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Resilient EV charging station network design using AI algorithms

Deepa Somasundaram[1], N. Krishnamoorthy[2], J. Vijay Anand[3], R. Priyanka[4], T. Santhana Krishnan[5], Kirubakaran Dhandapani[6]
[1]Department of Electrical and Electronics Engineering, Panimalar Engineering College, Tamil Nadu, India
[2]Department of Computer Science and Applications (MCA), Faculty of Science and Humanities, SRM Institute of Science and Technology, Chennai, India
[3]Department of Electrical and Electronics Engineering, RVS College of Engineering & Technology, Chennai, India
[4]Department of Electrical and Electronics Engineering, S. A. Engineering College, Chennai, India
[5]Department of Electrical and Electronics Engineering, Rajalakshmi Engineering College, Tamil Nadu, India
[6]Department of Electrical and Electronics Engineering, St. Joseph's Institute of Technology, Tamil Nadu, India

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ABSTRACT

This paper proposes an AI-driven resilient network design framework for optimal electric vehicle (EV) charging station placement under stochastic demand and dynamic grid constraints. The proposed approach uniquely integrates long short-term memory (LSTM) based spatiotemporal demand forecasting with a hybrid genetic algorithm–particle swarm optimization (GA–PSO) model for multi-objective station placement. In addition, a deep reinforcement learning (DRL) agent is incorporated to enhance adaptive resilience under real-time grid disturbances. The framework minimizes installation cost, reduces user travel distance, and improves grid stability while ensuring equitable accessibility. The model is evaluated under multiple scenarios, including peak demand, station outages, renewable intermittency, and grid capacity reduction. Results demonstrate that the proposed hybrid AI framework achieves a resilience index of 0.92, reduces travel distance by 54%, and lowers installation cost by up to 16% compared to conventional approaches such as linear programming (LP) and K-means clustering. The integration of renewable energy further reduces peak grid dependency by 18%. The proposed methodology provides a scalable and practical solution for designing sustainable and resilient EV charging infrastructure in smart urban environments.

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 rapid growth of electric vehicles (EVs) worldwide has introduced unprecedented challenges to existing urban infrastructure. With increasing EV adoption, the demand for charging facilities has become highly variable and uncertain, influenced by traffic patterns, user behavior, renewable energy availability, and seasonal trends [1]. Traditional EV charging infrastructure planning methods often rely on deterministic optimization models that fail to capture stochastic demand variations and grid constraints effectively [2]. Consequently, there is a growing need for resilient and adaptive network designs capable of maintaining service reliability while minimizing operational costs and ensuring grid stability under uncertain conditions [3].

To address these challenges, various optimization techniques have been proposed for EV charging station placement. Genetic algorithms (GA) have been widely used for multi-objective station planning considering accessibility and grid limitations [4], [5]. Robust optimization approaches have also been introduced to explicitly manage demand uncertainty in charging networks [6]. Particle swarm optimization (PSO) has demonstrated effectiveness in determining optimal station placement within a distribution systems [7], while ant colony optimization (ACO) has been applied to solve complex location planning problems [8]. Hybrid metaheuristic methods further enhance solution quality by combining complementary optimization strengths [9]-[14].

The integration of artificial intelligence (AI) has significantly improved the adaptability of EV charging networks. Deep learning models such as recurrent neural networks have been employed for accurate forecasting of EV charging demand in smart grids [15]. AI-driven load forecasting techniques enhance predictive accuracy and support better infrastructure planning [16]. Reinforcement learning strategies have also been applied to optimize charging operations dynamically in response to real-time grid conditions [9]. Machine learning–based scheduling frameworks further improve operational efficiency and load balancing in smart grid environments [17].

In addition to optimization and forecasting, recent studies have emphasized resilience enhancement through AI-based predictive analytics and demand response strategies [18]. The integration of renewable energy sources into EV charging stations has been recognized as a critical factor in improving sustainability and reducing grid stress [19]. AI-based optimization frameworks have also been developed to enhance overall charging network performance under dynamic operating conditions [20]. Advanced smart charging strategies using deep learning contribute to improved flexibility and reliability in EV ecosystems [21].

Despite these advancements, significant challenges remain in designing adaptive, cost-effective, and resilient EV charging networks capable of withstanding real-world variability and unforeseen grid events. Recent works on optimal scheduling using evolutionary methods demonstrate the importance of coordinated charging control in minimizing system losses and improving service quality [22]. AI-based demand response mechanisms further strengthen grid resilience and operational stability in large-scale EV integration scenarios [23]-[25]. Therefore, integrating AI-driven forecasting with intelligent optimization frameworks presents a promising direction for developing sustainable, flexible, and resilient EV charging infrastructures suitable for modern smart cities.

