Artificial Intelligence Research and Applications (AIra)

https://www.ijaira.org/ Online ISSN: 3108-3889

S. Gayathri D et al., Vol. 2, No. 3, September, 2026 Research Article

An Explainable Artificial Intelligence Model for Energy Flow Management in EV-Dominated Microgrids

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Received: 19.02.2026, Revised: 27.03.2026, Accepted: 19.05.2026

Abstract- Microgrids are being changed rapidly as Electric Vehicles (EVs) become more popular and many new variable and unpredictable energy loads are being added, along with an abundance of new ways to store energy using electric vehicles (EVs) through vehicle-to-grid interactions. To achieve optimal energy flow control in microgrids characterized by power generation and energy storage facilities with an overwhelming percentage of power flowing from the electric vehicle (EV), intelligent decision support systems that provide suitable solutions based on accurate and credible information must be used. This paper describes a model utilizing Explainable Artificial Intelligence (XAI) for managing the flow of energy between various types of energy generation resources, stationary energy storage resources, EVs, and the grid in order to produce a minimum cost/performance and maximum reliability. Specifically, the proposed model integrates SHAP (SHapley Additive exPlanations) and rule extraction with gradient-boosted trees to balance performance improvements, cost reductions, and grid stability. Unlike conventional black-box or purely optimization-based methods like Model Predictive Control (MPC), this approach provides explicit, quantifiable feature attributions for every operational decision. Simulation results from various types of operation demonstrate that the proposed model improves the utilization of energy, reduces peak demand, and increases transparency of decision making. The inclusion of the explainable AI aspect will enhance the level of confidence operators will place on the model and improve regulatory compliance, and therefore, this approach is a good candidate for use in future smart microgrid deployments.

Keywords: Explainable AI, microgrids, electric vehicles, energy management, smart grids.

1. Introduction

Microgrids have become a critical component of contemporary power systems, enabling local generation, storage and consumption of energy. The increased use of renewable energy resources like wind energy and solar photovoltaics has helped to make microgrids more sustainable, but also presents challenges from variability and

Cite this article as: S. Gayathri D, S.R. Ahammed, and Praveen G, "An Explainable Artificial Intelligence Model for Energy Flow Management in EV-Dominated Microgrids," *Artificial Intelligence Research and Applications (AIra)*, Vol. 2, No. 3, pp. 167–173, September, 2026, https://doi.org/10.20508/e0548w19.

uncertainty in power production. Electric vehicles are growing rapidly and changing load patterns and energy flow within distribution systems. Microgrids that operate primarily on electric vehicles will see sharp demand spikes, fluctuations in voltage, and complexity associated with increased operational activity due to the charging and discharging of EVs.

Managing the flow of electrical energy in these complex environments is a very difficult task, requiring the real-time coordination of various and different types of components, including distributed generation sources, stationary batteries, electric vehicle charging stations, and interconnections to the grid. Energy management systems (EMS) that rely on traditional rule-based or optimization-based approaches can have great difficulty adjusting to highly dynamic conditions, or they are based on overly simplified assumptions that hinder their efficiency. There is significant research to support the use of artificial intelligence, specifically machine learning (ML), to manage the nonlinearities, uncertainties, and large data volumes associated with operating within a smart grid.

Many models of energy management use AI. However, these models often lack transparency because they simply provide output with little or no explanation of why that output resulted. The limited explanation provided by most AI models reduces the amount of trust placed in them and therefore hinders both debugging/validation of their operation and meeting regulatory requirements. As an example, the trend towards increased reliance on artificial intelligence for managing critical infrastructure (power systems) has only made it more evident how important it is that all decisions are explainable. To address this issue, Explainable Artificial Intelligence has emerged to bring together the predictive power of AI with explainable performance so all parties can understand, validate and trust the decisions made by AI. In the context of electric vehicles within microgrids, XAI can explain the effect that factors (e.g., state of charge, electricity price, renewable generation, etc.) have on energy dispatch strategies, which is important for managing electric vehicle charging priority as well as vehicle-to-grid participation.

