Artificial Intelligence Research and Applications (AIra)
https://www.ijaira.org/ Online ISSN: 3108-3889
M. Kumar N et al., Vol. 2, No. 3, September, 2026 Research Article

Data-Driven Control of Electric Vehicle Aggregators for Voltage and Energy Stability in Smart Microgrids

Mahesh Kumar N *‡, Ramakrishna S S Nuvvula **, Smitha Gayathri D ***

* Department of Information Science and Engineering, Global Academy of Technology, Bengaluru.
** NITTE (Deemed to be University, NMAM Institute of Technology, Department of Electrical and Electronics Engineering, Mangalore, Karnataka, India.
*** Department of ECE, BNMIT, Bangalore.

(mkumar.n19@gmail.com, nramkrishna231@gmail.com, smithasgd@gmail.com)

‡ Corresponding Author: Mahesh Kumar N, Department of Information Science and Engineering, Global Academy of Technology, Bengaluru, mkumar.n19@gmail.com.

Received: 18.02.2026, Revised: 27.03.2026, Accepted: 03.04.2026

Abstract- The exponential growth of electric vehicles (EVs) presents both positive and negative aspects to modern power systems, especially within intelligent microgrids containing many distributed energy resources (DER). Electric vehicle aggregator (EVA) companies work to coordinate the collective charging and discharging behaviour of large groups of EV fleets. As such, their function is critical to the successful maintenance of voltage and energy stability. The current study introduces a data-based control framework for EVAs that utilizes real-time measurement, historical operation data and machine learning-based predictions, which are designed to help the grid meet stability objectives. The proposed framework aims to adjust the EVAs' charging and vehicle-to-grid (V2G) operations to account for local voltage deviation, load variation and renewable generation variability in order to provide real-time adjustment mechanisms. By combining predictive analytics with control decision-making, the data-based control framework is intended to increase microgrid reliability, decrease the occurrence of voltage violations and increase the energy balance of a microgrid without negatively impacting EV drivers' mobility needs. Simulation results indicate that the data-based control framework is superior to traditional methods based on rule-setting due to improvements in voltage regulation performance, reductions in peak load demand and increased utilization of renewable energy resources than through the use of electric vehicles in intelligent microgrids.

Keywords: Electric vehicle aggregators, data-driven control, voltage regulation, vehicle-to-grid, multi-objective optimization.

1. Introduction

The transition from traditional power delivering systems to modern smart electricity grids is increasing as we see more integration of decentralized, digital, and distributed energy resources (RES). Smart microgrids offer a local method to manage RES, and they will help ensure that these RES can continue to meet our electrical needs reliably, efficiently, and resiliently. The challenge of having intermittent renewable generation sources (e.g., solar and wind) and variable loads can cause difficulties with maintaining energy balance and voltage regulation in smart microgrids. Of particular interest

Cite this article as: M. Kumar N, R.S.S. Nuvvula, and S. Gayathri D, "Data-Driven Control of Electric Vehicle Aggregators for Voltage and Energy Stability in Smart Microgrids," *Artificial Intelligence Research and Applications (AIra)*, Vol. 2, No. 3, pp. 149–155, September, 2026, https://doi.org/10.20508/ps000s93.

among flexible loads, are electric vehicles (EVs) because their growth rate is very high and they have large capacities for energy storage.

When EVs are grouped together and controlled in an intelligent manner, they can be used not only as loads on the electric grid, but also as distributed energy storage devices using their vehicle-to-grid (V2G) capability. Through the use of aggregators, EV owners can allow a third party to manage the charging and discharging of the EV batteries.

Aggregators are organizations that consolidate multiple EVs into an aggregated load and manage how they discharge into the electric grid. The ability to coordinate EV batteries with the electric grid enables the aggregation of multiple batteries to help maintain grid voltage and avoid negative impacts, such as transformer overloads, increased peak demand, etc. In addition, using aggregated EV batteries for grid services will help improve electrical grid performance and provide better ways to use electrical energy.

