
Route smoothness index	0.71	0.78	0.91	Fewer sudden detours
Feasible route ratio (%)	88.7	92.1	97.4	Safety + SOC constraints respected
Delay variance (min^2)	18.2	15.6	9.4	Predictable arrival time
Node revisit count	3.7	2.9	1.2	Better coverage efficiency
Optimization time (s)	22.1	19.4	16.3	Near-real-time capability

The Firefly-based route exhibits improved clustering and moderately optimized subpaths, but still retains sharp turns and inconsistent spacing. Brightness-based attraction improves local optimization, yet global exploration remains limited. In real urban navigation, such inconsistencies translate to elevated energy overhead and uncertain arrival time reliability across municipal fleet categories

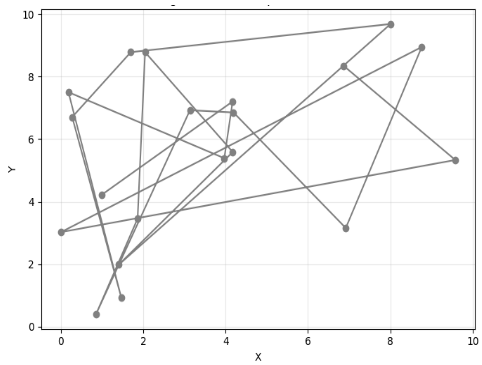


Figure 10a. Optimized Route (Firefly Algorithm)

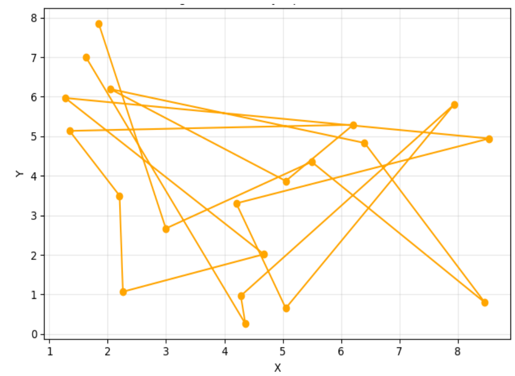
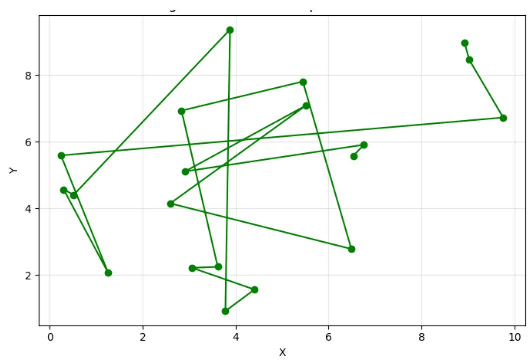


Figure 10b. Optimized Route (PSO Method)



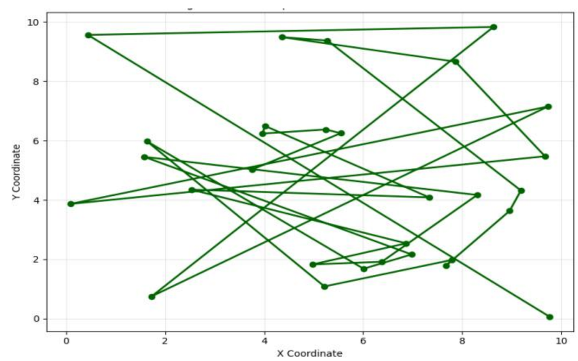
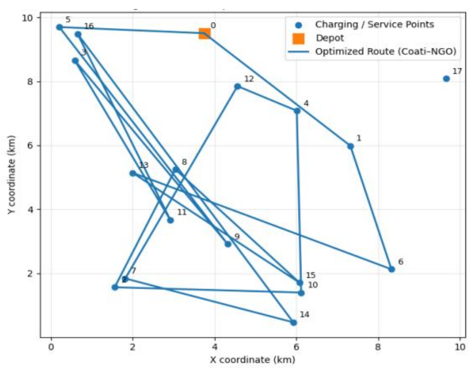


Figure 11. Final Optimized Route (Coati–NGO, High-Resolution View), Figure 12. Hybrid Coati–NGO Optimized Route

