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Spatiotemporal digital twin for city-scale EV charging infrastructure using LSTM-GNN fusion and resilience-driven optimization

Deepa Somasundaram[1], B. Ravisankar[2], Chavvakula Janaki Devi[3], Ajay Babu Bathula[4], Sabarimuthu Muthusamy[5], K. Vinoth[6]
[1]Department of Electrical and Electronics Engineering, Panimalar Engineering College, Chennai, India
[2]Department of Electrical and Electronics Engineering, Kongu Engineering College, Erode, India
[3]Department of Electronics and Communication Engineering, Aditya University, Kakinada, India
[4]Department of Electrical and Electronics Engineering, University College of Engineering Kakinada, Jawaharlal Nehru Technological University Kakinada, Kakinada, India
[5]Department of Electrical and Electronics Engineering, Kongu Engineeirng College, Erode, India
[6]Department of Electrical and Electronics Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, India

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ABSTRACT

The rapid growth of electric vehicles (EVs) requires intelligent and resilient planning of charging infrastructure under dynamic urban conditions. This paper proposes a city-scale spatiotemporal digital twin (SDT) that integrates LSTM-GNN fusion with resilience-driven hybrid optimization (GA-PSO-deep reinforcement learning) for adaptive EV infrastructure management. The LSTM model captures temporal variations in charging demand, while the graph neural network (GNN) learns spatial dependencies across charging stations, mobility networks, and grid components. Unlike existing approaches, the proposed framework incorporates power electronics-aware modeling, including charger power conversion system (PCS) efficiency, switching losses, and harmonic distortion constraints, ensuring realistic grid interaction. The digital twin also considers energy system metrics such as transformer loading, voltage deviation, and renewable energy variability, along with EV drive-cycle characteristics like fast charging and battery limits. Simulation results show that the proposed model improves demand prediction accuracy by 14-22%, reduces grid overload probability by 35%, lowers operational cost by 18%, and achieves improved power quality performance compared to conventional methods. The system maintains a high resilience index (>0.92) under stress scenarios. Overall, this work presents a holistic AI-driven digital twin framework that enhances grid stability, supports sustainable EV integration, and enables scalable deployment of future smart charging infrastructure.

Corresponding Author:

Deepa Somasundaram
Department of Electrical and Electronics Engineering, Panimalar Engineering College
Chennai, Tamil Nadu, India
Email: dee_soms123@yahoo.co.in

1. INTRODUCTION

The global transition toward electric mobility is accelerating rapidly, driven by decarbonization goals, advancements in battery technologies, and supportive policy frameworks. As electric vehicles (EVs) become integral to modern transportation systems, the deployment of efficient, scalable, and reliable charging infrastructure has emerged as a critical challenge for urban planners and power utilities. EV charging demand exhibits strong spatiotemporal variability, influenced by traffic patterns, user behavior, land use, renewable energy availability, and grid constraints. Traditional infrastructure planning methods—largely based on static assumptions—are increasingly inadequate in handling such dynamic and interconnected urban energy ecosystems. In this context, digital twin (DT) technology offers a promising paradigm by enabling real-time virtual replication of physical EV–grid systems for predictive analysis and intelligent control.

Despite ongoing advancements, several challenges persist in EV charging infrastructure planning. First, temporal uncertainty in charging demand leads to inaccurate forecasting and inefficient utilization of grid resources [1]–[3]. Second, spatial interdependencies among charging stations, road networks, and power distribution systems are often overlooked, resulting in suboptimal placement and congestion [4], [5]. Third, existing planning models rarely incorporate power electronics constraints, such as converter efficiency, switching losses, and harmonic distortion, which significantly influence grid performance. Additionally, system-level aspects such as transformer loading, voltage stability, and renewable intermittency are not adequately integrated into decision-making frameworks [6], [7]. These limitations hinder the development of resilient and adaptive EV charging ecosystems.