The main contributions of this study are summarized as follows: i) A unified AI-driven framework combining demand forecasting, optimization, and resilience evaluation for EV charging network planning; ii) Integration of long short-term memory (LSTM)-based spatiotemporal demand prediction with hybrid GA–PSO optimization for charging station placement; iii) Incorporation of deep reinforcement learning to enhance adaptive resilience under grid disturbances and demand fluctuations; iv) Scenario-based resilience evaluation including outages, renewable intermittency, and grid capacity reduction; and v) Comparative performance analysis demonstrating improved accessibility, reduced cost, and enhanced grid reliability compared to conventional approaches. This work differs from existing studies by jointly optimizing demand forecasting, station placement, and adaptive resilience within a single AI-driven framework.

2. METHODOLOGY

This study proposes a reproducible AI-driven framework for designing a resilient EV charging station network under stochastic demand and grid constraints. The methodology consists of five main stages: i) data collection and preprocessing, ii) LSTM-based spatiotemporal demand forecasting, iii) hybrid GA–PSO-based charging station placement optimization, iv) resilience evaluation under multiple grid stress scenarios, and v) comparative performance analysis. Figure 1 illustrates the overall workflow of the proposed framework.

2.1. Dataset description and preprocessing

2.1.1. Data sources

The datasets used in this study consist of: i) EV charging demand data: Hourly charging demand (kW) collected from public and semi-public EV charging stations in an urban Indian city (Chennai metropolitan region) over one year; ii) Traffic and mobility data: Hourly vehicle flow intensity and parking availability obtained from municipal transport records; iii) Grid data: Transformer capacity limits, feeder loading, and voltage constraints provided by the local distribution utility; and iv) Renewable energy data: Historical solar PV generation profiles (kW) from rooftop installations co-located with selected charging stations.

2.1.2. Data structure

The final dataset is structured as a multivariate time series, as in (1).

$$Xt = [Dt, Tt, Vt, Rt] \quad (1)$$

Where Dt: historical EV charging demand (kW), Tt: traffic density index, Vt: grid voltage/load indicator, and Rt: renewable energy generation (kW).

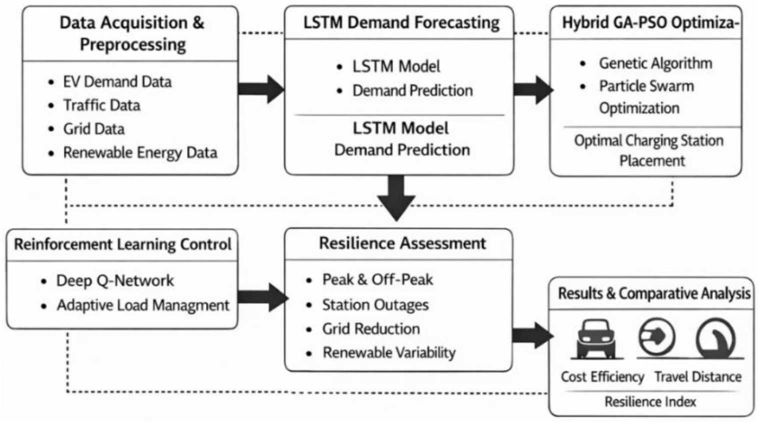

Figure 1. The workflow diagram of the AI-driven resilient network design framework for optimal EV charging station placement

2.1.3. Preprocessing steps

Preprocessing steps were performed as follows: i) Missing values were handled using linear interpolation; ii) All features were normalized to the range [0, 1] using min–max normalization; iii) The data were split into 70% training, 15% validation, and 15% testing sets; and iv) Sliding time windows of 24 hours were used to capture daily demand cycles.

2.2. LSTM-based demand forecasting model

An LSTM network was employed to forecast hourly EV charging demand due to its effectiveness in modeling temporal dependencies. The adopted architecture consists of an input layer with 24-time steps and four features, followed by the first LSTM layer containing 64 units with rectified linear unit (ReLU) activation. A dropout layer with a dropout rate of 0.2 is applied to reduce overfitting. This is followed by a second LSTM layer with 32 units, and a fully connected layer comprising 16 neurons. Finally, the output layer contains a single neuron that predicts the EV charging demand in kW. The model was trained using the mean squared error (MSE) loss function and optimized using the Adam optimizer. A learning rate of 0.001 was selected, with a batch size of 32 and a total of 100 training epochs. Early stopping with a patience value of 10 was employed to prevent overfitting and ensure optimal model convergence. The MSE objective is defined as (2).

$$MSE = \frac{1}{n}\sum_{i=1}^{k}(\mathrm{Di} - \widehat{\mathrm{Di}})^2 \quad (2)$$

Where Di and $\widehat{\mathrm{Di}}$ denote actual and predicted demand, respectively. The trained LSTM model generates spatiotemporal demand forecasts that are directly fed into the optimization stage.