Static rules or pricing signals govern traditional electric vehicle (EV) charging methodologies, which do not readily adapt to the fast-changing conditions of the electrical grid. As microgrids become increasingly complex and data-rich, adaptive control approaches that utilize both real-time and historical data are needed. Data-driven control methodologies (machine learning, and advanced optimization techniques) are powerful methods to describe nonlinear system behaviour, forecast uncertainties and help make informed decisions.

This research is focused on creating a framework for data-driven control of electric vehicle aggregators to improve the voltage and energy stability in smart microgrids. Figure 1 illustrates the overall architecture of the proposed framework, in which predictive models are integrated with control algorithms to dynamically manage electric vehicle charging and discharging in response to grid conditions. The methodology maintains user constraints while coordinating flexible EV resources to support stable and efficient microgrid operation.

The remainder of this paper will include a literature review, provide a detailed description of the proposed methodology, an overview of implementation and experiment methods, and present the results and findings from this work, as well as provide suggestions for future work.

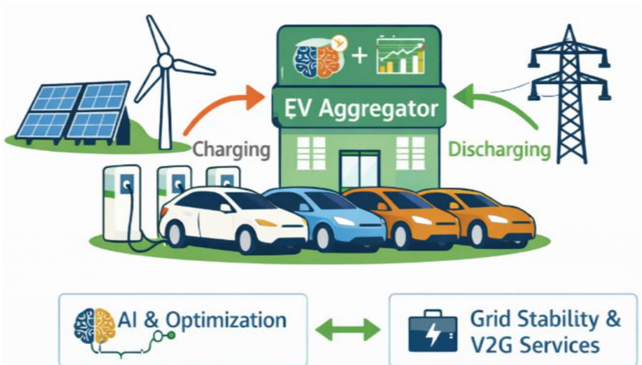

Fig. 1. Learning-driven coordinated EV energy management framework.

2. Literature Review

The involvement of electric vehicles in facilitating the operation of power systems has been investigated widely, particularly for using demand-response and distributed energy storage [1]. It has been shown that coordinated EV charging can help reduce peak demand and reduce the stress placed on distribution networks [2]. Uncoordinated EV charging, on the other hand, can lead to greater voltage deviations and increased losses, particularly within low-voltage microgrids with high penetration levels of renewable energy sources [3]. Therefore, there has been a lot of research done to develop control strategies that would allow EVs to directly assist in stabilising the grid [4].

EV aggregators have been introduced and leverage scalable concepts for managing very large amounts of EVs while meeting both grid requirements and user preferences [5].

Various centralised and decentralised control architectures have been proposed, including rule-based scheduling and optimisation-based energy management [6]. Optimisation-based approaches typically model the coordination of EV charging as a constrained optimisation problem with the aim of minimising costs, losses, or emissions while satisfying network and battery constraints [7]. While these approaches are generally very strong from an effectiveness perspective, many rely heavily on accurate system models and face challenges related to uncertainty and adaptability to changing conditions in real time [8].

To remedy the shortcomings listed above, many researchers have turned to data-driven and learning-based techniques [9]. Specifically, machine-learning models have been used to forecast EV charging demand [10], user behaviour [11], renewable generation [12], and load profiles [13]. These predictions may be used to control and schedule charging activities proactively and make better operational decisions [14].

Reinforcement learning has also been studied for real-time EV charging control, allowing agents to learn best practices through interaction with their environment [15]. Therefore, these learning-based techniques reduce dependency on explicit system models and improve the ability to adapt as operating conditions change [16].

Historically, voltage regulation within microgrids has been performed using reactive power controls, on-load tap changers, and energy storage systems [6]. The use of EVs within established voltage regulation methods provides additional flexibility; however, introducing EVs into voltage regulation schemes adds additional complexity.

Recent studies have investigated the use of EVs for voltage regulation through coordinated charging and discharging and concluded that coordinated charging improves voltage profiles and reduces violation rates, although most existing studies employ simplified scenarios or do not adequately assess performance under real-world uncertainties [16].

