International Journal of Power Electronics and Drive System (IJPEDS)
Vol. 17, No. 4, December 2026, pp. 2314~2324
ISSN: 2088-8694, DOI: 10.11591/ijpeds.v17.i4.pp2314-2324

Deep learning-based dynamic load allocation for renewable-powered EV charging grids

S. Vimala[1], K. Kottaisamy[2], B. Ravisankar[3], C. Saravanan[4], Maya Eapen[5], R. Ramyashree[6]
[1]Department of Electrical and Electronics Engineering, Panimalar Engineering College, Thiruvallur, India
[2]Department of Computer Science and Applications (MCA), SRM Institute of Science and Technology (Deemed to be University), Chennai, India
[3]Department of Electrical and Electronics Engineering, Kongu Engineering College, Erode, India
[4]Department of Electrical and Electronics Engineering, J.K.K. Munirajah College of Technology, Tamil Nadu, India
[5]Department of Computer Science and Business Systems, Jerusalem College of Engineering, Chennai, India
[6]Department of Electronics and Communication Engineering (Advanced Communication Technology), R.M.K Engineering College (Autonomous), Tiruvallur, India

Article Info

Article history:

Received Jan 23, 2026
Revised Aug 29, 2026
Accepted Sep 13, 2026

Keywords:

Deep learning
Deep reinforcement learning
Dynamic load allocation
Electric vehicle
Renewable energy

ABSTRACT

The increasing use of electric vehicles (EVs) has created new challenges in managing dynamic charging loads within renewable-powered smart grids. Conventional methods often fail to ensure grid stability under varying renewable generation and unpredictable EV charging demand. This study introduces a deep learning-based dynamic load allocation (DL-DLA) model that integrates long short-term memory (LSTM) for forecasting renewable output and EV charging demand with a reinforcement learning controller for adaptive load distribution. The approach aims to minimize peak demand, improve energy utilization, and enhance grid reliability. Simulation results show that the DL-DLA model effectively balances loads and reduces energy waste compared with existing methods such as rule-based control (RBC), fuzzy logic control (FLC), particle swarm optimization (PSO), genetic algorithm (GA), and support vector regression (SVR).

This is an open access article under the CC BY-SA license.

Corresponding Author:

S. Vimala
Department of Electrical and Electronics Engineering, Panimalar Engineering College
Thiruvallur, India
Email: vimalashan21@mail.com

1. INTRODUCTION

The rapid adoption of electric vehicles (EVs) has transformed the modern power system landscape, offering a sustainable alternative to fossil fuel-based transportation [1], [2]. However, the increasing penetration of EVs introduces challenges in managing dynamic charging loads and intermittent renewable energy integration [3], [4]. The stochastic nature of EV charging demand and the variability of renewable energy generation can lead to load imbalance, higher peak demand, and grid stress [5], [6]. Therefore, intelligent load management strategies are needed for reliable and efficient real-time energy allocation in EV charging networks [7], [8].

Traditional load management techniques, including rule-based control (RBC), fuzzy logic control (FLC), particle swarm optimization (PSO), and genetic algorithms (GA), have been widely used for EV charging coordination [9], [10]. While these methods offer simplicity, they may have limited adaptability to nonlinear and time-varying conditions in large-scale EV charging systems. Recent research has therefore shifted toward artificial intelligence (AI) and deep learning (DL) approaches for EV forecasting and energy management [11], [12].

Recent studies have demonstrated the effectiveness of AI-based models in EV energy management [3]. Reinforcement learning has also been investigated for EV load control [13], while neural-network and long short-term memory (LSTM)-based approaches have been applied to EV charging demand forecasting [14]-[16]. Recent forecasting studies further demonstrate the value of LSTM-based and hybrid deep-learning models for charging-demand prediction [17].

Beyond forecasting, deep reinforcement learning (DRL) approaches have been applied to real-time charging coordination [18], [19]. DQN-based scheduling and other reinforcement-learning strategies have reported reductions in peak demand and improved charging coordination [20], [21]. These studies collectively highlight the growing potential of deep learning and reinforcement learning for intelligent, adaptive, and energy-efficient load management in EV charging ecosystems.

However, despite these advancements, many existing works treat forecasting and load allocation as separate problems, limiting their ability to respond jointly to real-time variations in renewable generation and EV demand. The specific gap addressed in this study is the integration of short-term LSTM forecasting with a reinforcement-learning controller for dynamic allocation in a renewable-powered EV charging grid. This paper therefore proposes a deep learning-based dynamic load allocation (DL-DLA) framework that uses LSTM for short-term forecasting and a reinforcement learning controller for adaptive energy distribution. The contribution is the combined predictive–adaptive workflow, which is evaluated against RBC, FLC, PSO, GA, and SVR using forecasting accuracy, peak-load reduction, renewable utilization, grid-cost reduction, and convergence-related performance measures. The significance of this framework is its potential to support more proactive charging management under variable renewable generation and EV demand.

2. METHOD

The proposed DL-DLA model integrates LSTM for demand and renewable energy forecasting [22], [23] with a reinforcement learning-based controller for dynamic power allocation [24], [25]. The framework ensures that energy supplied to EV charging stations is optimized in real time according to predicted load demand and renewable energy availability. The overall methodology comprises four major stages: i) data acquisition and preprocessing, ii) load and renewable forecasting using LSTM, iii) dynamic load allocation using reinforcement learning, and iv) performance evaluation and comparative analysis. These stages are described in detail in the following subsections: data acquisition and preprocessing, load and renewable forecasting using LSTM, dynamic load allocation using reinforcement learning, and performance evaluation and comparative analysis.