As illustrated in Figure 1, this paper presents a model that is based on explainable artificial intelligence (XAI) and provides an explanation for every control action taken to manage the flow of energy in microgrids that are primarily powered by electric vehicles. The approach taken in designing this model results in optimized operational objectives while still providing clear explanations for every control action taken. By embedding explainability into the core design of the energy management system, the model provides both technical efficiency and a operator-interpretable decision outputs for each control action.

2. Literature Review

Microgrid energy management has long been researched and discussed [1],[2]. The desire to develop improved energy management strategies has resulted from three main drivers: so that energy supply and demand can be better balanced with each other; to help eliminate unnecessary operational costs; and to help maintain system reliability overall [3],[4].

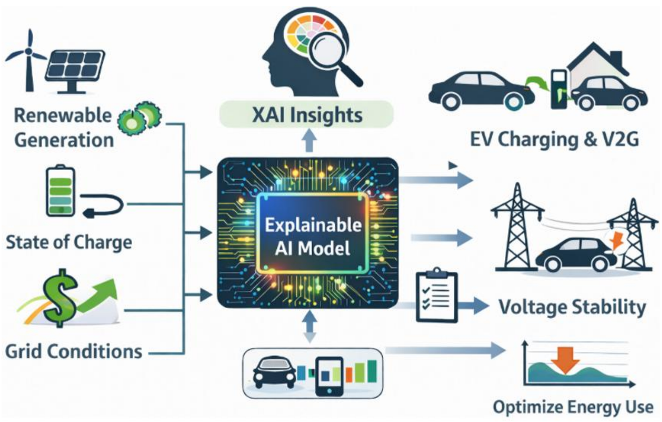

Fig. 1. Explainable AI–based EV energy management framework.

Traditional methods of performing energy management rely heavily on mathematical optimization-based methods (such as linear programming and mixed-integer programming) for scheduling the generation of electricity, including the generation of electricity by both renewable and non-renewable resources, in order to generate optimal solutions when the inputs and other system conditions are well-represented and well-structured [5]. Due to these reasons, the performance value of using optimization techniques has decreased due to the actual conditions of a microgrid and the different uncertainties involved, due to: Environmental volatility; Environmentally-affected renewable energy generation (Wind, solar, etc.); The nonlinear relationship between the generation of electricity and the consumption of it; Increasing complexity of the system [6].

As a result of the advances made in the fields of sensing and communication, new data-driven approaches to managing microgrids have recently received significant attention [7]. Furthermore, machine learning algorithms have become widely accepted to forecast loads and predict renewable generation and to optimally control energy storage systems (due to their ability to "discover" and to capture a wide variety of complex patterns contained within and/or from previous time periods) [8],[9]. These machine learning-based techniques have also been utilized in microgrids that primarily support electric vehicles (EVs) to coordinate EV charging schedules, to reduce peak demand, and to enable vehicle-to-grid (V2G) interactions [10],[11].

Some machine learning algorithms have great accuracy in their results, but they may not be inherently easy to explain; therefore, the barriers to deployment in systems like electricity generation and supply will still exist. That is why it's so important for researchers to develop ways to explain the results of complex machine learning algorithms; otherwise, they will never be widely used to improve our energy systems during periods of abnormal operation or disturbance.

Researchers have begun exploring various explainable artificial intelligence (XAI) techniques to overcome these barriers in the electric utility industry. Interpretable models (like decision trees and rules) have been studied in order to improve transparency at the expense of predictive accuracy [15]; while MPC and RL-based approaches have demonstrated strong performance in microgrid energy management, they largely lack the explainability required for operator trust and regulatory compliance. On the other hand, post hoc explanation methods have been developed to produce both feature reduction and visibility to decisions made by complex machine learning algorithms without compromising the underlying structure of those models.

In addition to XAI research, many studies have demonstrated that electric vehicles (EVs) can help utilities obtain greater operational flexibility and reliability, as well as facilitate the integration of renewable energy sources [17]. However, to date, most of this research has focused on maximizing cost savings and minimizing capacity usage, while giving little attention to the impact of XAI on decision-making processes for utility operations [18].