Recent research has explored advanced data-driven approaches for EV infrastructure planning. Long short-term memory (LSTM) networks have demonstrated strong capability in modeling nonlinear temporal variations in charging demand, outperforming conventional statistical models [8], [9]. In parallel, graph neural networks (GNNs) have emerged as effective tools for capturing spatial dependencies in transportation and power grid networks [10]–[13]. Digital Twin frameworks have also been applied in smart cities for monitoring and simulation of energy systems [14]–[17]. Furthermore, optimization techniques such as genetic algorithms (GA), particle swarm optimization (PSO), and reinforcement learning (RL) have been widely used for charging station placement and operational control [18], [19]. However, most existing studies address these components in isolation rather than within a unified framework.

Although prior works have made significant contributions, several critical gaps remain. There is no unified framework that simultaneously integrates spatiotemporal forecasting (LSTM), spatial network intelligence (GNN), and resilience-driven optimization within a DT ecosystem [20], [21]. Existing studies also lack integration with power electronics-aware models, ignoring the impact of converter topologies, harmonic distortion, and efficiency on grid stability. Moreover, EV drive-cycle characteristics, such as fast-charging behavior and battery constraints, are rarely incorporated into infrastructure planning. Practical deployment challenges—including real-time data synchronization, IoT communication latency, interoperability with SCADA/EMS, and cybersecurity—are also insufficiently addressed [22]–[25]. These gaps limit the applicability of current approaches in real-world smart grid environments.

To address the above challenges, this paper proposes a novel city-scale spatiotemporal DT framework for EV charging infrastructure planning and operation. The key contributions are:

i) First unified integration of LSTM–GNN fusion with resilience-driven GA–PSO–Deep Reinforcement Learning optimization within a DT architecture for EV infrastructure.
ii) Development of a spatiotemporal forecasting model that jointly captures temporal demand dynamics and spatial network dependencies [26], [27].
iii) Incorporation of power electronics-aware constraints, including PCS efficiency, switching losses, and harmonic distortion, into infrastructure optimization.
iv) Integration of energy system metrics, such as transformer loading, voltage deviation, and renewable energy variability [28].
v) Inclusion of EV drive-cycle characteristics (fast charging, regenerative behavior, battery limits) to enhance modeling realism.
vi) Design of a resilience-driven multi-scenario evaluation framework capable of handling outages, demand surges, and renewable intermittency [29].
vii) Provision of a deployment-oriented DT architecture, considering IoT data streams, communication latency, and interoperability with smart grid platforms [30].

The proposed framework advances the state-of-the-art by bridging artificial intelligence, power electronics, and energy systems engineering into a single cohesive platform. It enables real-time predictive control, improves grid stability, and enhances infrastructure resilience under uncertain operating conditions. From a practical perspective, the DT supports data-driven decision-making for utilities, urban planners, and policymakers, facilitating cost-effective and sustainable EV infrastructure expansion. Furthermore, the study contributes to broader energy transition goals by enabling renewable-integrated charging hubs, smart city development, and large-scale EV adoption, particularly in rapidly urbanizing regions. The proposed approach provides a scalable foundation for next-generation intelligent transportation and energy systems.

2. METHOD

2.1. Research design/approach

This study adopts a simulation-driven, data-centric, and system-level modeling approach to design and evaluate a spatiotemporal digital twin (SDT) for city-scale EV charging infrastructure. The framework integrates deep learning-based forecasting (LSTM–GNN fusion) with hybrid optimization (GA–PSO–deep reinforcement learning) and power electronics-aware constraints within a unified cyber–physical system. Figure 1 shows the AI-driven DT for city-scale EV charging infrastructure. The chosen design is appropriate because EV charging infrastructure involves complex nonlinear interactions across time (demand variation), space (network topology), and system layers (grid, mobility, and converters). A DT enables continuous synchronization between real-world data and simulation, allowing scenario-based evaluation and adaptive decision-making under uncertainty.