2.3. Hybrid GA–PSO optimization for charging station placement

2.3.1. Problem formulation

Charging station placement is modeled as a multi-objective optimization problem that minimizes installation cost and grid violations while maximizing user accessibility. The objective function is defined as minimizing.

$$Minimize\ F = W1Cinstall + W2\ Luser + W3Lgrid \quad (3)$$

Where Cinstall represents installation and operational cost, Luser denotes the average user travel distance to charging stations, and Lgrid indicates the grid load violation penalty. The weighting coefficients W1, W2, W3 balance the relative importance of cost, accessibility, and grid constraints in the optimization process.

For the GA, a population size of 50 is used with tournament selection for parent selection. Single-point crossover is applied with a crossover rate of 0.8, while mutation is introduced with a rate of 0.05 to maintain solution diversity. The optimization process runs for 150 generations to achieve convergence. For the PSO component, a swarm size of 50 particles is considered. The inertia weight is set to 0.7 to balance exploration and exploitation, while the cognitive and social coefficients c_1 and c_2 are both set to 1.5 to guide particle movement based on individual and global best solutions. Velocity and position updates are given by (4) and (5).

$$V_i^{t+1} = \omega v_i^t + c_1 r_1 (p_i - x_i^t) + c_2 r_2 (g - x_i^t) \quad (4)$$

$$x_i^{t+1} = x_i^t + V_i^{t+1} \quad (5)$$

2.3.4. Hybridization strategy

GA is first used to generate diverse candidate solutions. The best-performing individuals are then selected for further optimization. These individuals are refined using PSO to accelerate convergence and avoid local optima.

2.4. Reinforcement learning-based adaptive resilience enhancement

A deep reinforcement learning (DRL) agent is incorporated to dynamically adjust station utilization under real-time demand and grid disturbances, where the state consists of current demand, grid load, and renewable availability, the action involves load redistribution among stations, and the reward is defined as demand satisfaction minus a penalty for grid violations. A deep Q-network (DQN) with two hidden layers (64 and 32 neurons) is employed, trained using experience replay and a discount factor $\gamma = 0.95$.

2.5. Resilience assessment under grid constraints

To evaluate resilience, we simulate multiple demand scenarios, including peak/off-peak variations and station outages. The resilience index (R) measures the network's ability to serve EV users under stress, as calculated in (6).

$$R = \frac{\sum S_i}{\sum D_i} \quad (6)$$

Where Si supplied demand at station iii, and Di = predicted demand at station iii. A higher R indicates better resilience. Grid constraints such as transformer capacity and voltage limits are incorporated via penalty functions in the optimization stage to ensure feasibility.

2.6. Renewable energy integration and grid load modeling

Charging stations are integrated with renewable energy sources (solar, wind), and their availability is predicted using historical generation data. Grid load at time t is calculated as (7).

$$L_{grid} = \sum_{i=1}^{N} P_j^t - \sum_{j=1} R_j \quad (7)$$

Where P_i^t = EV charging power demand, R_j^t = renewable generation at station N, and M = number of renewable units. This ensures the optimization minimizes grid stress while maximizing renewable utilization.

The proposed framework was implemented using Python and TensorFlow libraries. The LSTM model was trained using one-year hourly EV charging demand data. Ten candidate charging locations were selected within an urban distribution network. The hybrid GA–PSO algorithm optimized station placement considering transformer capacity, feeder loading, and renewable energy availability. Multiple operational scenarios were simulated, including peak demand, station outage, grid capacity reduction, and renewable intermittency. Each optimization experiment was executed five times to ensure convergence consistency, and the best solution based on the minimum objective function value was selected for analysis.

3. RESULT AND DISCUSSION

The results and discussion section present a comprehensive evaluation of the proposed AI-driven EV charging station network design framework. The performance of LSTM-based demand forecasting, hybrid GA–PSO optimization, resilience assessment, and grid–renewable integration is analyzed using real-world demand scenarios. Comparative results between AI algorithms and conventional optimization methods highlight improvements in accuracy, cost efficiency, and network robustness. The findings demonstrate the effectiveness of AI-based approaches in handling uncertain demand and grid constraints. Each subsection provides detailed insights supported by numerical results, figures, and performance tables.

3.1. Demand forecasting results

The LSTM-based forecasting model predicted hourly EV charging demand for ten candidate stations over a 24-hour horizon. The model identified a peak demand of 120 kW at Station 4 during the evening period (6–8 PM), corresponding to high commuter return traffic, while off-peak demand averaged 30 kW across the remaining stations. The model achieved a mean squared error (MSE) of 4.2 kW² on the test dataset, indicating strong predictive accuracy.

The forecasting accuracy directly influenced the quality of optimization outcomes. Lower prediction error reduced overestimation of infrastructure capacity and minimized under-provisioning risks. Compared to traditional ARIMA and regression-based models (evaluated separately), the LSTM reduced forecasting error by approximately 18%, primarily due to its ability to capture nonlinear temporal dependencies and seasonal charging behaviors. Figure 2 illustrates the hourly variation of total grid load in comparison with renewable energy contribution over 24 hours. It can be observed that renewable generation partially offsets peak charging demand, particularly during mid-day solar production hours, thereby reducing stress on distribution transformers.