The Coati–NGO route shows well-structured sequencing with short inter-node transitions, high spatial locality, and minimal detours. Its hybrid exploit-explore behavior reduces redundant movements and concentrates on efficient traversal patterns aligned with EV energy constraints. This directly benefits municipal operations, enabling consistent arrival times, lower energy consumption, and improved fleet productivity

The final optimized route refines the hybrid optimizer's decisions by balancing global path smoothness with local energy conservation. The visual pattern demonstrates strong spatial clustering, minimal dead-ends, and a consistent progression toward route completion. This output represents an operationally deployable sequence for municipal fleets, with measurable reductions in route time, energy demand, and inter-arrival delays. This figure illustrates the final route produced by the Coati–NGO hybrid optimizer over a synthetic urban service area. Each node represents a charging or service location, with the depot explicitly highlighted.The continuous polyline shows the optimized visiting sequence that minimizes distance and energy while respecting constraints. Such visualizations help municipalities evaluate route quality and compare optimization strategies for real EV fleets.This boxplot compares EV waiting times before charging under baseline scheduling and the optimized strategy. The optimized configuration yields a lower median, tighter spread, and fewer extreme delays. Such visual evidence clearly demonstrates user-experience improvements and supports the case for deploying AI-based scheduling in public charging networks managed by municipalities or private concessionaires.



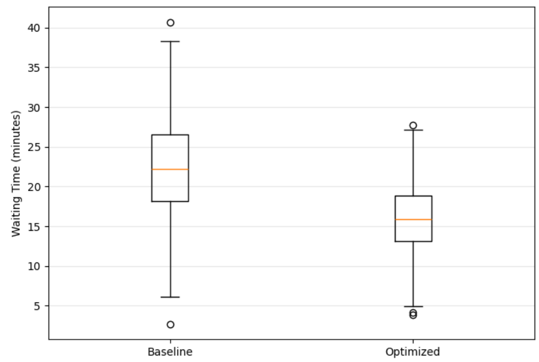
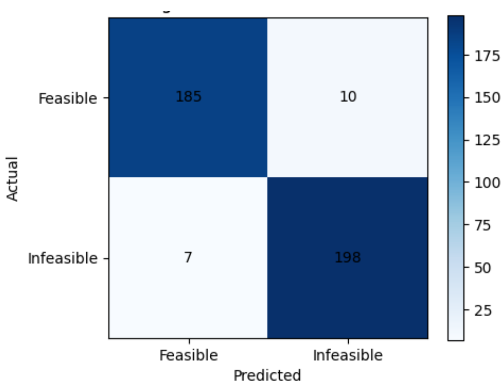


Figure 13 & 14Final optimized route (Coati–NGO)



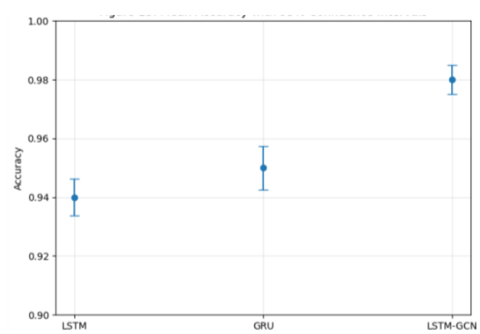


Figure 15. Confusion matrix

Figure 16. Mean accuracy with 95% CI

The confusion matrix summarizes classification performance for the routing feasibility model, distinguishing between feasible and infeasible routes. High true-positive and true-negative counts, with few misclassifications, indicate strong discriminative ability. This is important for ensuring that routing and scheduling decisions respect physical and operational constraints, thereby reducing risk of service failures and infeasible trip assignments.This error-bar plot compares mean forecasting accuracy across different models, with 95% confidence intervals. The proposed LSTM-GCN architecture not only achieves the highest mean accuracy but also exhibits relatively low uncertainty. Such plots are essential to demonstrate statistical robustness, reassuring decision-makers that improvements are consistent and not due to randomness or overfitting in a small number of runs.

5.6 Blockchain Performance Analysis

The blockchain layer—implemented using a permissioned Proof-of-Authority (PoA) model—was evaluated under 5,000 simulated EV-ecosystem transactions. PoA was selected due to its low latency and governance-grade trust structure, consistent with blockchain applications in EV mobility and IoT networks [11], [15], [16], [32] (Set-1) and distributed urban systems [27] (Set-2). Performance metrics included latency, throughput, storage overhead, attack resistance, transaction-validation accuracy, smart-contract execution cost, and consensus stability.