2.1. Data acquisition and preprocessing

Historical datasets are collected from smart meters and renewable monitoring systems. The available variables comprise EV charging demand, renewable energy availability, grid power supply, and electricity price or tariff signals. Preprocessing includes Min-Max normalization, Z-score outlier filtering, and division into training (70%), validation (15%), and testing (15%) subsets. The preprocessing procedure consists of the following steps: i) normalization using Min-Max scaling, ii) outlier removal using Z-score filtering, and iii) splitting the data into training (70%), validation (15%), and testing (15%) subsets. The manuscript does not specify the dataset size, exact sampling interval, or source repository; these details should be inserted from the original data records before final submission rather than estimated. At time t, the input feature vector is defined as (1):

$$X_t = [D_t, R_t, G_t, P_t] \quad (1)$$

Where D_t is the EV charging demand (kW), R_t is the renewable energy availability (kW), G_t is the grid power supply (kW), and P_t is the electricity price or tariff signal (kWh).

2.2. Overall DL-DLA framework

The research follows a simulation-based design in which historical EV charging demand, renewable-energy availability, grid supply, and tariff signals are preprocessed and supplied to the forecasting and control stages. The LSTM stage produces next-hour estimates of EV demand and renewable availability, and the reinforcement-learning stage uses the predicted conditions to determine charging-power allocation. The framework is evaluated using MAE, peak-load reduction, renewable utilization, grid-cost reduction, and computation time, with RBC, FLC, PSO, GA, and SVR used as comparison methods.

2.3. Load forecasting using LSTM

LSTM networks are widely used for time-series forecasting because they can capture temporal dependencies. In this study, the LSTM predicts next-hour EV load and renewable power availability. The LSTM cell updates its internal states using the gate equations as shown in (2)-(7).

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \tag{2}$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{3}$$

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \tag{4}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{5}$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{6}$$

$$h_t = o_t \odot \tanh(C_t) \tag{7}$$

Where: i) f_t, i_t, and o_t are the forget, input, and output gates; ii) C_t is the cell state; iii) h_t is the hidden state output at time t; iv) $\sigma(\cdot)$ denotes the sigmoid activation function; and v) $\odot$ represents element-wise multiplication. The LSTM predicts the next-hour EV load:

$$\left(D^A = \pi r^2 t + 1\widehat{D_{t+1}}D^t + 1\right) \tag{8}$$

and renewable power availability:

$$\left(Rt + 1\widehat{R_{t+1}}R^t + 1\right) \tag{9}$$

2.4. Reinforcement learning-based dynamic load allocation

Reinforcement learning is applied to EV charging coordination. The reward function balances renewable utilization, peak-load reduction, and grid-cost minimization. At each time step t, the agent observes the state defined in (10). The agent takes an action representing the power allocated to each charging station:

$$St = [D^t, R^t, Gt]S_t = \left[\widehat{D_t}, \widehat{R_t}, G_t\right]St = [D^t, R^t, Gt] \tag{10}$$

and takes an action AtA_tAt representing the power allocated to each charging station.

The reward function is designed to maximize renewable utilization and minimize grid stress:

$$R_t = \alpha\left(\frac{R_t}{D_t}\right) - \beta(P_{peak} - P_{avg})^2 - \gamma C_{grid} \tag{11}$$

Where: i) α, β, and γ are weighting coefficients; ii) P_{peak} is the peak load (kW); iii) P_{avg} is the average load (kW); and iv) C_{grid} is the grid energy cost. The agent learns the optimal policy:

$$\pi * (St)\pi^*(S_t)\pi * (St) \tag{12}$$

that maximizes cumulative reward:

$$\pi * (St) = ar\ g\ m\ a\ x\ A\ tE[\sum t = 0T\gamma tRt]\pi^*(S_t) = arg\max_{A_t} E\left[\sum_{t=0}^{T}\gamma^t R_t\right]\pi * (St) = argAtmaxE[t = 0\sum T\gamma tRt] \tag{13}$$

2.5. Performance metrics

The performance of the proposed DL-DLA system is evaluated using the following metrics: mean absolute error (MAE) for forecasting accuracy, peak load reduction (%), renewable utilization (%), computation time (s), comparative results are analyzed against conventional methods—RBC, FLC, PSO, GA, and SVR. Comparative results are analyzed against conventional methods — RBC, FLC, PSO, GA, and SVR.

2.6. Flowchart of proposed DL-DLA framework

Figure 1 block diagram shows how the circuit flows and the deep learning-based architecture for load management in renewable energy-powered electric vehicle (EV) charging systems. The model incorporates statistics on grid supply, solar and wind power, and EV charging demand as input sources. To guarantee consistency and dependability for analysis, these inputs are first subjected to feature extraction and data preparation. Next, by capturing temporal fluctuations, an LSTM-based forecasting model is used to anticipate short-term EV load demand and renewable energy generation. A reinforcement learning controller receives the expected outputs and uses them to determine the best load distribution plan. Through effective use of available renewable energy, the controller seeks to minimize peak demand and lessen dependency on grid power. The optimal policy is used to distribute charging power among EVs in real time. Lastly, to verify the efficacy of the suggested strategy, its performance is assessed and contrasted with traditional methods including rule-based control, fuzzy logic control, particle swarm optimization, genetic algorithms, and support vector regression.