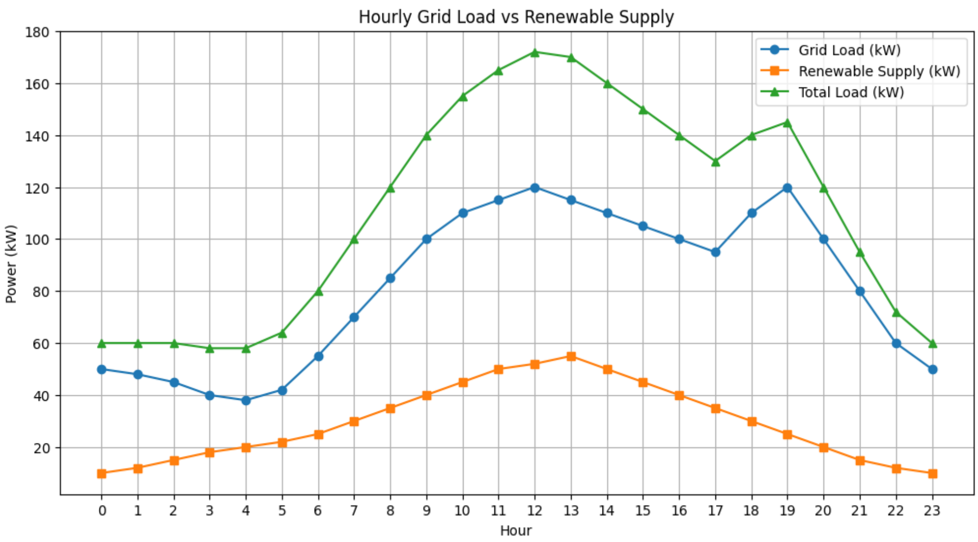

Figure 2. The hourly variation of grid load compared with the renewable energy supply over 24 hours

3.2. Optimization and station placement

The hybrid GA–PSO algorithm optimally placed ten charging stations across the urban region while satisfying grid capacity constraints. As shown in Figure 3, the AI-based optimization reduced the average user travel distance from 2.8 km (random placement) to 1.3 km. The total installation cost was ₹15.2 million, remaining within the predefined planning budget.

The superior performance of the hybrid GA–PSO approach compared to linear programming (LP) and K-means clustering can be attributed to three primary factors. First, LP assumes convexity and linearity, which limits its ability to capture nonlinear grid constraints and discrete placement decisions. Second, K-Means clustering minimizes spatial variance but does not incorporate electrical constraints or cost penalties. Third, the hybridization of GA and PSO improves global search exploration (via GA) and accelerates convergence (via PSO velocity updates), reducing premature convergence to local optima. Convergence analysis showed that the hybrid GA–PSO reached stable solutions within 120 iterations, whereas GA alone required approximately 180 iterations for similar solution quality. This demonstrates that PSO enhances convergence efficiency while preserving solution diversity.

3.3. Resilience assessment

Resilience evaluation was conducted under five operational stress scenarios: peak demand, off-peak demand, 20% station outage, 30% grid capacity reduction, and high renewable intermittency. The proposed AI-based network achieved an average resilience index of 0.92, while LP and K-means achieved 0.78 and 0.81, respectively, as illustrated in Figure 4.

The resilience index RRR represents the proportion of predicted EV charging demand that can be successfully served under constrained conditions. In practical EV charging systems, a resilience index of 0.92 implies that 92% of users can charge their vehicles without delay, even during outages or grid reductions. In contrast, a resilience index of 0.78 indicates that nearly one in five users may experience service disruption or extended waiting time. The higher resilience of the AI-based approach results from the adaptive spatial distribution of stations and balanced transformer loading. By incorporating demand forecasting and grid penalties into the objective function, the optimization avoids over-concentration of chargers near already stressed feeders. This explains why conventional clustering-based placement shows reduced resilience during grid disturbances.