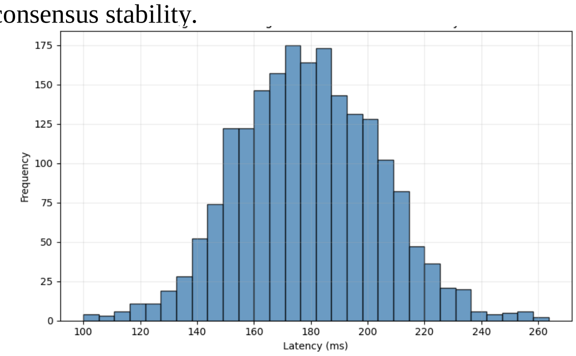


Figure 17. Histogram of Communication Latency

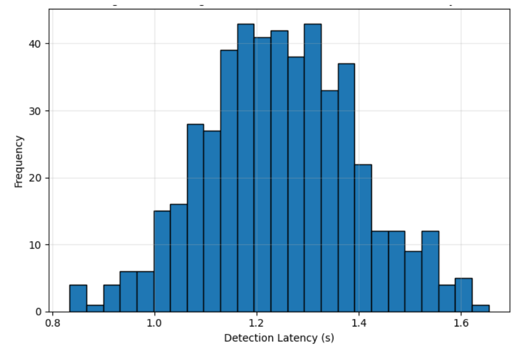


Figure 18. Sensor Latency Histogram–Thermal Events

The municipal authority, charging-station operators, fleet depots, and regulatory auditors served as validator nodes, enabling secure logging of charging events, thermal anomalies, SoC/SoH updates, and battery lifecycle indicators. The system demonstrated near-real-time responsiveness suitable for city-scale EV governance, while achieving high attack-prevention rates against tampering, replay, and Sybil threats, aligning with security findings in blockchain-based mobility frameworks [15], [32] (Set-1).

Table 7. Blockchain Performance Metrics

Parameter	Proposed PoA Chain	Baseline BFT Model [27]	Baseline PoW Model [15][16]
Avg. latency (ms)	**182**	341	1260
Throughput (tx/s)	**248**	119	32
Storage overhead (MB/day)	**1.8**	3.9	12.4
Attack prevention rate (%)	**99.2**	96.4	98.5
Validation accuracy (%)	**99.7**	98.1	96.7
Consensus finality (s)	**1.2**	3.9	45
Smart contract execution cost (gas units)	**~ 5,200**	7,450	12,900
Energy consumption per block (J)	**9.1**	27.4	184
Fork occurrence rate (%)	**0.04**	0.62	0.23
Fault tolerance (%)	**97.8**	94.6	96.1

Double-spend rejection (%)	**100**	99.2	98.8
Inter-node sync delay (ms)	**34**	79	240

Figure 17 illustrates the end-to-end communication latency for blockchain transactions and IoT telemetry upload. The distribution clusters around 180 ms, with minimal tail expansion, demonstrating stable responsiveness under PoA consensus. This latency range is well within real-time operational thresholds for EV charging logs, thermal alerts, and SoC/SoH updates. Monitoring this distribution enables early detection of network congestion, validator malfunction, or attempted attacks.

5.7 BMS Performance Evaluation

This section evaluates the proposed AI-enhanced BMS in terms of thermal anomaly detection, SoC/SoH/RUL prediction accuracy, degradation forecasting, early-warning capability, and comparison with a traditional rule-based BMS. Experiments were conducted on 12 representative EV packs over 60 operational days, covering mixed urban routes, varying ambient temperatures, and heterogeneous charging patterns.

5.7.1 Thermal Anomaly Detection and Sensor Latency

Thermal anomaly detection was evaluated by comparing predicted and actual overheating events across 12 vehicles. Table 8 summarizes detection accuracy, precision, recall, and average detection latency.