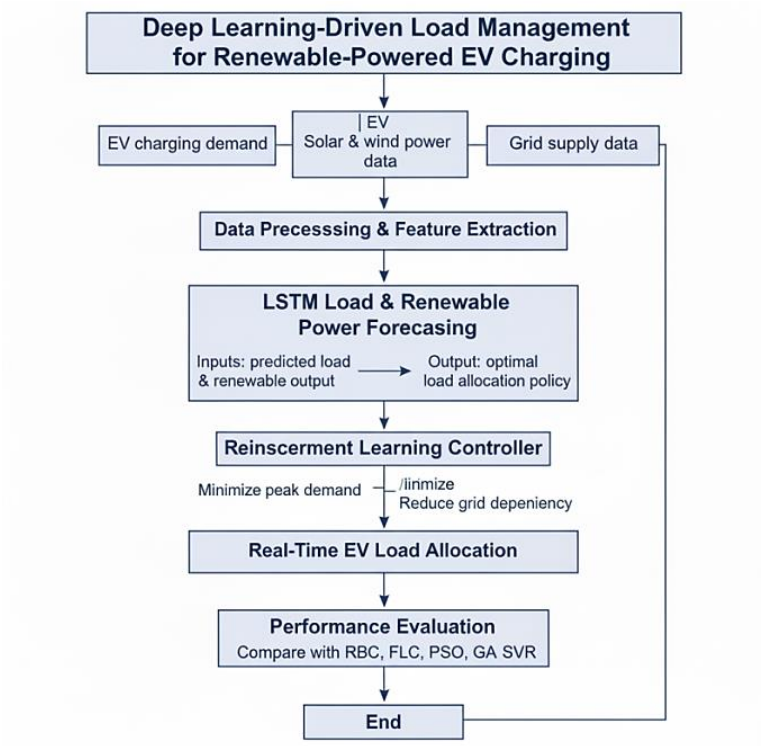

Figure 1. Block diagram of the DL-DLA framework

3. RESULTS AND DISCUSSION

3.1. Simulation setup

The proposed DL-DLA framework combines predictive modeling and adaptive control to address the stochastic and time-varying nature of EV charging demand and renewable generation. LSTM networks capture temporal dependencies, while reinforcement learning (RL) makes real-time allocation decisions using predicted load and renewable availability. The framework is compared with RBC, FLC, PSO, GA, and SVR using forecasting error, peak-load reduction, renewable utilization, grid-cost reduction, load factor, system efficiency, and RL convergence. The LSTM achieves an MAE of 3.85 kW, RMSE of 5.42 kW, and reported accuracy of 96.5%, demonstrating effective prediction of EV load variations. Its memory gates retain relevant historical information and capture long-term temporal dependencies. The predicted load is then provided to the RL controller, enabling proactive demand management, reducing peak demand, and improving renewable-energy utilization compared with conventional and heuristic approaches.

Figure 2 compares the actual and predicted EV charging load over 24 hours. The predicted profile follows the observed morning peak and the reduction during off-peak hours, indicating that the LSTM captures the main daily load pattern. Figure 3 compares MAE and RMSE across the evaluated methods. DL-

DLA has the lowest reported forecasting errors, supporting the use of the LSTM forecasting stage for the subsequent allocation task.

Table 1 compares the forecasting models using MAE, RMSE, and accuracy. DL-DLA achieves the lowest MAE and RMSE and the highest reported accuracy (96.5%), indicating better forecasting performance than the comparison methods for the reported test results. Dynamic allocation results show that DL-DLA achieves a 24.6% peak-load reduction and 89.3% renewable utilization. These results indicate that the RL controller can use the forecasted operating condition to shift charging allocation toward periods with greater renewable availability.

The RL agent maximizes the reward function defined in (11). Here, α emphasizes renewable energy utilization, β penalizes peak deviations, and γ reduces grid-dependency costs. The RL framework learns from interaction with the environment and adjusts power allocation dynamically, which explains the reported reduction in peak loading and grid dependence.