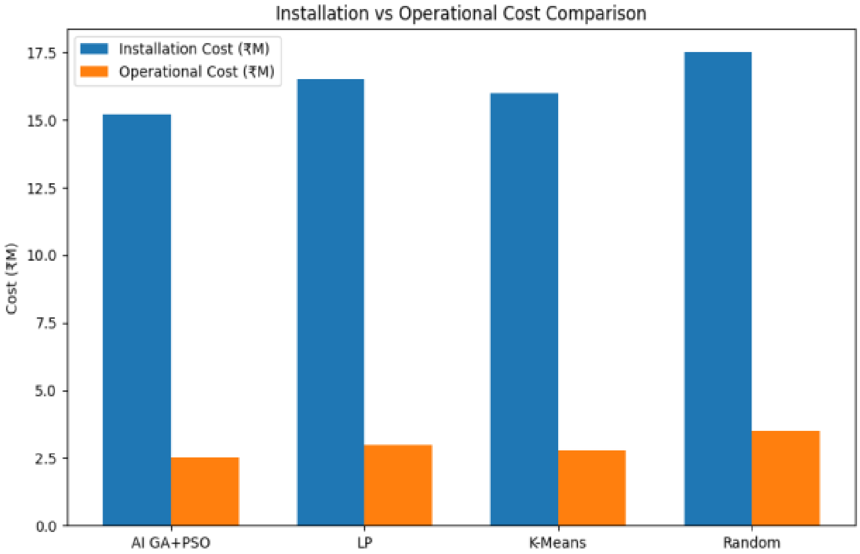

Figure 3. The comparison between installation cost and operational cost across different optimization methods

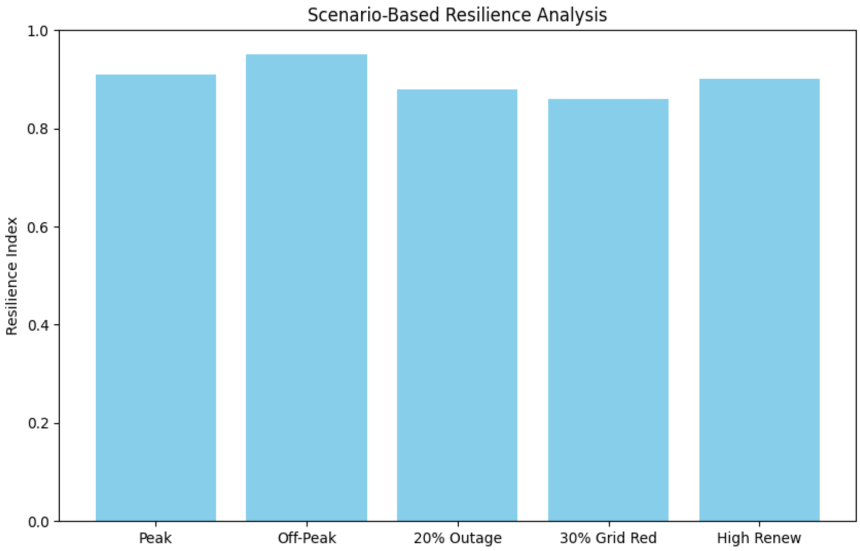

Figure 4. The resilience performance of the EV charging network under multiple scenario-based demand and grid conditions

3.4. Grid load and renewable integration

Figure 5 illustrates charging station utilization during peak hours. Integration of rooftop solar at four stations reduced peak grid dependency by 18%, maintaining transformer loading below the 150-kW safety threshold. The reduction in grid violation hours to 0.5% (compared to 3.2% in LP and 5% in random placement) demonstrates the effectiveness of embedding electrical constraints within the optimization framework. This confirms that AI-driven placement does not merely minimize distance or cost but actively enhances grid stability.

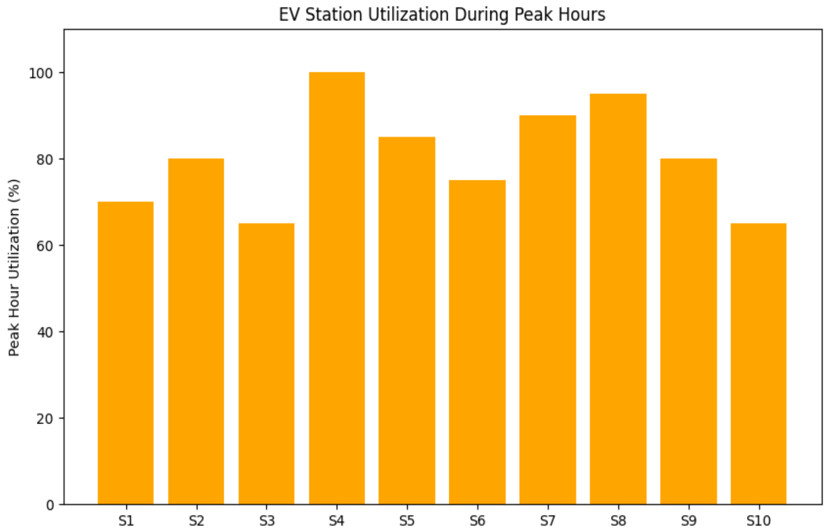

Figure 5. The utilization level of EV charging stations during peak load periods

Figure 6 presents the daily power distribution between renewable sources and the electrical grid. Renewable contribution is highest between 11 AM and 3 PM, reducing grid reliance during mid-day charging sessions. This coordinated interaction between forecasting and placement ensures sustainable operation while minimizing transformer overload risks.