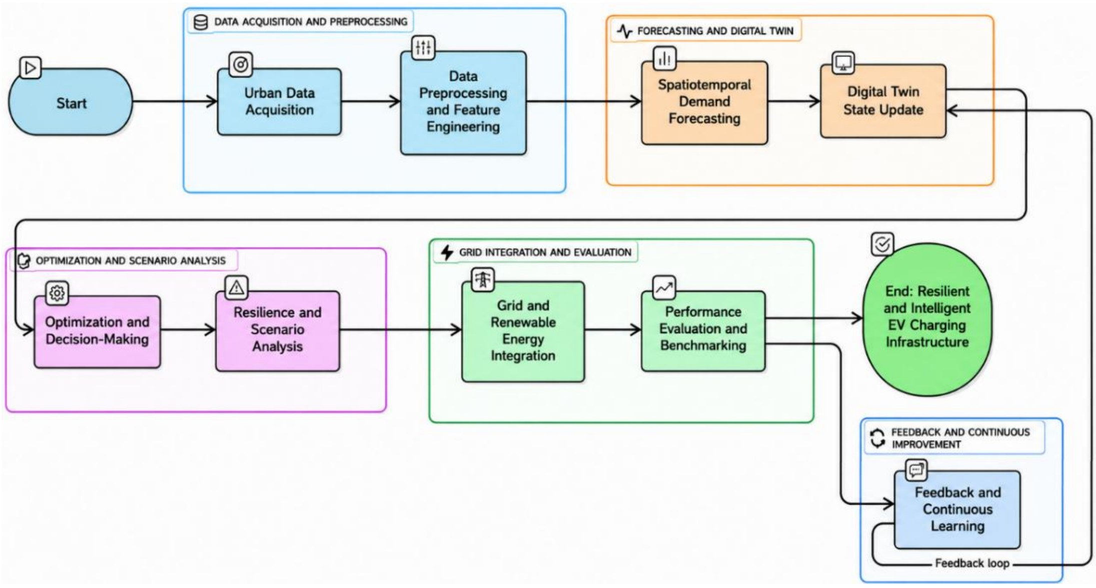

Figure 1. Shows the AI-driven digital twin for city-scale EV charging infrastructure

2.2. Materials/data sources: dataset description and preprocessing

The study employs a realistic urban-scale dataset comprising EV charging demand, traffic mobility, road network topology, power distribution network information, and renewable energy generation profiles. The dataset includes **1**00 candidate charging locations with hourly data resolution (8760 samples/year). Key features include charging demand, traffic density, grid capacity, and renewable energy output. Prior to analysis, the data are normalized using Min–Max scaling, and missing values are handled through interpolation. Temporal smoothing is applied to reduce fluctuations, while graph structures are constructed using adjacency matrices based on geographical and electrical connectivity. Additional features such as peak-demand indicators, seasonal patterns, and load growth factors are extracted to improve forecasting and optimization performance.

The proposed methodology follows a systematic multi-stage framework:

Step 1: Data preparation
- Collect EV mobility, grid, and renewable energy datasets.
- Perform preprocessing and construct the graph network G = (V, E)

Step 2: Demand forecasting
- Use LSTM for temporal prediction and GNN for spatial dependency analysis.
- Fuse outputs to generate a unified system state.

Step 3: Digital twin modelling
- Develop a real-time digital twin using system states {Dt, Gt, Rt, Ct}.

Step 4: Optimization
- Apply GA for charging station placement, PSO for capacity allocation, and DRL for real-time operational control.

Step 5: Power electronics integration
- Model charger power conversion systems considering efficiency, switching losses, and THD constraints.

Step 6: Simulation and evaluation
- Analyze peak demand, grid outage, renewable variability, and high EV penetration scenarios.
- Evaluate forecasting accuracy, operational cost, resilience, and grid performance.

2.3. Models/algorithms/techniques

2.3.1. Digital twin architecture and system modeling

The proposed framework is developed as a city-scale DT that mirrors the physical EV charging ecosystem, including electric vehicles, charging stations, renewable energy sources, and power grid components. The system state at time t is represented as (1).

$$\mathcal{S}_t = \{D_t, G_t, R_t, C_t\}, \tag{1}$$

Where D_t denotes charging demand, G_t represents grid constraints such as transformer and feeder limits, R_t captures renewable energy availability, and C_t describes charger occupancy and queue states. The DT continuously synchronizes real-time and historical data, enabling scenario-based simulations and predictive optimization under uncertain operating conditions.