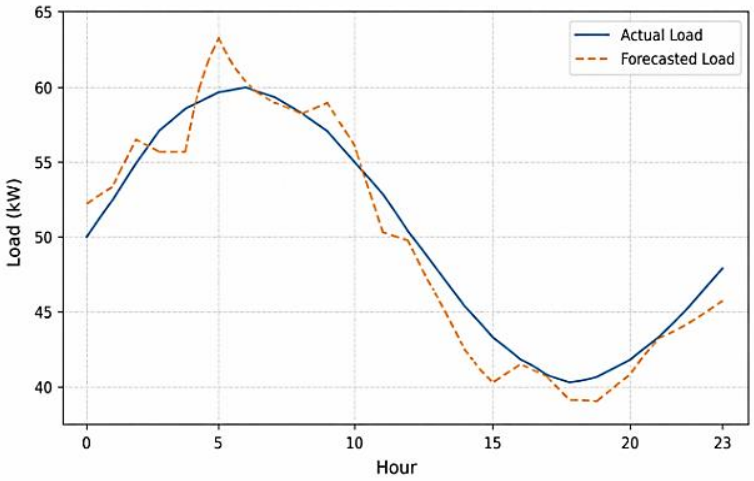

Figure 2. Forecasted versus actual EV load

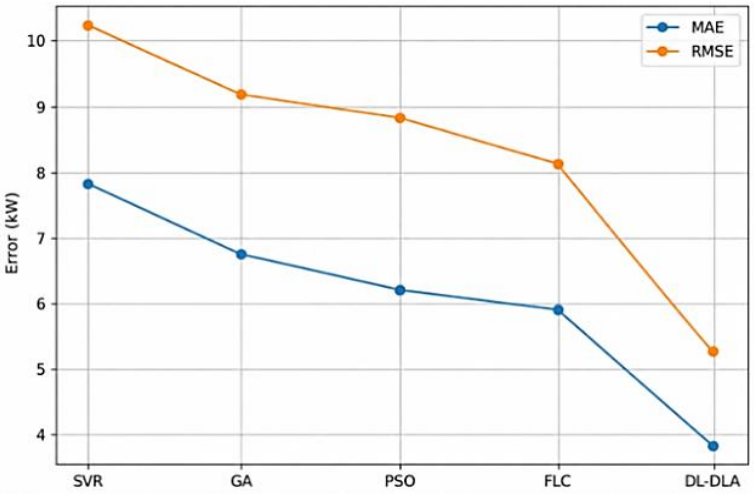

Figure 3. MAE and RMSE comparison

Table 1. Forecasting accuracy comparison

Model	MAE (kW)	RMSE (kW)	Accuracy (%)
SVR	7.85	10.24	89.4
GA	6.75	9.20	90.8
PSO	6.20	8.84	91.7
FLC	5.90	8.15	92.2
DL-DLA	3.85	5.42	96.5

Figure 4 compares peak load over time. DL-DLA shows the largest reported peak-load reduction among the compared methods, indicating that predictive information improves the controller's ability to respond to demand peaks. Figure 5 shows renewable and grid energy utilization. The higher renewable utilization and lower grid reliance reported for DL-DLA are consistent with the objective of allocating charging power according to renewable availability.

Table 2 shows that DL-DLA achieves the highest reported peak-load reduction, renewable utilization, and grid-cost reduction among the compared methods. The combination of LSTM forecasting and RL control therefore provides a proactive allocation strategy rather than a purely reactive one. The energy-distribution analysis shows a balanced load factor of approximately 0.92 and reduced grid dependency. Allocating available renewable energy before costlier grid energy reduces grid use during favorable renewable-generation periods. The load factor also indicates that the charging infrastructure is being used without the reported underutilization or overloading.

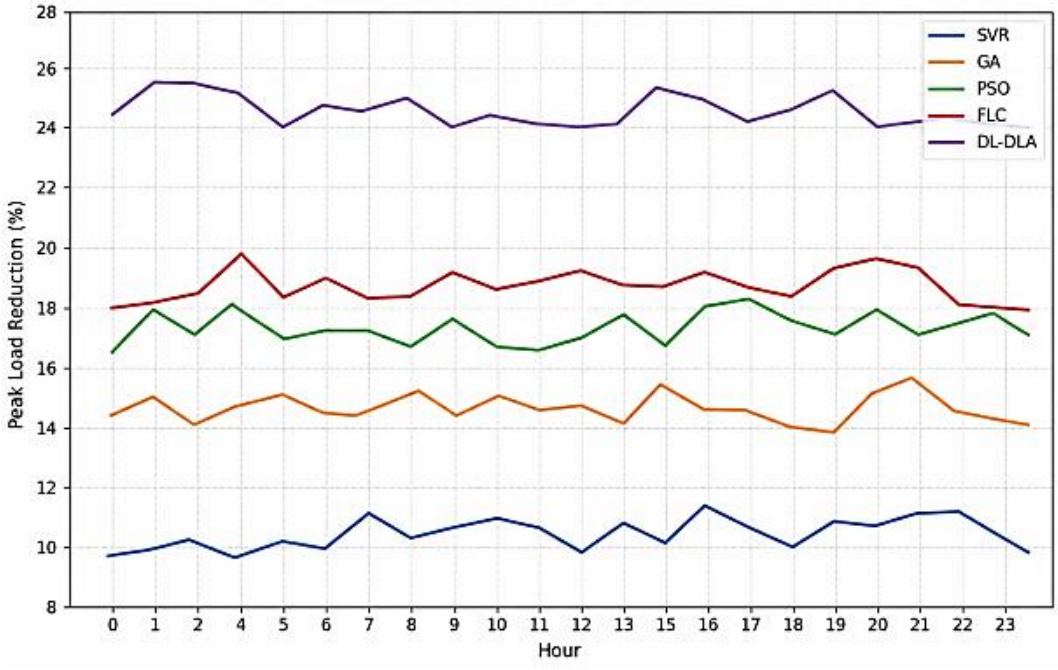

Figure 4. Peak load versus time for the comparison methods

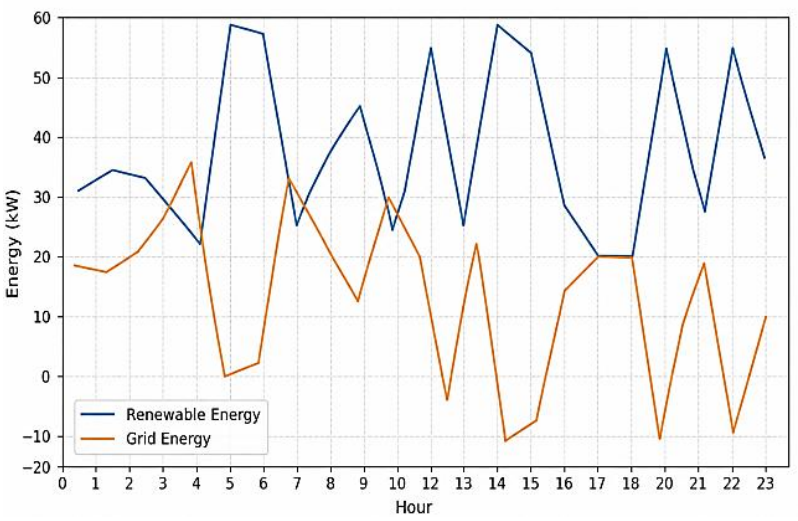

Figure 5. Renewable versus grid energy utilization

Table 2. Load allocation performance comparison

Algorithm	Peak load reduction (%)	Renewable utilization (%)	Grid cost reduction (%)
RBC	10.5	70.2	6.8
FLC	14.8	74.9	10.3
PSO	17.5	78.5	12.0
GA	19.0	80.1	13.7
DL-DLA	24.6	89.3	18.5