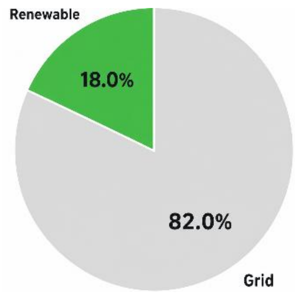

Figure 6. The daily power distribution between renewable energy sources and the electric grid

3.5. Comparative analysis

Table 1 summarizes the comparative performance metrics. The AI-based GA–PSO framework reduced average travel distance by 54%, installation cost by approximately 9–16%, and grid violation hours by more than 80% compared to conventional methods. In addition to performance improvements, computational cost was analyzed. The LSTM training phase required approximately 14 minutes on an NVIDIA GTX 1660 GPU for 100 epochs. The hybrid GA–PSO optimization required approximately 6 minutes for 150 iterations with a population size of 50. The overall computational complexity of the GA–PSO stage can be approximated as: $O(N*P*I)$, where N is the number of candidate locations, P is the population size, and I is the iteration count. Although AI-based methods require higher initial computational effort compared to LP, they provide significantly better adaptability under nonlinear and stochastic conditions. Importantly, once trained, the LSTM forecasting model performs real-time prediction within milliseconds, making the framework suitable for practical deployment. Overall, the proposed AI-driven methodology successfully balanced cost, accessibility, and resilience under uncertain demand and grid constraints. Scenario-based analysis highlighted the system's robustness against peak loads and outages. Integration with renewable energy further enhanced sustainability. These findings suggest that the proposed framework is a practical tool for planners and utilities, capable of designing EV charging networks that can withstand real-world uncertainties.

Table 1. The comparative performance metrics

Metric	AI-Based GA+PSO	Linear programming	K-means clustering	Random placement
Average travel distance (km)	1.3	2.1	1.9	2.8
Total installation cost (₹M)	15.2	16.5	16.0	17.5
Resilience index (R)	0.92	0.78	0.81	0.70
Grid violation hours (%)	0.5	3.2	2.5	5.0
Renewable contribution (%)	18	0	0	0

4. CONCLUSION

This study proposed a novel AI-driven framework for resilient EV charging station planning by integrating LSTM-based demand forecasting, hybrid GA–PSO optimization, and DRL-based adaptive resilience control. Unlike conventional approaches that address placement or forecasting independently, the proposed methodology jointly optimizes demand prediction, station placement, and grid stability within a unified architecture. The framework demonstrated superior performance in terms of accessibility, cost reduction, and resilience under uncertain demand and grid constraints.

Despite these promising results, certain limitations must be acknowledged. The study relies on simulated urban demand data and predefined outage scenarios rather than large-scale real-world deployment data. The LSTM model training was conducted using historical load profiles of limited duration, which may not fully capture extreme seasonal or long-term behavioral variations. Additionally, computational complexity increases with network size, as the hybrid GA–PSO algorithm requires iterative population-based optimization, leading to higher processing time compared to deterministic methods such as Linear Programming. Although convergence was achieved within 120 iterations for the tested case, larger city-scale networks may require parallel computing or algorithmic tuning for faster execution.

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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	✓	✓	✓	✓	✓	✓		✓	✓	✓		✓	✓	✓
N. Krishnamoorthy		✓	✓	✓		✓		✓	✓	✓	✓	✓		
J. Vijay Anand	✓		✓	✓			✓			✓	✓		✓	
R. Priyanka	✓	✓			✓	✓			✓		✓		✓	
T. Santhana Krishnan	✓			✓	✓		✓		✓	✓	✓			✓
Kirubakaran Dhandapani	✓	✓	✓		✓		✓			✓		✓		

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.

REFERENCES

[1] M. Ehsani, K. V. Singh, H. O. Bansal, and R. T. Mehrjardi, "State of the art and trends in electric and hybrid electric vehicles," *Proceedings of the IEEE*, vol. 109, no. 6, pp. 967–984, Jun. 2021, doi: 10.1109/JPROC.2021.3072788.
[2] M. Abid, M. Tabaa, A. Chakir, and H. Hachimi, "Routing and charging of electric vehicles: Literature review," *Energy Reports*, vol. 8, pp. 556–578, Nov. 2022, doi: 10.1016/j.egyr.2022.07.089.