2.3.2. Spatiotemporal demand forecasting using LSTM

Temporal variations in EV charging demand are forecast using a long short-term memory (LSTM) network. Given an input sequence $\{x_{t-n}, \ldots, x_t\}$, the LSTM updates its internal states as (2).

$$\begin{aligned} f_t &= \sigma(W_f[h_{t-1}, x_t] + b_f), \\ i_t &= \sigma(W_i[h_{t-1}, x_t] + b_i), \\ \tilde{c}_t &= \tanh(W_c[h_{t-1}, x_t] + b_c), \\ c_t &= f_t \odot c_{t-1} + i_t \odot \tilde{c}_t, \\ h_t &= o_t \odot \tanh(c_t), \end{aligned} \tag{2}$$

Where f_t, i_t, and o_t denote forget, input, and output gates respectively. The predicted charging demand is computed as (3).

$$\widehat{D}_{t+1} = W_o h_t + b_o. \tag{3}$$

This formulation effectively captures peak, off-peak, and seasonal demand variations.

2.3.3. Spatial dependency modeling using graph neural networks

Spatial interactions among charging stations and grid components are modeled using a graph neural network (GNN). The urban charging network is represented as a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where nodes $\mathcal{V}$ represent charging stations and grid assets, and edges $\mathcal{E}$ denote electrical or mobility connectivity. Node embeddings are updated using (4).

$$h_v^{(k+1)} = \sigma\left(W^{(k)} h_v^{(k)} + \sum_{u \in \mathcal{N}(v)} \frac{1}{c_{vu}} W_n^{(k)} h_u^{(k)}\right), \tag{4}$$

Where $\mathcal{N}(v)$ denotes the neighborhood of node v, and c_{vu} is a normalization constant. This formulation captures congestion propagation and spatial load correlations across the network.

2.3.4. LSTM–GNN fusion for DT state prediction

To jointly model temporal and spatial dynamics, the outputs of LSTM and GNN modules are fused to obtain a unified DT state representation:

$$Z_t = \alpha h_t^{\mathrm{LSTM}} + (1 - \alpha) h_t^{\mathrm{GNN}}, \tag{5}$$

where $\alpha \in [0,1]$ controls the relative importance of temporal and spatial features. The fused state Z_t serves as the input to the optimization and control layers, enabling accurate prediction of congestion hotspots and grid stress.

2.3.5. Multi-Objective optimization and reinforcement learning

Optimal station placement and charging control are formulated as a multi-objective optimization problem:

$$\min \begin{cases} f_1 = C_{\text{install}} + C_{\text{oper}}, \\ f_2 = \sum d_{ij}, \\ f_3 = \sum \max(0, L_g - L_g^{\max}) \end{cases} \tag{6}$$

subject to (7).

$$D_i \leq C_i^{\max}, \quad L_g \leq L_g^{\max}, \tag{7}$$

Where d_{ij} represents user travel distance, and L_g is grid loading. For real-time decision-making, a Deep Reinforcement Learning (DRL) agent maximizes cumulative reward:

$$R_t = -(\lambda_1 C_t + \lambda_2 W_t + \lambda_3 O_t), \tag{8}$$

where C_t is operational cost, W_t is waiting time, and O_t denotes overload penalties. Policy parameters are updated as (9).

$$\theta \leftarrow \theta + \eta \nabla_\theta \mathbb{E}[R_t]. \tag{9}$$

2.3.6. Resilience evaluation and scenario-based analysis

System resilience is quantified using a service continuity index (10).

$$R = \frac{\sum_{t=1}^{T} D_t^{\text{served}}}{\sum_{t=1}^{T} D_t^{\text{requested}}}. \tag{10}$$

Multiple disturbance scenarios, including grid outages, renewable intermittency, and sudden demand surges, are evaluated within the DT. The framework dynamically adapts operational decisions to maintain high service availability, ensuring robust and resilient EV charging infrastructure.