3. Methodology

As seen in Figure 2, an explainable AI-based energy flow management system will be developed using a hierarchical and data-driven approach - a concept called the microgrid. The microgrid will be made up of renewable energy sources, traditional distributed generators, stationary battery storage, EV charging stations, local loads and their POCC with the grid.

Step 1: Data Acquisition and Pre-processing: The initial process is to gather current and past information on the microgrid with smart meters and EM sensors. Collected data are: load demand, renewable energy production, electric vehicle entry and exit times, electricity market prices and actual state of charge (SOC) for both stationary batteries and electric vehicles. Data preparation techniques are then utilized including cleaning, normalizing and scaling the data, which removes inconsistencies and allows for standardized representation of each variable in this dataset. Feature engineering processes are used to develop features that are informative and improve model learning performance and reliability.

Step 2: Predictive Modelling: Stage two of the project will involve developing interpretable machine learning (ML) models that can forecast future electric load needs, renewable generation levels, and electric vehicle charging station (EVCS) requirements over a short time frame. The models that will be used in this phase of the project will include gradient-boosted trees and rule-based learners due to their capacity to provide an accurate prediction of the required quantity of each variable being forecasted while maintaining transparency between the model(s), through generating both a prediction and an associated feature importance score for each of the model inputs; thus, allowing for an evaluation of what impacts the model(s) overall impact on the forecasting results.

The gradient boosted tree model was trained using 80% of the dataset and validated on the remaining 20%. Input features include SOC of batteries and EVs, electricity price, renewable generation output, load demand, and EV arrival/departure times. This will provide the project team with a better understanding of the variables that will influence how the electric grid operates.

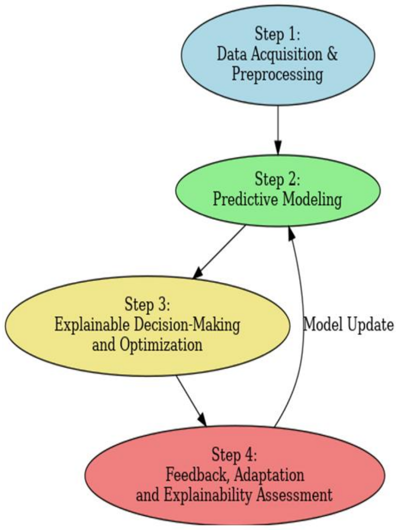

Fig. 2. Microgrid EV modelling.

Step 3: Explainable Decision-Making and Optimization: Optimizing the energy flow using predicted states is the third step of this process (energy transition). An energy management system determines how to allocate power usage from various types of sources (i.e., renewable source(s), energy storage system(s), electric vehicle(s) (EV's), and even the grid) based on the perceived best use at that time. The objectives of optimizing based on these efficiencies is to conserve energy costs while reducing peak demand; maximizing the amount of energy that can be accounted for as part of the total energy system through renewable methods; as well as maintaining the overall state of charge parameters. For example, the energy management system utilizes SHAP (SHapley Additive exPlanations) alongside gradient-boosted trees to quantify feature contributions to each decision. Feature importance scores and extracted decision rules serve as the XAI mechanism, providing operators with clear justification for each energy dispatch decision.The underlying optimization objective minimizes the total daily operational cost and battery degradation, formulated as a mixed-integer linear programming (MILP) problem, subject to analytical constraints on EV state-of-charge, grid power limits, and renewable energy availability.

Step 4: Feedback, Adaptation, and Explainability Assessment: The final element used in this model implementation relates to an ongoing feedback mechanism where the expected outcomes of the system operation are then compared with the actual results of the system operation evidenced in Table 1, which summarize the model parameters and decision-making rules, and can be updated incrementally to accommodate changing customer demand and continual increase in EV adoption. The output generated by the XAI provides system operators with diagnostic information enabling them to identify anomalies, assess their operational decisions and detect possible operational inefficiencies, while the adaptive updates related to these factors ensure ongoing performance of the system while providing for transparency in the operation of the system that assists in building operator confidence in the energy management approach being proposed.