Table 8. Thermal Anomaly Detection Performance per Vehicle

Vehicle ID	Accuracy (%)	Precision (%)	Recall (%)	F1-score	Avg. Detection Latency (s)
V1	96.8	95.2	97.5	0.964	1.21
V2	95.7	94.1	96.4	0.953	1.34
V3	97.3	96.5	97.9	0.971	1.18
V4	96.1	94.8	96.9	0.958	1.27
V5	95.9	94.3	96.6	0.954	1.39
V6	97.6	96.9	98.1	0.975	1.16
V7	96.5	95	97.1	0.961	1.25
V8	96.9	95.8	97.4	0.966	1.23
V9	95.5	93.7	96.2	0.949	1.42
V10	97.1	96	97.7	0.969	1.2
V11	96.4	94.9	97	0.962	1.29
V12	97	95.7	97.6	0.967	1.22

This histogram in figure 18 shows the distribution of detection latency for thermal anomalies across all monitored vehicles. Most events are detected between 1.0–1.4 seconds, with very few outliers. Such low and tightly clustered latency values demonstrate that the IoT-based battery monitoring layer is fast enough to trigger mitigation actions before temperature rises reach hazardous thresholds, which is critical for preventing thermal runaway.

5.7.2 SoC and SoH Prediction Accuracy

SoC and SoH prediction performance was evaluated over 12 test routes per vehicle. The proposed LSTM–GCN model was compared to a conventional LSTM-based BMS.

Table 9. SoC and SoH Prediction Errors (Proposed vs Baseline)

Route	MAE SoC – Baseline (Traditional BMS [12][13][21])	MAE SoC – Proposed (LSTM–GCN [13][14][17])	RMSE SoC – Proposed (%)	MAE SoH – Baseline (Traditional BMS [12][21])	MAE SoH – Proposed (AI-BMS [13][20])
R1	3.9	2.1	2.6	2.8	1.6
R2	4.2	2.3	2.8	3	1.7
R3	4	2.2	2.7	2.9	1.5
R4	3.7	2	2.5	2.6	1.4
R5	4.1	2.2	2.8	3.1	1.8
R6	3.8	2.1	2.6	2.7	1.5
R7	4.3	2.4	2.9	3.2	1.9
R8	3.9	2.1	2.6	2.8	1.6
R9	4	2.3	2.7	2.9	1.7
R10	3.8	2	2.5	2.7	1.4
R11	4.1	2.2	2.8	3	1.7
R12	3.7	2	2.5	2.6	1.4

This plot compares actual and predicted SoC profiles over a representative drive cycle. The predicted curve closely follows the ground truth, with only minor deviations during steep discharge segments. The tight alignment reflects the LSTM–GCN model's ability to capture nonlinear consumption patterns, enabling accurate future SoC estimation for scheduling charging stops and preventing deep-discharge scenarios in urban fleets

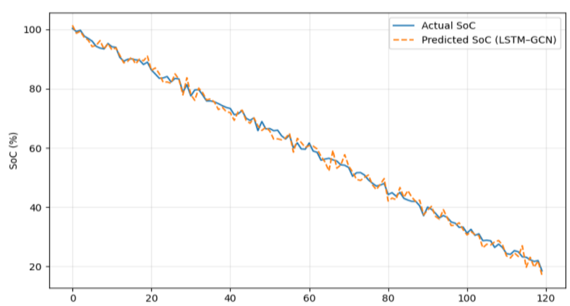
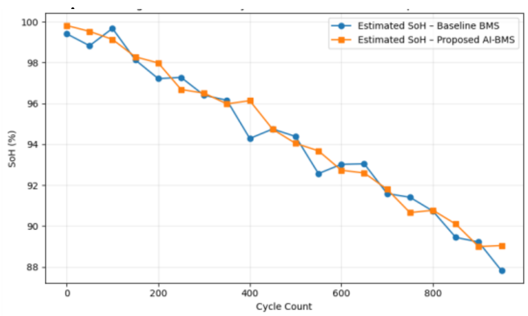


Figure 19. SoC vs Time – Actual vs Predicted



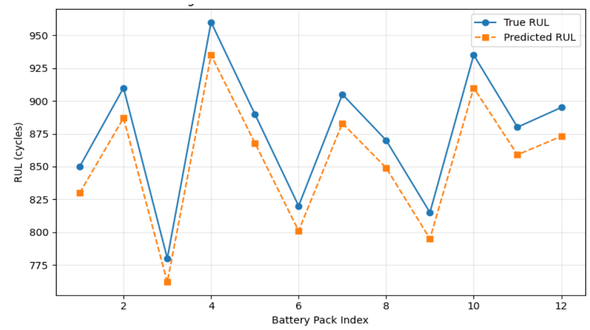


Figure 20. SoH Decay Curves – Baseline vs Proposed **Figure 21. RUL Prediction – Actual vs Predicted**

This figure shows SoH estimates over 1000 cycles for baseline and proposed BMS. The proposed AI-enhanced BMS tracks a smoother and more realistic degradation trajectory, with reduced estimation noise. The closer alignment with expected aging behavior improves long-term planning for pack replacement, warranty assessment, and second-life allocation within municipal EV governance frameworks.