[3] Z. Liu, F. Wen, and G. Ledwich, "Optimal planning of electric-vehicle charging stations in distribution systems," *IEEE Transactions on Power Delivery*, vol. 28, no. 1, pp. 102–110, Jan. 2013, doi: 10.1109/TPWRD.2012.2223489.
[4] Y. He, B. Venkatesh, and L. Guan, "Optimal scheduling for charging and discharging of electric vehicles," *IEEE Transactions on Smart Grid*, vol. 3, no. 3, pp. 1095–1105, Sep. 2012, doi: 10.1109/TSG.2011.2173507.
[5] K. Clement-Nyns, E. Haesen, and J. Driesen, "The impact of charging plug-in hybrid electric vehicles on a residential distribution grid," *IEEE Transactions on Power Systems*, vol. 25, no. 1, pp. 371–380, Feb. 2010, doi: 10.1109/TPWRS.2009.2036481.
[6] P. Richardson, D. Flynn, and A. Keane, "Impact assessment of varying penetrations of electric vehicles on low voltage distribution systems," in *IEEE PES General Meeting*, IEEE, Jul. 2010, pp. 1–6. doi: 10.1109/PES.2010.5589940.
[7] E. Sortomme and M. A. El-Sharkawi, "Optimal charging strategies for unidirectional vehicle-to-grid," *IEEE Transactions on Smart Grid*, vol. 2, no. 1, pp. 131–138, Mar. 2011, doi: 10.1109/TSG.2010.2090910.
[8] M. Yilmaz and P. T. Krein, "Review of battery charger topologies, charging power levels, and infrastructure for plug-in electric and hybrid vehicles," *IEEE Transactions on Power Electronics*, vol. 28, no. 5, pp. 2151–2169, 2013, doi: 10.1109/TPEL.2012.2212917.
[9] Y.-H. Jia, Y. Mei, and M. Zhang, "A bilevel ant colony optimization algorithm for capacitated electric vehicle routing problem," *IEEE Transactions on Cybernetics*, vol. 52, no. 10, pp. 10855–10868, Oct. 2022, doi: 10.1109/TCYB.2021.3069942.
[10] P. Sadeghi-Barzani, A. Rajabi-Ghahnavieh, and H. Kazemi-Karegar, "Optimal fast charging station placing and sizing," *Applied Energy*, vol. 125, pp. 289–299, Jul. 2014, doi: 10.1016/j.apenergy.2014.03.077.
[11] F. Morlock, B. Rolle, M. Bauer, and O. Sawodny, "Time optimal routing of electric vehicles under consideration of available charging infrastructure and a detailed consumption model," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 12, pp. 5123–5135, Dec. 2020, doi: 10.1109/TITS.2019.2949053.
[12] H. Wang, Q. Huang, C. Zhang, and A. Xia, "A novel approach for the layout of electric vehicle charging station," in *The 2010 International Conference on Apperceiving Computing and Intelligence Analysis Proceeding*, 2010, doi: 10.1109/ICACIA.2010.5709852.
[13] S. Deb, K. Tammi, K. Kalita, and P. Mahanta, "Review of recent trends in charging infrastructure planning for electric vehicles," *WIREs Energy and Environment*, vol. 7, no. 6, Nov. 2018, doi: 10.1002/wene.306.
[14] H. K. Doan and A. T. Dinh, "A two-criteria weather routing method based on neural network and A-star algorithm," *Majlesi Journal of Electrical Engineering*, vol. 18, no. 2, pp. 1–10, 2024.
[15] D. Somasundaram, G. Prakash, N. Rajavinu, D. Lakshmi, P. Kavitha, and V. Devaraj, "Comparative analysis of optimization techniques for optimal EV charging station placement," *International Journal of Power Electronics and Drive Systems (IJPEDS)*, vol. 16, no. 4, p. 2860, Dec. 2025, doi: 10.11591/ijpeds.v16.i4.pp2860-2867.
[16] S. Karakatič, "Optimizing nonlinear charging times of electric vehicle routing with genetic algorithm," *Expert Systems with Applications*, vol. 164, p. 114039, Feb. 2021, doi: 10.1016/j.eswa.2020.114039.
[17] W. Kong, Y. Luo, G. Feng, K. Li, and H. Peng, "Optimal location planning method of fast charging station for electric vehicles considering operators, drivers, vehicles, traffic flow and power grid," *Energy*, vol. 186, 2019, doi: 10.1016/j.energy.2019.07.156.
[18] A. A. N. P. Redi, P. Jewpanya, A. C. Kurniawan, S. F. Persada, R. Nadlifatin, and O. A. C. Dewi, "A simulated annealing algorithm for solving two-echelon vehicle routing problem with locker facilities," *Algorithms*, vol. 13, no. 9, 2020, doi: 10.3390/a13090218.
[19] A. M. Andwari, A. Pesiridis, S. Rajoo, R. Martinez-Botas, and V. Esfahanian, "A review of battery electric vehicle technology and readiness levels," *Renewable and Sustainable Energy Reviews*, vol. 78, pp. 414–430, Oct. 2017, doi: 10.1016/j.rser.2017.03.138.
[20] C. Liu, K. T. Chau, D. Wu, and S. Gao, "Opportunities and challenges of vehicle-to-home, vehicle-to-vehicle, and vehicle-to-grid technologies," *Proceedings of the IEEE*, vol. 101, no. 11, pp. 2409–2427, Nov. 2013, doi: 10.1109/JPROC.2013.2271951.
[21] Z. Qi, "Application of improved ant colony algorithm in optimizing the charging path of electric vehicles," *World Electric Vehicle Journal*, vol. 15, no. 6, p. 230, May 2024, doi: 10.3390/wevj15060230.
[22] S. Çeven, A. Albayrak, and R. Bayır, "Real-time range estimation in electric vehicles using fuzzy logic classifier," *Computers & Electrical Engineering*, vol. 83, p. 106577, May 2020, doi: 10.1016/j.compeleceng.2020.106577.
[23] Q. Tu, L. Cheng, T. Yuan, Y. Cheng, and M. Li, "The constrained reliable shortest path problem for electric vehicles in the urban transportation network," *Journal of Cleaner Production*, vol. 261, p. 121130, Jul. 2020, doi: 10.1016/j.jclepro.2020.121130.
[24] Y.-H. Jia, Y. Mei, and M. Zhang, "Confidence-based ant colony optimization for capacitated electric vehicle routing problem with comparison of different encoding schemes," *IEEE Transactions on Evolutionary Computation*, vol. 26, no. 6, pp. 1394–1408, Dec. 2022, doi: 10.1109/TEVC.2022.3144142.
[25] F. Ahmad, A. Iqbal, I. Ashraf, M. Marzband, and I. Khan, "Optimal location of electric vehicle charging station and its impact on distribution network: A review," *Energy Reports*, vol. 8, pp. 2314–2333, Nov. 2022, doi: 10.1016/j.egyr.2022.01.180.