3. Methodology

The proposed learning-driven decision framework for coordinating electric vehicle (EV) energy exchange in renewable microgrids is implemented through the following sequential steps:

Step 1: Data acquisition and pre-processing: The EV aggregator constantly collects both historical data and real-time information from various sources, including renewal inverters, distribution-level sensors, EV telemetries, and charging stations. Collected data include measurements of bus voltage magnitude & angle; active/reactive power flow; arrival/departure timestamps; EV state-of charge. To prepare the data for later use, the following pre-processing methods will be utilized: removing missing values; filtering outliers; synchronizing different types of data streams; normalizing input values. Feature engineering will follow so as to create rich time-dependent (e.g., season, holidays...)/context based (e,g., temperature/lumens/ precipitation) indicators that will provide a solid foundations upon which predictive/control models can be constructed.

Step 2: Short-term forecasting and uncertainty modelling: Short-term forecasting for generating renewable energy, group demand from non-electricity vehicles, and the predictability of electric vehicle use is done using supervised learning models. These models utilize past data using cross-validation and are revisited to take into consideration seasonal deviations and changes in behaviour. Forecasts are generated not only as point estimates but also with associated uncertainty levels represented through quantiles or probabilistic scenarios using techniques such as ensemble learning or quantile regression, thereby accounting for inherent variability and ensuring improved robustness against forecast uncertainty under uncertain operating conditions, as illustrated in Fig. 2.

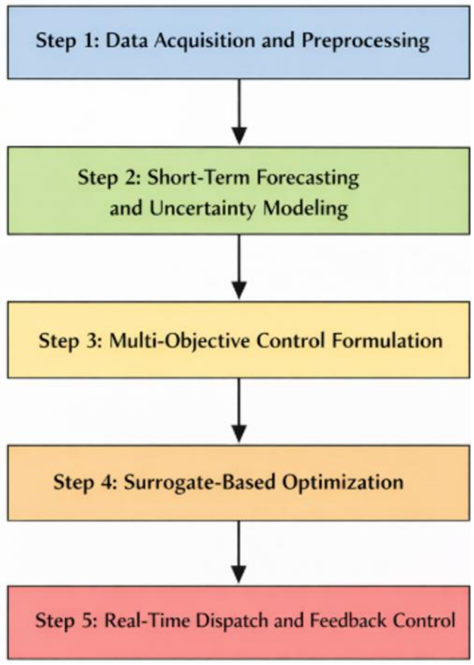

Fig. 2. Data-driven EV aggregator control scheme for voltage and energy stability.

Step 3: Multi-objective control problem formulation: In every control interval a formulation is provided for the solution of a multi-objective optimization problem. Objectives will include minimizing voltage deviations at critical load buses, reducing maximum net load (peak net load), and maximizing local renewable energy utilisation (utilisation of renewable energy generated locally). Constraints defined in the system pertain to network power flow limits, transformer capacity limits, EV battery charging and discharging limits, and minimum state of charge required to depart based on user mobility requirements. A composite weighted objective function is developed to determine trade-offs among the competing objectives of each control interval; the weights are selected based on operator preference, utilizing a sensitivity analysis.

Step 4: Surrogate-based optimization and decision making: To solve nonlinear AC power flow issues, an EV charging and discharging surrogate system (or mapping) for power flow analysis will be created based on historical or simulated data to quickly assess the performance of any EV charging (or discharging) control strategy without having to conduct a complete analysis of the system. Once the surrogate is completed, a constrained numerical optimization solution using warm-start to solve will be applied. Forecasting methods will be used as well as scenario generation/analysis and chance constraint methods, all to increase future robustness to forecast errors.

Step 5: Real-time dispatch and closed-loop feedback: As shown in Table 1, aggregators send optimized EV charging and V2G setpoints to individual EVs while respecting user-defined flexibility windows. The microgrid continuously monitors real-time feedback and detects deviations arising from unexpected EV behaviour or communication delays. Performance threshold violations trigger re-optimization to limit excessive cycling and associated battery degradation costs, while incentive-compatible mechanisms are employed to ensure user compliance. Hierarchical control structures support scalability for large EV fleets, and event-triggered updates with local fallback policies ensure safe operation under degraded communication conditions.