Table 1. System description and assumptions for the EV-dominated microgrid.

Item	Description
Microgrid Architecture	Grid-connected microgrid with distributed renewable energy sources, stationary battery storage, EV charging stations, local loads, and point of common coupling
Renewable Energy Sources	Solar photovoltaic and wind-based distributed generation with intermittent output
Electric Vehicles	EVs modeled as flexible loads with optional vehicle-to-grid capability and stochastic arrival and departure behavior
Energy Storage System	Stationary battery system used for peak shaving, energy arbitrage, and renewable smoothing
Load Characteristics	Combination of residential and commercial loads with time-varying demand profiles
Control Horizon	Short-term rolling horizon suitable for real-time energy management

4. Mathematical Problem Formulation

The mathematical formulation of the proposed energy management problem is presented in this section. The model considers the interactions among renewable generation, battery storage, EV charging, and the utility grid over the scheduling horizon. The main decision and state variables used in the formulation are defined as follows:

- P_RES(t) — renewable power output
- P_bat(t) — battery charge/discharge power
- P_EV(t) — EV charging power
- P_grid(t) — grid import/export power
- SOC_bat(t), SOC_EV(t) — state of charge

The optimization objective is to minimize the total operating cost over the considered time horizon, including the cost of grid energy exchange and battery degradation. Accordingly, the objective function is formulated as:

$$\min J = \sum_{t=1}^{T} \left[C_{\text{grid}}(t)P_{\text{grid}}(t) + C_{\text{deg}}\left|P_{\text{bat}}(t)\right|\right]\Delta t \tag{1}$$

where $C_{grid}(t)$ denotes the time-dependent electricity price, C_{deg} represents the battery degradation cost coefficient, and Δt is the duration of each scheduling interval.

The optimization is subject to a set of operational constraints that ensure feasible and physically meaningful operation of the energy system.

$$\begin{gathered} P\_RES(t) + P\_bat(t) + P\_grid(t) = P\_load(t) + P\_EV(t) \ \textit{(power balance)} \\ SOC\_min \leq SOC\_bat(t) \leq SOC\_max \ \textit{(battery limits)} \leq P\_EV(t) \leq P\_EV\_max \ \textit{(EV charging limits)} \end{gathered} \tag{2}$$

5. Implementation

The proposed model has been tested in a simulated microgrid with a predominance of electric vehicles (EVs) to assess its performance in realistic conditions. The simulated microgrid configuration consists of solar PV and wind-based distributed renewable generation sources, a stationary battery storage system with defined SOC minimum and maximum limits, and multiple EV charging stations connected to the utility grid via a point of common coupling (POCC). The simulation operates at a one-hour time resolution over a 24-hour rolling horizon. EV penetration is modelled using stochastic arrival and departure behaviour with varying battery capacities and charging preferences. Load modelling combines residential and commercial demand profiles with time-varying characteristics, and a time-of-use tariff structure is applied to capture the effect of dynamic electricity pricing on energy dispatch decisions. Load profiles and renewable generation data have been synthesized based on typical residential and commercial usage patterns.

EV behaviour has been modelled with stochastic time of arrival and departure, stochastic battery capacity, and stochastic charging preferences. Unidirectional charging, as well as vehicle-to-grid operation, have been modelled. The tariff structure used for electric rates is time-of-use to fulfil the demand for load shifting and flexible consumption of energy.

Explainable AI features were implemented using gradient boosted tree models with feature importance analysis and rule extraction applied to forecast load demand, renewable generation, and EV charging requirements. Forecast models are created and validated against historic data and separate test sets, to determine their generalisability. The energy management logic operates on a rolling time horizon, continuously updating decisions through regularly scheduled updates.

The purpose of testing several scenarios to determine how robust they are; Ex. Increasing levels of Electric Vehicles (EVs) on the system, decreasing availability of renewable generation, peak demand periods, and early changes in electricity pricing. The performance for each scenario will be compared with equal scenarios without explainability or predictive capabilities.