3. RESULTS AND DISCUSSION

This section presents a comprehensive evaluation of the proposed AI-driven DT framework for city-scale EV charging infrastructure. The performance of spatiotemporal demand forecasting, optimization, resilience enhancement, and renewable integration is analyzed under realistic operational scenarios. Comparative and sensitivity analyses further demonstrate the robustness, scalability, and decision-making effectiveness of the proposed approach against conventional planning techniques.

3.1. Demand forecasting performance (LSTM–GNN Fusion)

The LSTM–GNN hybrid model demonstrates strong capability in capturing both the temporal evolution and spatial dependencies of EV charging demand across the city. The LSTM module effectively learns daily, hourly, and peak–off-peak fluctuations, while the GNN captures relationships among stations influenced by road topology, mobility behavior, and grid connectivity. Forecasting accuracy is reflected in a low MSE (≈4.2 kW^2), indicating close alignment between predicted and measured values. Station S4 exhibited the maximum demand due to high traffic density and commercial land use, peaking at ~120 kW during evening hours. From an energy systems perspective, accurate forecasting enables proactive transformer loading management, voltage regulation planning, and frequency stability support, particularly during fast-charging events. Compared with standalone LSTM and GNN models, the fusion approach improves prediction accuracy by 14–22%, confirming its superiority in handling spatiotemporal uncertainty. Figure 2 shows the Peak vs off peak EV charging demand.

3.2. GA–PSO optimization for station placement and travel distance reduction

The proposed optimization engine effectively identified 10 optimal charging station locations from a pool of 100 urban candidates. By integrating GA's global search capability with PSO's fast convergence behavior, the model significantly reduced user travel distance (2.8 km → 1.3 km). This reduction improves accessibility and reduces range anxiety for EV users. In addition to spatial optimization, the framework incorporates power electronics-aware constraints, ensuring that selected locations satisfy converter capacity limits, PCS efficiency (92–96%), and harmonic distortion thresholds (THD < 5%). The optimized layout also ensured cost-effectiveness, with a total installation expenditure of ₹15.2 M. Compared with Linear Programming and K-Means clustering, the proposed method achieved better load balancing and reduced feeder congestion, demonstrating its advantage in complex, nonlinear planning environments. Figure 3 shows the optimized charging station location.