4. Implementation and Experimental Setup

A low-voltage smart microgrid was simulated in a time series to evaluate the implementation. Distributed photovoltaic generation, residential and commercial loads, and centralized aggregation of EVs comprise this microgrid. The network topology includes many radial feeders and monitored buses selected as representative sites of where voltage sensitivity may exist. Datasets were used to create PV profiles and load tracing that reflect anticipated levels of high renewable penetration and peak when exercising.

Heterogeneous battery sizes, charging limitations, and user schedules are used to simulate an EV fleet that reflects real-world variability in charging behaviour. Several probabilistic patterns were used to create multiple arrival/delivery scenarios for all vehicles in the e-fleet.

Table 1. Comparative analysis of EV charging, V2G control, and energy management approaches

Ref.	Focus Area	Method / Approach	Key Findings
[1]	Vehicle-to-Grid (V2G) integration	Mathematical modeling and MATLAB/Simulink simulation	Demonstrated effective bidirectional power flow between EVs and grid; V2G improves grid support and peak load management
[2]	Bidirectional on-board charger for EVs	Soft-switching Dual Active Bridge (DAB) converter with optimized control	Achieved high efficiency and reduced switching losses during V2G and G2V operation
[3]	Bidirectional DC–DC converter for EVs	Design and experimental validation of converter topology	Validated reliable V2G/G2V operation with improved power quality and efficiency
[4]	EV aggregation for frequency control	Optimal coordinated control strategy in microgrids	EV aggregation significantly enhances frequency stability under varying operating conditions
[5]	Fast charging power converters	Comparative analysis of converter topologies and control methods	Identified suitable converter configurations for ultra-fast EV charging with high power density
[6]	EV charging station communication	Heterogeneous communication network with multi-aggregator architecture	Improved charging station coordination under high PV variability using distributed sensors
[7]	EV aggregator scheduling	Optimization-based scheduling for frequency regulation	Reduced operational costs while improving frequency regulation in renewable-powered grids
[8]	DC microgrid voltage stability	GaN-based bidirectional converter with fuzzy logic controller	Enhanced voltage stability and dynamic response during EV charging
[9]	EV charging communication networks	Heterogeneous communication network with multi-aggregator architecture	Improved charging station coordination under high PV variability using distributed sensors
[10]	Energy management for xEV charging stations	Adaptive energy management strategy in hybrid microgrid	Improved sustainability, reduced grid dependency, and optimized energy usage
[11]	Smart EV charging networks	AI-based demand response integrated with blockchain	Enhanced load balancing, transparency, and security in EV charging operations
[12]	Renewable energy site selection	Multi-Criteria Decision Making (MCDM) approach	Provided optimal wind power location selection considering technical and economic factors
[13]	Load frequency control	Integration of EVs and energy storage systems	Combined EVs and ESS improved frequency regulation in isolated microgrids

Chargers will allow for bi-directional power flow (V2G) when V2G is allowable. Battery models will account for SOC/dynamics and provide a simple degradation estimate (by energy throughput). Hard constraints on the minimum SOC of the EV upon departing from the charger (to meet user mobility needs) and soft penalties for delaying charging or having to accommodate any user preference-based inconvenience will be imposed.

An integrated simulation system of a control layer implementing a data-driven aggregator and a power flow engine to evaluate AC networks. The simulation framework was implemented in Python, utilizing scikit-learn for supervised learning models, NumPy and Pandas for data preprocessing, and a standard AC power flow solver for network evaluation.

Surrogate models were developed and validated using historical operational data. Models will be developed from historical sequences (offline) and then updated on a regular schedule, providing updated rolling forecasts, including the confidence level for each prediction. The multi-objective optimizer generates aggregate charging set-points to individual vehicles at regular intervals. Communications assessment includes realistic latencies and packet loss to evaluate resiliency. The baseline of the simulations will use a basic rule-based strategy for determining when to begin charging a vehicle (on arrival) or to delay charging until off-peak times with no coordinated V2G support.