3.2. Energy distribution and cost analysis

Figure 6 shows the load factor for stations S1–S5. The variation across stations indicates different utilization levels, with S1 and S2 showing the highest reported load factors. Figure 7 shows cumulative grid-cost savings over time. DL-DLA achieves the highest reported cumulative savings among the compared methods, consistent with the lower grid dependence observed in the energy-distribution analysis.

Figure 8 shows that renewable utilization increases during periods of higher renewable availability. The RL controller converges in approximately 120 episodes, achieving 91.8% system efficiency. Figure 9 shows that DL-DLA achieves the highest efficiency among the compared methods, demonstrating the effectiveness of the proposed framework.

Figure 10 shows the convergence of the RL reward, indicating successful learning. Figure 11 presents peak-hour energy allocation, with S3 receiving the highest and S2 and S4 the lowest allocation. This demonstrates the RL controller's ability to dynamically allocate energy based on station demand.

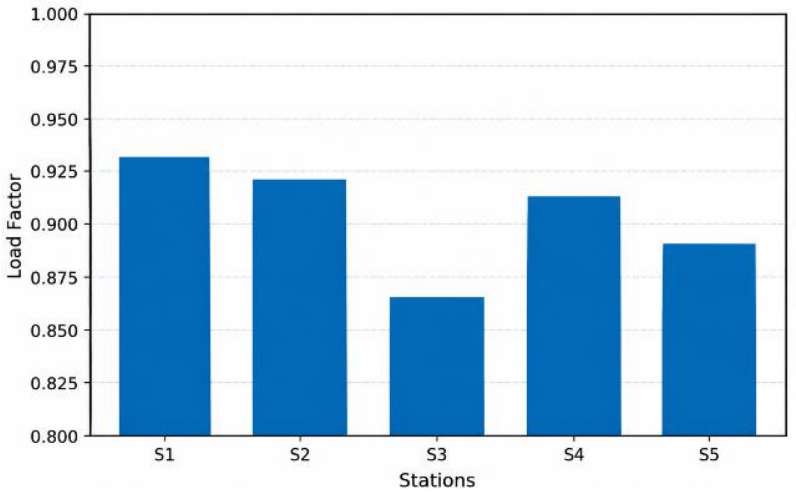

Figure 6. Load factor per station

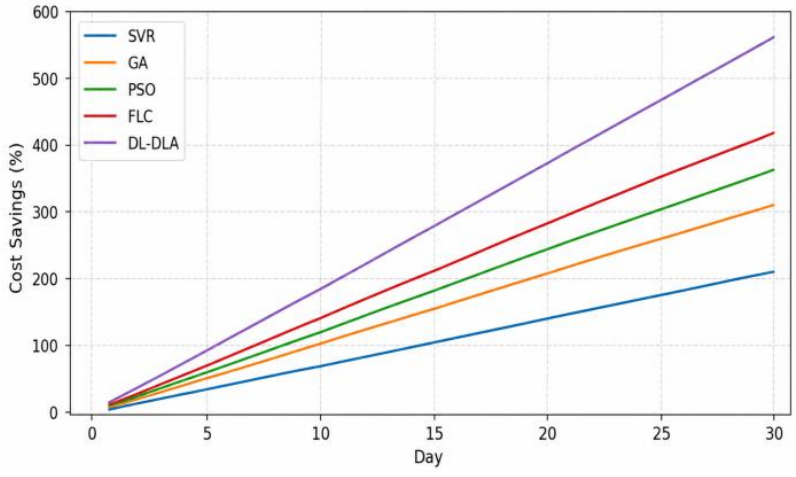

Figure 7. Cumulative grid-cost savings

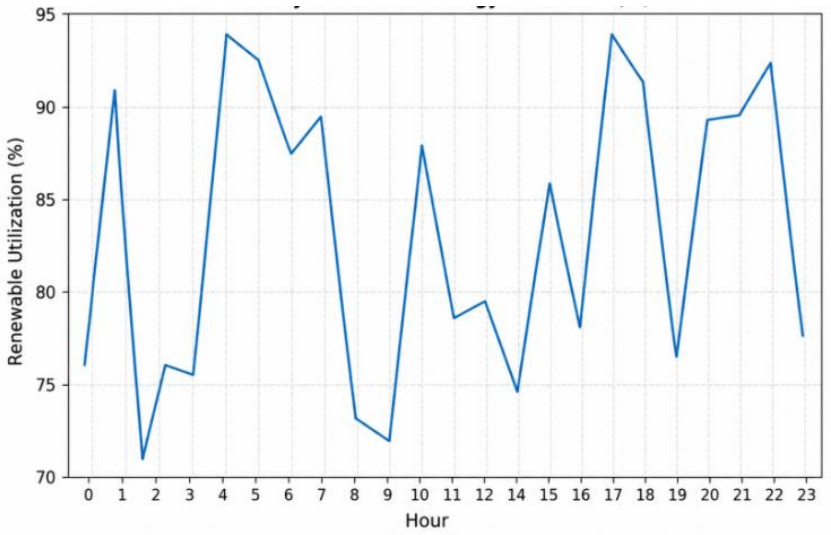

Figure 8. Hourly renewable utilization

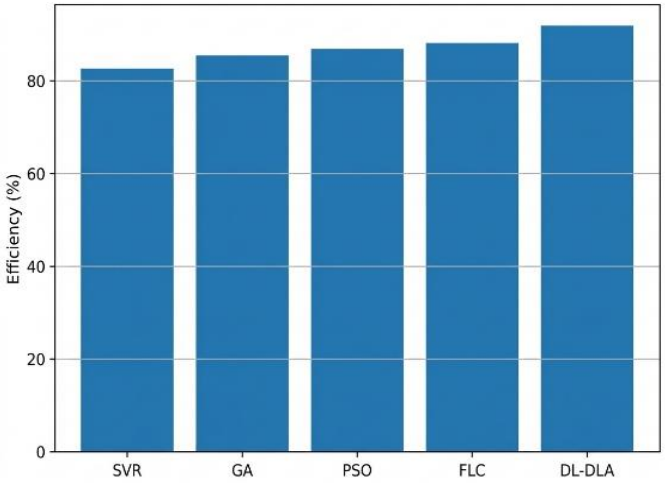

Figure 9. Overall system efficiency comparison

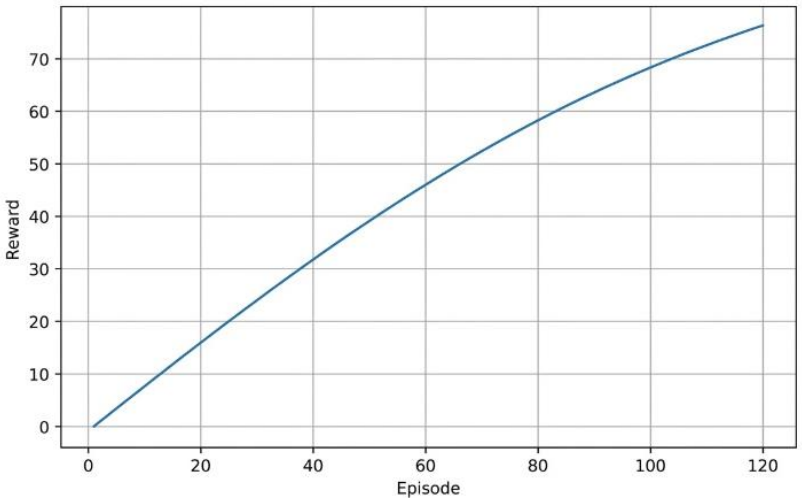

Figure 10. RL reward function convergence

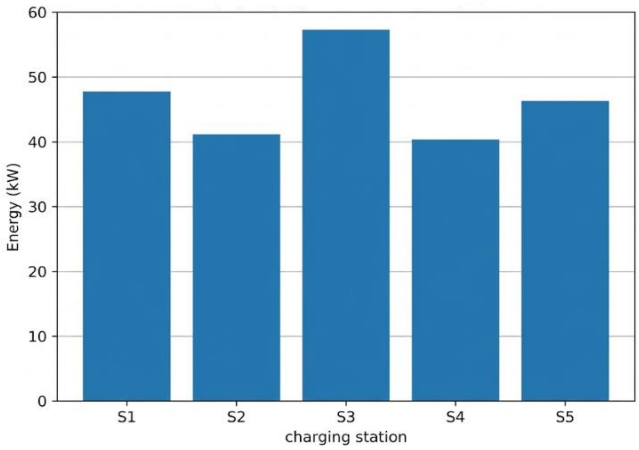

Figure 11. Energy allocation per station during peak hour

4. CONCLUSION