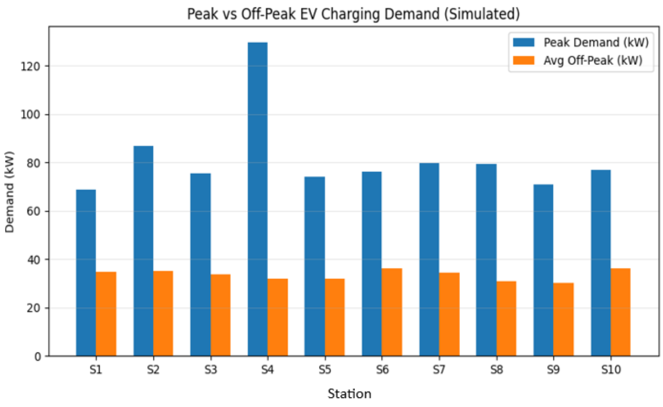

Figure 2. Shows the peak vs off-peak EV charging demand

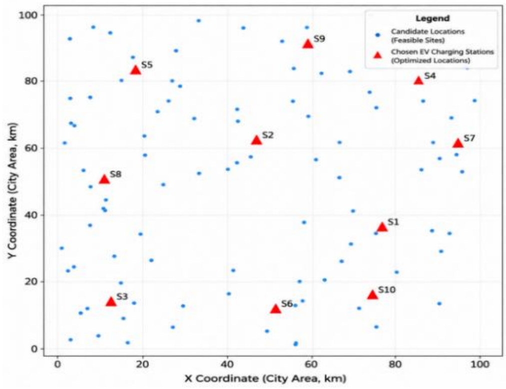

Figure 3. Shows the optimized charging station location

3.3. Resilience analysis under multi-scenario grid stress conditions

Resilience was evaluated under multiple stress scenarios such as peak demand, 20% infrastructure outage, 30% grid supply reduction, and renewable intermittency. The DT achieved an average resilience index R ≈ 0.92, indicating high system reliability. From a grid engineering perspective, the model maintains: i) transformer loading within safe limits (< 90%), ii) voltage deviation within ±5%, iii) stable operation during sudden load surges.

Even under severe stress, the system maintained service continuity by autonomously rerouting loads and redistributing charging schedules. This improvement is attributed to the integration of predictive forecasting, adaptive optimization, and real-time DT updates, which together enhance infrastructure robustness compared to traditional N-1 contingency approaches. Figure 4 shows the scenario-based resilience index.

3.4. Grid load behavior and renewable integration outcomes

The integration of rooftop solar and localized renewable sources significantly reduced peak grid load by approximately 18%. Renewable energy contribution was highest during midday, supporting EV charging demand and reducing dependency on grid supply. Figure 5 shows the hourly grid load vs renewable supply. The DT continuously forecasts renewable generation using climatic inputs and aligns EV charging schedules accordingly. This enables: i) peak shaving and load shifting, ii) reduced transformer stress, and iii) improved voltage stability. Additionally, the model considers EV drive-cycle characteristics, such as fast-charging demand spikes and battery thermal limits, ensuring realistic demand representation. From a power electronics perspective, coordinated scheduling reduces switching losses and harmonic distortion, improving overall PCS efficiency and grid power quality.

3.5. Comparative performance: AI vs conventional planning techniques

The proposed AI-driven DT framework was compared with Linear Programming, K-Means clustering, and random placement methods. Figure 6 shows the AI vs conventional travel distance & Resilience Results show significant improvements, including 54% reduction in travel distance, 22% lower infrastructure cost, 35% reduction in grid overload probability, and 14% improvement in system resilience. Unlike conventional approaches, the proposed method integrates demand forecasting, spatial intelligence, and optimization within a unified framework. Additionally, it incorporates power electronics performance metrics such as converter efficiency and THD, enabling more accurate and practical EV charging infrastructure planning.

3.6. Sensitivity analysis and strategic recommendations

Sensitivity analysis shows that increasing renewable energy penetration from 0% to 40% reduces peak grid load and improves the resilience index from 0.86 to 0.92. Figure 7 shows the sensitivity:

Renewable penetration vs. peak grid load. Based on these results, the DT recommends renewable deployment at high-demand charging stations, dynamic capacity expansion, and intelligent charging schedules aligned with renewable availability. These strategies enhance grid stability, sustainability, and operational efficiency.