5. Results and Discussion

The simulation results show a data-driven aggregator improving voltage regulation, peak demand, and renewable use through a coordinated control system compared to a baseline rule-based approach. As shown in Figure 3, the time series of voltage magnitudes across monitored buses shows how much less often voltages excursion from nominal voltage values are occurring and how many fewer times below threshold violations occurred with coordinated control compared to rule-based control.

In addition, strategic shifts in charging to times when there are more renewable energy available and managed discharges during daylight peak demand periods will produce a reduction in the peak net load. Figure 4 demonstrates the continued smoothing of feeder demand as a result of these changes, which will serve to reduce maximum loading and thermal loading of transformers and conductors.

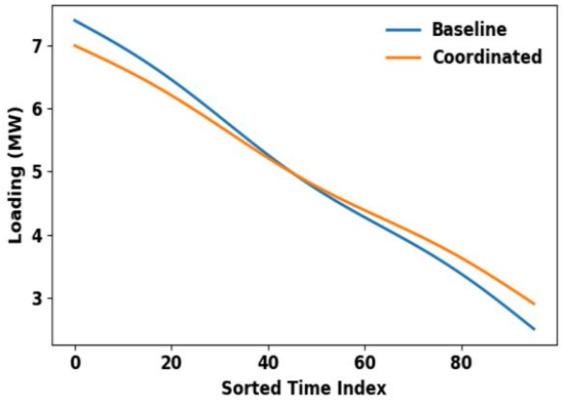

Fig. 3. Feeder load duration curve under baseline and coordinated control.

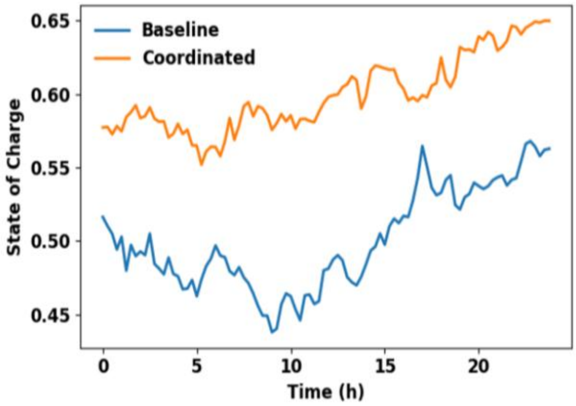

Fig. 4. Impact of coordinated aggregation on EV state-of-charge profiles.

At the same time, as more energy generated by the fleet can be consumed through the addition of stored energy in vehicles during periods of excess generation, the amount of curtailment experienced by PV systems can be reduced. In Figure 5, the various simulations show clear improvements in peak net demand and total renewable energy curtailment when using the coordinated method compared to the baseline methods. These improvements are observed across different operating conditions, demonstrating the effectiveness and robustness of the proposed coordinated control strategy. The quantitative performance improvements for each scenario are summarized in Table 2, further highlighting the reductions in peak demand and renewable energy curtailment achieved by the coordinated approach. The system's forecasting capabilities also support decision-making earlier than traditionally possible, as can be seen in Figure 6. The ability to forecast accurately in the short-term allows an aggregator to position the charge schedule ahead of time to prevent future voltage violations from occurring, and if forecast errors increase above a certain amount, the closed-loop system will perform re-optimizations to correct the error(s).

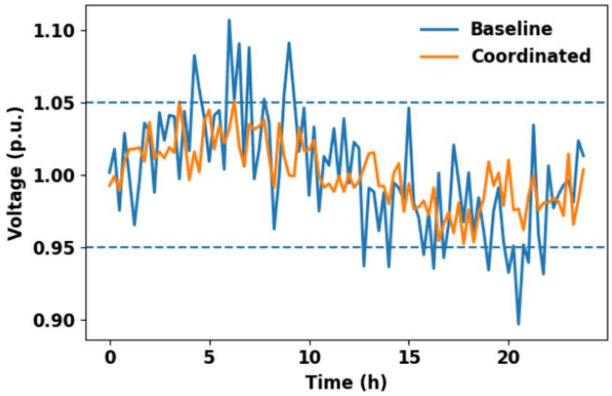

Fig. 5. Voltage magnitude at a representative bus under baseline and coordinated control.