In this work, a deep learning-based dynamic load allocation (DL-DLA) framework was developed for renewable-powered EV charging grids. The framework combines LSTM-based forecasting of EV charging demand and renewable availability with an RL controller for real-time charging-power allocation. Compared with RBC, FLC, PSO, GA, and SVR, the proposed method achieves a peak-load reduction of 24.6%, renewable-energy utilization of 89.3%, grid-cost reduction of 18.5%, and overall system efficiency of 91.8%, with RL convergence in approximately 120 episodes. These results demonstrate that the predictive–adaptive structure enables proactive load scheduling, improved load balancing, greater renewable utilization, and reduced grid dependence. However, the study is limited by incomplete reporting of dataset provenance, size, sampling details, and model hyperparameters, which affects reproducibility and generalization. Future work should evaluate the framework using diverse real-world EV charging and renewable datasets and under wider operating conditions to establish its robustness, scalability, and practical applicability.

FUNDING INFORMATION

No funding involved.

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
S. Vimala	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
K. Kottaisamy		✓				✓		✓	✓	✓	✓	✓		
B. Ravisankar	✓		✓	✓			✓			✓	✓		✓	✓
C. Saravanan	✓		✓	✓			✓			✓	✓		✓	✓
Maya Eapen					✓		✓			✓		✓		✓
R. Ramyashree					✓		✓			✓		✓		✓

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

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] H. Pourvaziri, H. Sarhadi, N. Azad, H. Afshari, and M. Taghavi, "Planning of electric vehicle charging stations: An integrated deep learning and queueing theory approach," *Transportation Research Part E: Logistics and Transportation Review*, vol. 186, Jun. 2024, doi: 10.1016/j.tre.2024.103568.