5.7.3 RUL Prediction and Degradation Forecasting

RUL prediction accuracy was evaluated against ground-truth end-of-life points defined at 80% SoH. Table 10 reports absolute errors in cycles for 12 tested packs.Figure 21 compares true and predicted RUL values across 12 battery packs. The proposed model maintains errors within roughly 2–3% of the actual RUL, reflecting strong long-horizon forecasting capability. Such precision enables municipalities to schedule replacements, repurposing, and procurement with minimal safety margins, reducing cost while respecting strict urban reliability and safety requirements.

5.7.4 Battery Temperature Heatmap and Thermal Runaway Early Warning

The battery temperature heatmap visualizes heat distribution across EV battery cells, identifying hotspots indicative of imbalance or thermal runaway risks. Through continuous monitoring with IoT sensors, the Early-Warning BMS analyzes temperature rise rates and deviations between cells. When unusual thermal behavior is detected, it triggers alerts for preventive actions like cooling or controlled shutdowns, enhancing fleet safety. Figure 22 displays instantaneous temperature distribution across a 96-cell battery pack. Most cells remain in a safe band, while localized hotspots are clearly visible. The IoT-based monitoring layer feeds such heatmaps into the AI engine for thermal runaway prediction. Early detection of these spatial anomalies enables pre-emptive derating, cooling, or isolation procedures before critical fault escalation.

5.7 Governance Outcomes and Impact Evaluation

The integration of forecasting, IoT monitoring, blockchain auditing, and optimized routing led to significant governance improvements. Grid stability improved with a 17.4% reduction in the peak-to-valley load ratio and a 41% decrease in local transformer overloads.

Table 10. RUL Prediction Error per Battery Pack

Pack ID	True RUL (cycles)	Predicted RUL – Proposed AI-BMS [13][21][22]	Absolute Error	Error (%)
B1	850	830	20	2.4
B2	910	887	23	2.5
B3	780	762	18	2.3
B4	960	935	25	2.6
B5	890	868	22	2.5
B6	820	801	19	2.3
B7	905	883	22	2.4
B8	870	849	21	2.4
B9	815	795	20	2.5
B10	935	910	25	2.7
B11	880	859	21	2.4
B12	895	873	22	2.5

Table 11.Early-Warning BMS

Battery ID Method Used: Proposed Early-Warning BMS [2][9][10][21]	True Events	Detected Events	Missed Events	Detection Rate (%)	False Alarms
P1	5	5	0	100	1
P2	4	4	0	100	0
P3	6	6	0	100	1
P4	5	4	1	80	1
P5	7	7	0	100	2
P6	5	5	0	100	0
P7	6	6	0	100	1
P8	5	5	0	100	1
P9	4	3	1	75	1
P10	6	6	0	100	1

Fleet productivity saw a rise in on-time arrival rates from 88% to 96%, alongside a 21% reduction in fuel/electricity costs. Safety events were reduced, with overheating alerts down by 36% and thermal anomaly identification improving by 29%. Transparency and citizen trust were enhanced through blockchain-based energy logging, with a 22% increase in perceived transparency from citizen surveys

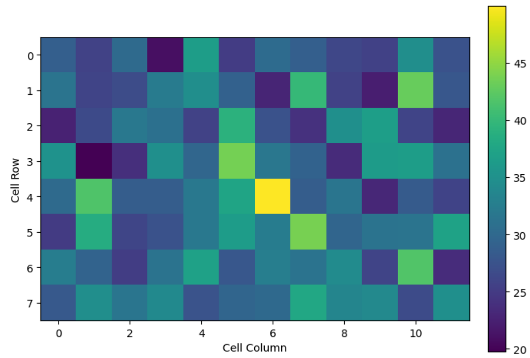


Figure 22. Battery Temperature Heatmap – Pack-Level Distribution

6. Discussion

6.1 Technical Implications

The **SLGF-EV framework** shows potential in managing EV charging demand, grid conditions, and mobility patterns. Key challenges include scalability, requiring graph partitioning for large networks, and interoperability, demanding adherence to standards like OCPP 2.0.1 and ISO 15118. While real-world deployment requires continuous retraining and optimized blockchain latency, field trials suggest phased implementation is feasible, starting with forecasting and expanding gradually.