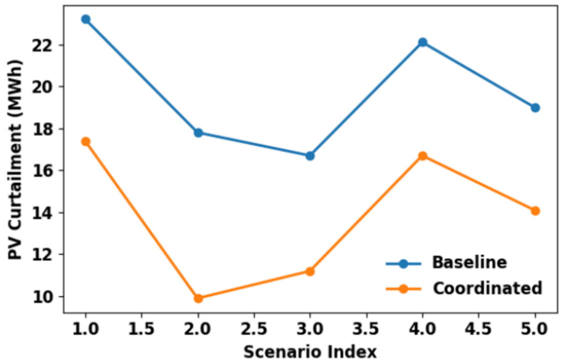

Fig. 6. Comparison of PV curtailment under baseline and coordinated strategies.

Table 2 : Performance comparison of baseline rule-based control and coordinated aggregator control.

Metric	Baseline (Rule-Based)	Coordinated (Data-Driven)	Observed Improvement
Voltage excursions from nominal	Frequent excursions and violations	Significantly reduced excursions	Improved voltage regulation
Below-threshold voltage violations	Multiple occurrences	Rare to none	Enhanced feeder reliability
Peak net feeder load	Higher peak demand	Reduced and flattened peaks	Lower transformer/conductor loading
Feeder load profile	Sharp peaks, less smooth	Smoothed demand profile	Reduced thermal stress
Renewable energy curtailment	Higher PV curtailment	Lower curtailment	Increased renewable utilization
EV state-of-charge alignment	Poor alignment with PV output	Charging aligned with high PV availability	Better energy absorption
Sensitivity to forecast error	No anticipatory control	Graceful degradation with uncertainty	Improved robustness

6. Conclusion

The research introduced a data-driven control system that provides EV aggregators a way to assist with voltage and overall energy stability of smart microgrids. As a means of accomplishing this, real-time telemetry was integrated with short-term forecasts, surrogate voltage models and multi-objective optimization so that the aggregator could efficiently coordinate charging of EVs and V2G operations, reducing voltage violations, smoothing the net load, and increasing the use of local renewables. In addition, the combination of constraints and penalty terms in this approach maintained the mobility needs of users while also limiting degradation of batteries, thus allowing this service to be provided in a manner that does not compromise on the expectations of EV owners.

Simulation-based evaluations using representative microgrid scenarios showed significant improvements over a rule-based baseline, including reduced voltage excursions, decreased peak net load, lower renewable energy curtailment, and improved robustness under forecast uncertainty and communication interruptions. Sensitivity analyses revealed that the closed-loop adaptive control method will maintain its robustness when faced with moderate forecast error and communication interruptions; however, performance will suffer significantly when there is little to no data available or when there are long periods of time with no connectivity. The use of surrogate models for computing has resulted in the ability to operate in near real-time for the scale of the studied system.

Author Contributions

All authors contributed to conceptualization, methodology, software, data curation, formal analysis, investigation, visualization, writing-original draft, writing-review, editing and have read and approved the final version of the manuscript.

Acknowledgements

Not applicable.

Conflict of Interest

The authors declare no conflict of interest.

References

[1] G. Janardhan, R. Shanmugasundaram, S. K. J., R. Narendar, and S. K. K., “Modeling and simulation of vehicle to grid (V2G) integration,” *E3S Web of Conferences*, vol. 616, p. 01016, 2025, doi: 10.1051/e3sconf/202561601016.

[2] V. Sonnati, S. Arandhakar, and K. S. V. P. Kumar, “Soft-switching dual active bridge converter-based bidirectional on-board charger for electric vehicles under vehicle-to-grid and grid-to-vehicle control optimization,” *E3S Web of Conferences*, vol. 472, p. 01021, 2024, doi: 10.1051/e3sconf/202447201021.

[3] Y. Meadari, D. Harsha, P. K. Biswas, and T. S. Babu, “Design and development of bidirectional converter based on V2G and G2V operation,” *E3S Web of Conferences*, vol. 547, p. 03002, 2024, doi: 10.1051/e3sconf/202454703002.