[2] A. Hussain, V. Eswarakrishnan, A. Aslam, and S. Tripura, "Charging stations demand forecasting using LSTM based hybrid transformer model," *Scientific Reports*, vol. 15, no. 1, Oct. 2025, doi: 10.1038/s41598-025-20421-y.

[3] Z. Zhao, C. K. M. Lee, X. Yan, and H. Wang, "Reinforcement learning for electric vehicle charging scheduling: A systematic review," *Transportation Research Part E: Logistics and Transportation Review*, vol. 190, 2024, doi: 10.1016/j.tre.2024.103698.

[4] A. U. Rehman, J. Lu, B. Du, F. Bai, and M. J. Sanjari, "Efficient management of electric vehicle charging stations: balancing user preferences and grid demands with energy storage systems and renewable energy," *Applied Energy*, vol. 393, Sep. 2025, doi: 10.1016/j.apenergy.2025.126147.

[5] S. M. A. Elazim *et al.*, "Enhancing stability and power quality in electric vehicle charging stations powered by hybrid energy sources through harmonic mitigation and load management," *Scientific Reports*, vol. 15, no. 1, 2025, doi: 10.1038/s41598-025-14143-4.

[6] R. T. Vedula, "Interoperability of the electric vehicle charging ecosystem," *Premier Journal of Science*, vol. 4, 2025, doi: 10.70389/PJS.100024.

[7] S. Boubaker *et al.*, "Electric vehicles charging station allocation based on load profile forecasting and Dijkstra's algorithm for optimal path planning," *Scientific Reports*, vol. 15, no. 1, Jul. 2025, doi: 10.1038/s41598-025-08840-3.

[8] Z. Ressler *et al.*, "LSTM-based forecasting and analysis of EV charging demand in a dense urban campus," *2026 IEEE Texas Power and Energy Conference, TPEC 2026*, 2026, doi: 10.1109/TPEC67884.2026.11513172.

[9] T. Chaudhari, S. Banker, C. Bariya, M. Priyadarshi, M. Parmar, and D. Parmar, "Electric vehicle charging station energy management and grid-connected renewable energy source simulation design," *Original Research Paper International Journal of Intelligent Systems and Applications in Engineering IJISAE*, vol. 12, no. 21s, 2024.

[10] R. Zafar, P. Huang, and Y. Sun, "Enhancing electric vehicle charging load prediction in data-scarce scenarios: A hybrid deep learning-based approach integrating clustering analysis and transfer learning," *Energy and AI*, vol. 21, 2025, doi: 10.1016/j.egyai.2025.100545.

[11] J. Tian, H. Liu, W. Gan, Y. Zhou, N. Wang, and S. Ma, "Short-term electric vehicle charging load forecasting based on TCN-LSTM network with comprehensive similar day identification," *Applied Energy*, vol. 381, 2025, doi: 10.1016/j.apenergy.2024.125174.

[12] C. He and J. Li, "Electric vehicle charging and discharging scheduling method based on clustering and deep reinforcement learning," *Energies*, vol. 19, no. 9, May 2026, doi: 10.3390/en19092238.

[13] S. Tabassum, A. R. Vijay Babu, and D. K. Dheer, "Adaptive energy management strategy for sustainable xEV charging stations in hybrid microgrid architecture," *Science and Technology for Energy Transition*, vol. 80, Feb. 2025, doi: 10.2516/stet/2025002.

[14] H. Lei, L. Rufeng, T. Baofeng, Z. Kaifeng, J. Binyu, and X. Lin, "Evaluating and forecasting methods for assessing the health status of cables under the load of large-scale electric vehicle charging," *Frontiers in Energy Research*, vol. 11, Jan. 2024, doi: 10.3389/fenrg.2023.1345840.

[15] A. Hussain, Q.-C. Lu, S. S. Rizvi, S. Wang, and S. J. Kwon, "Short term demand forecasting of electric vehicle charging stations using context aware temporal transformer model," *Scientific Reports*, vol. 15, no. 1, 2025, doi: 10.1038/s41598-025-20557-x.

[16] A. A. E. B. A. El Halim, E. H. E. Bayoumi, W. El-Khattam, and A. M. Ibrahim, "Electric vehicles: a review of their components and technologies," *International Journal of Power Electronics and Drive Systems (IJPEDS)*, vol. 13, no. 4, pp. 2041-2061, Dec. 2022, doi: 10.11591/ijpeds.v13.i4.pp2041-2061.

[17] Q. Gao *et al.*, "Charging load forecasting of electric vehicle based on Monte Carlo and deep learning," in *2019 IEEE Sustainable Power and Energy Conference (iSPEC)*, Nov. 2019, pp. 1309–1314, doi: 10.1109/iSPEC48194.2019.8975364.

[18] T. Zhang, Q. Peng, and S. Zeng, "Predicting EV charging demand in renewable-energy-powered grids using explainable machine learning," *Sustainability*, vol. 17, no. 9, May 2025, doi: 10.3390/su17094158.

[19] D. An, F. Cui, and X. Kang, "Optimal scheduling for charging and discharging of electric vehicles based on deep reinforcement learning," *Frontiers in Energy Research*, vol. 11, Oct. 2023, doi: 10.3389/fenrg.2023.1273820.