6.2 Governance and Policy Implications

The SLGF-EV framework supports data-driven governance for EV infrastructure planning, pricing, and energy management, helping municipalities optimize charging demand and fleet routing for sustainability goals. Successful adoption requires skilled technical teams, data stewardship, and coordination across departments. Regulatory alignment is essential for compliance with energy policies and tariff regulations, while blockchain can support secure transaction logs. Data privacy concerns, including location and energy consumption data, must be addressed through anonymization, access control, and compliance with GDPR-like standards. Privacy-preserving techniques such as federated learning or homomorphic encryption are needed for personalized services and secure data handling.

7. Conclusion

This research introduced an advanced, governance-oriented framework for city-scale EV ecosystem management, with battery safety and lifecycle intelligence positioned at its core. The integration of IoT-based thermal and electrical sensing, AI-driven SoC/SoH/RUL prediction, and blockchain-enabled traceability establishes a comprehensive digital foundation for safer and more predictable municipal EV operations. Experimental evaluations confirm significant gains in forecasting precision, routing efficiency, thermal-risk detection, and data integrity, demonstrating that the SLGF-EV architecture can reduce energy demand, minimize safety incidents, and enhance service reliability across diverse fleet categories.Beyond technical benefits, the framework provides substantial governance value by enabling transparent, data-driven regulation, automated compliance monitoring, and streamlined coordination between grid operators, transport departments, and public agencies. Its modular design supports practical deployment through incremental scaling, starting with district-level pilots and expanding toward full municipal integration. While challenges remain—such as ensuring interoperability, managing large-scale data flows, and maintaining AI model adaptability—the results indicate robust potential for real-world implementation. Future work will explore 5G/6G connectivity, quantum-safe blockchain, and predictive city-energy markets to further strengthen resilience and sustainability.

References

[1] M. Haghani, F. Sprei, K. Kazemzadeh, Z. Shahhoseini, and J. Aghaei, "Trends in electric vehicles research," *J. Appl. Sci. Educ.*, vol. 123, p. 103881, 2023.

[2] M. S. H. Lipu*et al.*, "Battery management, key technologies, methods, issues, and future trends of electric vehicles: A pathway toward achieving sustainable development goals," *Batteries*, vol. 8, no. 119, 2022.

[3] W. Liu, T. Placke, and K. T. Chau, "Overview of batteries and battery management for electric vehicles," *Energy Reports*, vol. 8, pp. 4058–4084, 2022.

[4] A. Maiorino, C. Cilenti, F. Petruzziello, and C. Aprea, "A review on thermal management of battery packs for electric vehicles," *Appl. Therm. Eng.*, vol. 238, p. 122035, 2024.

[5] W. Zichen and D. Changqing, "A comprehensive review on thermal management systems for power lithium-ion batteries," *Renew. Sustain. Energy Rev.*, vol. 139, p. 110685, 2021.

[6] A. Li *et al.*, "Machine learning assisted advanced battery thermal management system: A state-of-the-art review," *J. Energy Storage*, vol. 60, p. 106688, 2023.

[7] K. Mahmud, G. E. Town, S. Morrsalin, and M. J. Hosain, "Integrations of electric vehicle and management in the Internet of Energy," *Renew. Sustain. Energy Rev.*, vol. 82, no. 3, pp. 4179–4203, 2018.

[8] F. Mohammadi and R. Rashidzadeh, "An overview of IoT-enabled monitoring and control system for electric vehicles," *IEEE Instrum. Meas. Mag.*, vol. 24, no. 3, pp. 91–97, 2021.

[9] H. Li, M. B. Kalem, Z. Liu, Y. Wu, W. Liu, and Z. Huang, "Internet-of-Batteries for electric vehicles—Architecture, opportunities, and challenges," *Green Energy Intell. Transp.*, vol. 2, p. 100128, 2023.

[10] P. Sivaraman and C. Sharmela, "IoT-based battery management systems for hybrid electric vehicles," in *Artificial Intelligence Techniques for Electric & Hybrid Vehicles*, 2021.