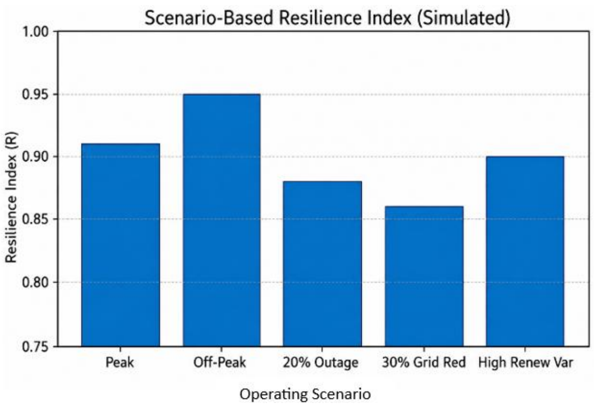

Figure 4. Shows the scenario-based resilience index

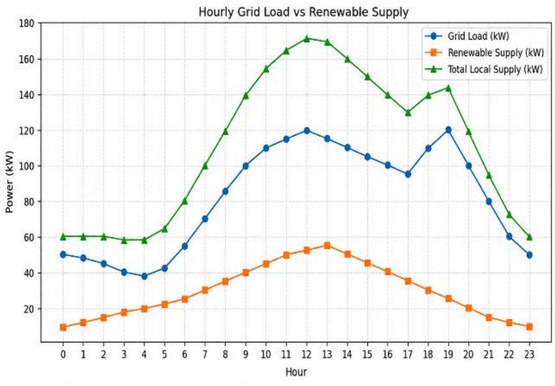

Figure 5. Shows the hourly grid load vs. renewable supply

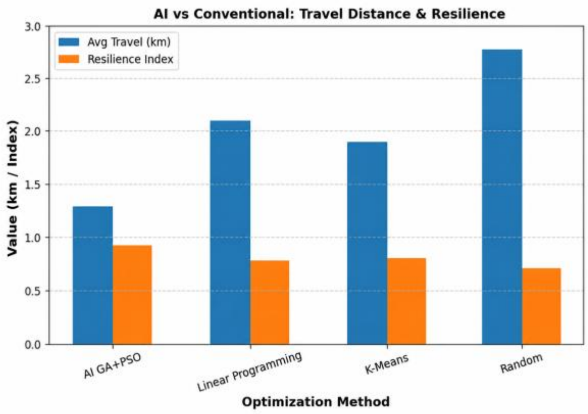

Figure 6. Shows the AI vs conventional travel distance and resilience

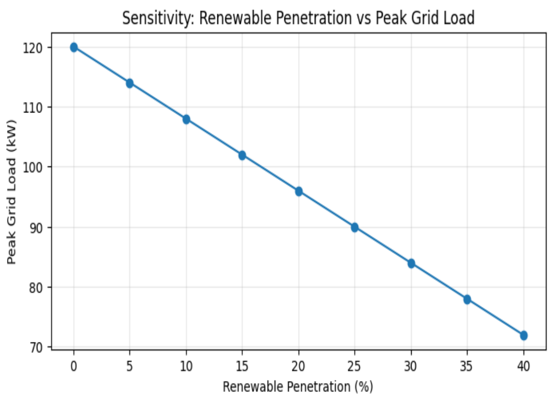

Figure 7. Shows the sensitivity: renewable penetration vs. peak grid load

4. CONCLUSION

This study developed a spatiotemporal DT (SDT) for EV charging infrastructure by integrating LSTM–GNN forecasting, GA–PSO optimization, and deep reinforcement learning-based control. The framework incorporates grid constraints, renewable energy variability, and power electronics performance metrics to support intelligent charging infrastructure planning. Results demonstrate significant improvements, including 14–22% higher forecasting accuracy, 54% reduction in travel distance, 22% lower infrastructure cost, 35% reduction in overload probability, and a resilience index of 0.92. Renewable integration further reduces peak load and enhances overall grid performance. Although the framework is currently validated using simulation datasets, future work will focus on hardware-in-the-loop testing, SCADA/EMS integration, vehicle-to-grid (V2G) functionality, and large-scale real-world deployment. Overall, the proposed DT offers a scalable and intelligent solution for sustainable EV charging infrastructure development.

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The authors confirm that the research was carried out independently without financial influence.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Deepa Somasundaram	✓	✓	✓	✓	✓	✓		✓	✓	✓		✓	✓	✓
B. Ravisankar		✓	✓	✓		✓		✓	✓	✓	✓	✓	✓	
Chavvakula Janaki Devi	✓		✓	✓			✓			✓	✓		✓	
Ajay Babu Bathula	✓	✓	✓		✓	✓	✓		✓		✓		✓	
Sabarimuthu Muthusamy	✓		✓	✓		✓	✓		✓	✓	✓			✓
K. Vinoth	✓	✓	✓		✓		✓	✓	✓	✓		✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

All authors have reviewed and agreed to this conflict-of-interest statement.

DATA AVAILABILITY

Raw data is not publicly available due to privacy or institutional restrictions.