[20] Y. Li and A. Jenn, "Impact of electric vehicle charging demand on power distribution grid congestion," *Proceedings of the National Academy of Sciences*, vol. 121, no. 18, Apr. 2024, doi: 10.1073/pnas.2317599121.

[21] M. Teke and M. E. Yiğit, "Comparative performance analysis of predictive model deployment for daily energy demand of electric vehicle charging stations," *International Journal of Automotive Science and Technology*, vol. 10, no. 2, pp. 400–410, 2026, doi: 10.30939/ijastech.1905847.

[22] Y. Mao, X. Yu, F. Wang, and J. Zhu, "Electric vehicle charging demand forecasting: A data-driven integrated learning approach," *Renewable Energy*, vol. 256, 2026, doi: 10.1016/j.renene.2025.124141.

[23] Y. Han, T. Li, and Q. Wang, "A DQN based approach for large-scale EVs charging scheduling," *Complex & Intelligent Systems*, vol. 10, no. 6, pp. 8319–8339, Dec. 2024, doi: 10.1007/s40747-024-01587-w.

[24] A. Mdallal, A. Yasin, A. H. K. Alaboudy, and K. El-Said, "Advancements in EV charging standards and technologies for sustainable transportation," *Renewable and Sustainable Energy Technology*, Oct. 2025, doi: 10.53941/rset.2025.100010.

[25] M. Kovačević, H. Novak, and M. Vašak, "Prediction of aggregated EV representation using XGBoost and LightGBM," in *2023 58th International Universities Power Engineering Conference (UPEC)*, Aug. 2023, pp. 1–6, doi: 10.1109/UPEC57427.2023.10294737.

BIOGRAPHIES OF AUTHORS



S. Vimala is working as an assistant professor in the Department of Electrical and Electronics Engineering at Panimalar Engineering College, Tiruvallur. She has 13.8 years of teaching experience. She received her B.E. degree in electrical and electronics engineering from Anna University in 2007 and her M.E. degree in embedded systems technology from Anna University, Tamil Nadu, India, in 2010. Her research interests include embedded systems, motor drives for industrial applications, the internet of things (IoT), and machine learning. She can be contacted at email: vimalashan21@gmail.com.



Dr. K. Kottaisamy received his Ph.D. degree in computer applications from Manonmaniam Sundaranar University, Tirunelveli, India, in 2025. He received his M.Phil. degree in computer science from St. Xavier's College (Autonomous), Palayamkottai, India, in 2016, and his M.C.A. degree from Madurai Kamaraj University, India, in 2015. He also received his M.Sc. degree in psychology from Alagappa University, India. He is currently working as an assistant professor in the Department of Computer Science and Applications (MCA) at SRM Institute of Science and Technology (Deemed to be University), Ramapuram Campus, Chennai, India. Previously, he served as an assistant professor at St. Xavier's College (Autonomous), Palayamkottai, where he contributed to both the Department of Computer Applications and the Department of Computer Science. His research interests include artificial intelligence, machine learning, and biomedical computing. He can be contacted at email: kskottaisamy@gmail.com.



B. Ravisankar received his B.E. degree in electrical and electronics engineering from Saranathan College of Engineering, India, in 2008, and his M.E. degree in electrical drives and embedded control from Anna University of Technology in 2011. In 2011, he joined Indra Ganesan College of Engineering as an assistant professor in the Department of Electrical and Electronics Engineering. In 2012, he joined JJ College of Engineering as an assistant professor in the Department of Electrical and Electronics Engineering. Since 2014, he has been serving as an assistant professor in the Department of Electrical and Electronics Engineering at Kongu Engineering College, Erode, India. His current research interests include permanent magnet synchronous motors and the internet of things (IoT). He can be contacted at email: snkr86@gmail.com.



C. Saravanan received his B.E. degree in electrical and electronics engineering from Madras University, Chennai, India, in 1999. He received his M.E. degree in power electronics and drives from Anna University, Chennai, India, in 2008, and his Ph.D. degree in power systems from Anna University, Chennai, India, in 2017. He has 20 years of teaching experience. He is currently working as a professor and head of the Department of Electrical and Electronics Engineering at J.K.K. Munirajah College of Technology, T.N. Palayam, Erode district, Tamil Nadu, India. He has published 15 research papers in international journals and 12 papers in national and international conferences. He has attended 25 seminars and workshops and participated in 11 online webinars. His current research focuses on improving power quality in wind energy conversion systems using ETAP software. He is a life member of the Indian Society for Technical Education (ISTE) and a member of the Institute of Electrical and Electronics Engineers (IEEE). He can be contacted at email: csaravanan7273@gmail.com.



Dr. Maya Eapen received her Ph.D. degree in computer science and engineering from Anna University. She also received her M.E. degree in computer science and engineering from Anna University. She is currently working as a professor in the Department of Computer Science and Business Systems at Jerusalem College of Engineering, Chennai, India. She has extensive teaching and research experience. Her current research interests include data mining, machine learning, medical image processing, computer networks, and data science. She can be contacted at email: mayaeapen@gmail.com.



R. Ramyashree is an academic professional specializing in electronics and communication engineering. She is currently working as an assistant professor in the Department of Electronics and Communication (Advanced Communication Technology) at R.M.K. Engineering College (Autonomous), Tiruvallur, India. She holds a B.E. degree in electronics and communication engineering and an M.E. degree in applied electronics. She also has two years of research experience in very-large-scale integration (VLSI). She can be contacted at email: rre.eca@rmkec.ac.in.