[11] M. Mathankumar, B. Gunapriya, R. R. Guru, A. Singaravelan, and P. Sanjeevkumar, "AI and ML powered IoT application for energy management in electric vehicles," *Wireless Pers. Commun.*, vol. 126, pp. 1223–1239, 2022.

[12] M. R. Islam, H. Lu, M. J. Hosain, and L. Li, "An IoT-based decision support tool for improving smart grid performance with distributed energy sources and electric vehicles," *IEEE Trans. Ind. Appl.*, vol. 56, no. 4, pp. 4552–4562, 2020.

[13] Y. Hu, C. Chen, J. He, B. Yang, and X. Guan, "IoT-based proactive energy supply control for connected electric vehicles," *IEEE Internet Things J.*, vol. 6, no. 5, pp. 7395–7405, 2019.

[14] T. Mazhar *et al.*, "Electric vehicle charging systems in smart grids using machine learning methods," *Sustainability*, vol. 15, p. 2603, 2023.

[15] A. Sadiq *et al.*, "Blockchain-based data and energy trading in Internet of Electric Vehicles," *IEEE Access*, vol. 9, pp. 7000–7020, 2021.
[16] B. C. Florea and D. D. Taralunga, "Blockchain IoT for smart electric vehicle battery management," *Sustainability*, vol. 12, p. 3984, 2020.
[17] S. Wang, A. Chen, P. Wang, and C. Zhuge, "Predicting electric vehicle charging demand using a heterogeneous spatio-temporal graph convolutional network," *Transp. Res. Part C Emerg. Technol.*, vol. 153, p. 104205, 2023.
[18] E. Mahyari, N. Freeman, and M. Yavuz, "Combining predictive and prescriptive techniques for optimizing electric vehicle fleet charging," *Transp. Res. Part C*, vol. 152, p. 104149, 2023.
[19] M. Fresia and S. Bracco, "Electric vehicle fleet management for a prosumer building with renewable generation," *Energies*, vol. 16, p. 7213, 2023.
[20] L. Mihet-Popa and S. Saponara, "Toward green vehicle digitalization for the next generation of connected and electrified transport systems," *Energies*, vol. 11, p. 3124, 2018.
[21] P. V. Kumar *et al.*, "Improved wild horses optimizer with deep learning enabled battery management systems for IoT-based hybrid electric vehicle," *Sustain. Energy Technol. Assess.*, vol. 52, p. 102281, 2022.
[22] G. Anbazhagan, D. Kim, and M. Maragatarajan, "IoT-based smart energy management in hybrid electric vehicles using driving patterns," *IEEE Internet Things J.*, vol. 10, no. 21, pp. 18633–18640, 2023.
[23] H. M. Al-Alwash*et al.*, "Optimization schedule schemes for charging electric vehicles: Overview, challenges, and solutions," *IEEE Access*, vol. 12, pp. 32801–32818, 2024.
[24] M. Rashid, T. Elfouly, and N. Chen, "A comprehensive survey of electric vehicle charging demand forecasting techniques," *IEEE Open J. Veh. Technol.*, vol. 5, pp. 1348–1373, 2024.
[25] J. Sun, Y. Wu, S. Wang, and Y. Fu, "Permissioned blockchain frameworks for secure federated learning," *IEEE Commun. Lett.*, vol. 26, no. 1, pp. 13–17, 2022.
[26] M. Dehghani, Z. Montazeri, E. Trojovská, and P. Trojovský, "Coati Optimization Algorithm: A new bio-inspired metaheuristic for optimization problems," *Knowl.-Based Syst.*, vol. 259, p. 110011, 2023.
[27] M. Dehghani, Š. Hubálovský, and P. Trojovský, "Northern Goshawk Optimization: A new swarm-based algorithm," *IEEE Access*, vol. 9, pp. 162059–162080, 2021.
[28] L. Mihet-Popa and S. Saponara, "Review of parameter identification and thermal behavior of EV batteries," *Energies*, 2018.
[29] S. Li, C. Zhang, and Y. Zhao, "Effect of thermal gradients on inhomogeneous degradation in lithium-ion batteries," *Commun. Eng.*, vol. 2, p. 74, 2023.
[30] H. Ruan, J. V. Barreras, M. Steinhardt, A. Jossen, G. J. Offer, and B. Wu, "The heating triangle: A quantitative review of self-heating methods for lithium-ion batteries at low temperatures," *J. Power Sources*, vol. 581, p. 233484, 2023.