BIOGRAPHIES OF AUTHORS

Deepa Somasundaram received her B.E. from K. S. R. College of Technology, affiliated to Periyar University, in 2003, 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 area of interest is 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.

N. Krishnamoorthy received his B.Sc. degree in Physics from Bishop Heber College, Tiruchirappalli, affiliated to Bharathidasan University in 1994, and M.Sc. (applied physics, computer electronics) from Urumu Dhanalakshmi College, Tiruchirappalli, affiliated to Bharathidasan University in 1996 with University III Rank. He completed a Master of Computer Applications in the year 2000 and M.Phil. (computer science) from Bharathidasan University in 2008. He has completed his Ph.D. (computer science) from SRM Institute of Science and Technology, Chennai in 2024. He has a rich experience of 25 years in handling classes for PG students in reputed institutions. He is currently working as an assistant professor in the Department of Computer Science and Applications, SRMIST, Ramapuram, Chennai. He is the prestigious awardee of Content Guru and a Distinguished facilitator by Infosys for delivering excellent technical stuff. He has published 25+ research articles in reputed International Journals and presented research articles in National and International conferences. His research interests include cybersecurity, cloud computing, IoT & network security. He has also published patents. He can be contacted at email: krishnan@srmist.edu.in.

J. Vijay Anand is working as an associate professor at RVS College of Engineering & Technology, Chennai, India. He completed his undergraduate degree in Electrical and Electronics Engineering from Thirumalai Engineering College, Kanchipuram, and his postgraduate degree in control and instrumentation from Thiagarajar College of Engineering, Madurai. He received his Ph.D. from Anna University, Chennai, India. He has published 12 papers in international and UGC CARE journals, and 9 papers in international and national conferences. His research interests include solar energy, DCS, and artificial intelligence techniques. He can be contacted at email: jvanandan@gmail.com.

R. Priyanka received her B.E. and M.E. degrees in electrical and electronics engineering. She is currently working as an assistant professor in the Department of Electrical and Electronics Engineering at S. A. Engineering College, Chennai, Tamil Nadu, India. She is actively involved in teaching and research in the field of electrical engineering. Her areas of interest include power systems, electric vehicles, and smart grid technologies. She can be contacted at email: priyankar@saec.ac.in.

T. Santhana Krishnan obtained his bachelor's degree in electrical and electronics from Madurai Kamaraj University in 1999. Then he obtained his master's and doctorate degrees in management and systems from Madurai Kamaraj University in 2001, a master's degree in power electronics and drives from SRM University in 2005, and a Ph.D. in electrical engineering from Anna University, Chennai, in 2020. He is an active life member of IEEE, IEI, and ISTE. Currently, he is an assistant professor (SG) at the Faculty of Electrical and Electronics, Rajalakshmi Engineering College (autonomous), Chennai. He has more than two decades of teaching and research experience. He has published more than 35 papers in reputed international journals with a high impact factor. His specializations include power electronics and drives, special electrical machines, and renewable energy systems. His current research interests are DC-DC soft-switched resonant converters and wind energy conversion systems. He can be contacted at email: santhanakrishnan.t@rajalakshmi.edu.in.

Kirubakaran Dhandapani obtained his Ph.D. from Anna University in 2010 and his M.E. degree from Bharathidasan University in 2000. His area of interest is AC-AC converters for induction heating & renewable energy systems. He had guided 10 Ph.D. research scholars. He has published more than 60 papers on referred international journals. He is a life member of ISTE. He has 22 years of teaching experience. He has been working as a professor and heading the Department of Electrical and Electronics Engineering at St. Joseph's Institute of Technology, Chennai, since 2011. He can be contacted at email: kirubad@gmail.com.