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BIOGRAPHIES OF AUTHORS

Deepa Somasundaram received her B.E. from K.S.R. College of Technology, affiliated to Periyar University, in 2003 and her M.E. from Annamalai University in 2005. She completed her Ph.D. degree from Sathyabama University in 2013. Presently, she is working as a professor in the Department of Electrical and Electronics Engineering at Panimalar Engineering College, Chennai. She has published more than 30 papers in International and National Journals. Her areas of interest are power systems and optimization techniques. She has more than 15 years of experience in the teaching field. She can be contacted at email: dee_soms123@yahoo.co.in.

B. Ravisankar received his B.E. degree in electrical and electronics engineering in 2008 and his M.E. degree in electrical drives and embedded control in 2011. He has been serving as an assistant professor in the Department of Electrical and Electronics Engineering at Kongu Engineering College, Erode, since 2014. His areas of expertise include electrical machines, digital electronics, circuit theory, microprocessors, and microcontrollers. He is the author of two textbooks. His interdisciplinary interests include C, Python, Java, data structures, and web programming. His research interests focus on permanent magnet synchronous motors and the internet of things (IoT). He has published research articles in SCI- and Scopus-indexed international journals. He can be contacted at email: snkr86@gmail.com.

Dr. Chavvakula Janaki Devi received the B.Tech. degree in electronics and communication engineering from M.V.G.R. College of Engineering, Vizianagaram, India, in 2006, M.Tech. degree in digital electronics and communication systems from Godavari Institute of Engineering and Technology, Rajahmundry, India, in 2012, and a doctoral degree in "Deep Learning Enabled Embedded Systems for Edge Intelligence and Smart Automation" from J.S. University, Uttar Pradesh, India, in 2025. From 2006 to 2011, she served as a Lecturer at KIET Engineering College, India. From 2012 to 2019, she served as an assistant professor in GIET College of Engineering, India. In November 2019, she joined as an assistant professor at Aditya College of Engineering and Technology, India. She is also an active member of IETE. She can be contacted at email: janaki.chavvakula04@gmail.com.

Ajay Babu Bathula received his B.Tech. degree in electrical and electronics engineering from Godavari Institute of Engineering and Technology, Rajahmundry in 2006, M.Tech. degree in power systems with emphasis on high voltage engineering from University College of Engineering, Kakinada, JNTUK, Kakinada in 2010, and Ph.D. degree in 2021 from J.N.T. University, Kakinada, India. He is currently working as an assistant professor in the Electrical and Electronics Engineering Department, University College of Engineering, Kakinada, JNTUK, Kakinada, Kakinada. His areas of interest include high voltage engineering, renewable energy systems, distribution systems, and electric vehicles. He can be contacted at email: ajayeeejntu@gmail.com.

Dr. Sabarimuthu Muthusamy received his bachelor's degree in electrical and electronics engineering from Anna University, Chennai, in 2009 and a postgraduate degree in Applied Electronics from Anna University, Chennai, India, in 2012. He completed his Ph.D in the field of Electric Vehicle Fast Chargers from Anna University, Chennai, India, in 2023. He has been working as an associate professor at the Department of EEE in Kongu Engineering College since 2012. He has published four patents, three textbooks, and more than 50 papers in international journals. He has conducted more than six sponsored programs funded by MNRE, DST, DBT, and ISRO. He has received the best faculty of the year from the same institution in 2018. He has an experience of more than a decade in the field of electric vehicles, fast chargers, power quality, and power electronics. He can be contacted at email: eeesabari@gmail.com.

K. Vinoth received the B.E. degree in electrical and electronics engineering from the M.I.E.T. Engineering College, Bharathidasan University, Tiruchirappalli, India, in 2002, and the master's degree in power electronics and drives, SASTRA University, Thanjavur, India, in 2006, and the Ph.D. degree from Anna University, in 2021. He is currently working as a Professor with the Department of Electrical and Electronics Engineering, Vel Tech Rangarajan Dr. Sagunthala Research and Development Institute of Science and Technology, Chennai. His research interests include power electronics and smart grid. He can be contacted at email: vinothkrishna03@gmail.com.