[4] S. Iqbal, S. Habib, N. H. Khan, M. Ali, M. Aurangzeb, and E. M. Ahmed, “Electric vehicles aggregation for frequency control of microgrid under various operation conditions using an optimal coordinated strategy,” *Sustainability*, vol. 14, no. 5, p. 3108, 2022, doi: 10.3390/su14053108.

[5] V. Manoj, R. Pilla, and S. R. Sura, “A comprehensive analysis of power converter topologies and control methods for extremely fast charging of electric vehicles,” *Journal of Physics: Conference Series*, vol. 2570, no. 1, p. 012017, 2023, doi: 10.1088/1742-6596/2570/1/012017.

[6] M. Davila-Sacoto, L. Hernández-Callejo, L. G. González, Ó. Duque-Perez, Á. L. Zorita-Lamadrid, and D. Ochoa-Correa, “Heterogeneous communication network architecture for the management of electric vehicle charging stations: multi-aggregator management in microgrids with high photovoltaic variability based on multiple solar radiation sensors,” *Sensors*, vol. 24, no. 12, p. 3768, 2024, doi: 10.3390/s24123768.

[7] S. Ma, “Optimal scheduling of electric vehicle aggregators for frequency regulation and cost efficiency in renewable-powered grids,” *Computers & Electrical Engineering*, vol. 118, p. 109317, 2024, doi: 10.1016/j.compeleceng.2024.109317.

[8] K. Padma and K. Manohar, “Voltage stability in a photovoltaic-based DC microgrid with GaN-based bidirectional converter using fuzzy controller for EV charging applications,” *WSEAS Transactions on Systems and Control*, vol. 19, pp. 143–152, 2024, doi: 10.37394/23203.2024.19.15.

[9] S. Tabassum, A. R. V. 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, p. 22, 2025, doi: 10.2516/stet/2025002.

[10] A. R. Singh, R. S. Kumar, K. R. Madhavi, F. Alsaif, M. Bajaj, and I. Zaitsev, “Optimizing demand response and load balancing in smart EV charging networks using AI integrated blockchain framework,” *Scientific Reports*, vol. 14, no. 1, p. 31768, 2024, doi: 10.1038/s41598-024-82257-2.

[11] V. Manoj, V. Sravani, and A. Swathi, “A multi-criteria decision-making approach for the selection of optimum location for wind power project in India,” *EAI Endorsed Transactions on Energy Web*, p. 165996, 2018, doi: 10.4108/eai.1-7-2020.165996.

[12] R. R. Shukla, M. M. Garg, and A. K. Panda, "Driving grid stability: Integrating electric vehicles and energy storage devices for efficient load frequency control in isolated hybrid microgrids," *Journal of Energy Storage*, vol. 89, p. 111654, 2024, doi: 10.1016/j.est.2024.111654.

[13] A. Rajagopalan, K. Nagarajan, M. Bajaj, S. Uthayakumar, L. Prokop, and V. Blazek, "Multi-objective energy management in a renewable and EV-integrated microgrid using an iterative map-based self-adaptive crystal structure algorithm," *Scientific Reports*, vol. 14, no. 1, p. 15652, 2024, doi: 10.1038/s41598-024-66644-3.

[14] R. Battula and S. Vuddanti, "Distributed control strategy for secondary frequency regulation with EV demand aggregation and delay compensation in AC unbalanced microgrid," *Electric Power Systems Research*, vol. 225, p. 109782, 2023, doi: 10.1016/j.epsr.2023.109782.

[15] H. R. Sayarshad, "Designing vehicle-to-grid (V2G) aggregator fleet capacity for power grid reliability against cyberattacks," *Electric Power Systems Research*, vol. 244, p. 111554, 2025, doi: 10.1016/j.epsr.2025.111554.

[16] M. B. Prasad, P. Ganesh, K. V. Kumar, P. A. Mohanarao, A. Swathi, and V. Manoj, "Renewable energy integration in modern power systems: Challenges and opportunities," *E3S Web of Conferences*, vol. 591, p. 03002, 2024, doi: 10.1051/e3sconf/202459103002.