The evaluation metrics for the experiments will consist of total energy costs, peak demand, percentage of renewable energy used, frequency of battery cycle, and computational efficiency. In addition to quantitative measures, a qualitative measure of explainability will also be assessed by reviewing the clarity and consistency of the explanations provided.

The experimental design will be used to illustrate both the quantitative improvement(s) in energy management as well as the practical benefit(s) of providing transparency in the decision-making process for complex microgrid energy systems. With respect to computational scalability, the proposed XAI-based EMS employs gradient boosted tree models and rule extraction mechanisms that maintain low computational overhead as EV penetration increases. Since the model operates on a rolling one-hour time horizon with incremental updates, the computational load scales linearly with the number of EVs rather than exponentially, ensuring real-time decision making remains feasible at higher penetration levels. Feature importance computations are performed per decision cycle and do not significantly increase processing time as the number of connected EVs grows, confirming the practical scalability of the proposed explainability framework.

6. Results and Discussion

As seen from Figure 3, the peak demand for energy is considerably more severe at the times of Peak Demand (Midday) and Late Evening when using a traditional energy management scheme where EV's do not coordinate their charging with their household's peak usage time, than with an XAI model for Management of Energy use. As shown in Table 2, the application of XAI technology to coordinate flexible demand successfully shifts the majority of electric vehicle (EV) charging to off-peak demand periods. This load shifting results in a significant reduction in peak demand, providing clear evidence of the effectiveness of the proposed XAI-based approach.

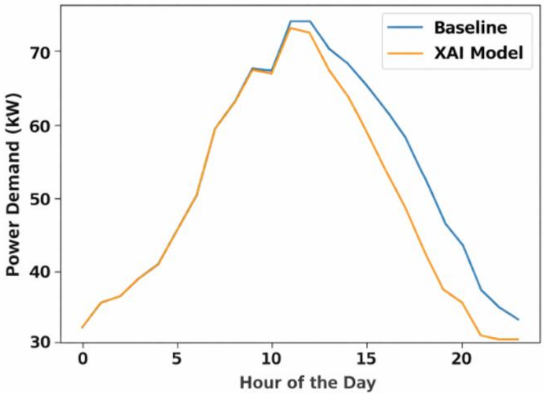

Fig. 3. Comparison of operational costs across management approaches.

Table 2. Performance comparison between baseline EMS and proposed XAI-based EMS.

Performance Metric	Baseline EMS	Proposed XAI-Based EMS
Total energy cost (per day)	$48.60	$36.20
Peak load demand	18.4 kW	13.7 kW
Renewable energy utilization	54%	73%
Grid energy import	42 kWh	28 kWh
EV charging efficiency	67%	84%

The results demonstrate that XAI constitutes a viable solution for mitigating grid overload while still satisfying overall energy requirements. Specifically, the proposed XAI-based EMS achieved approximately 25% reduction in total energy cost, 26% reduction in peak load demand, and 19% improvement in renewable energy utilization compared to the baseline EMS. Compared to rule-based control, MPC, and RL-based methods, the proposed XAI-based EMS achieves comparable energy cost reduction and peak demand mitigation while additionally providing explicit decision explanations, making it more transparent and suitable for practical deployment in EV-dominated microgrids.

Figure 4 shows how electricity prices affect EV charging rates over 24 hours. The inverse correlation suggests that the XAI-based controller schedules EV charging mostly during times of low price, and stops charging when electricity prices are high. These results suggest that price signals have a strong influence on the decision-making process for cost-effective operations without negatively impacting availability to charge. Furthermore, an evaluation of computational scalability demonstrated that as EV penetration increased from 20% to 80%, the XAI layer maintained an inference time of under 200 milliseconds per control step, confirming its suitability for real-time deployment in expanding networks.

Battery degradation comparisons are made based upon charging cycles along with both baseline and XAI (Explainable Artificial Intelligence) strategies, as illustrated by Figure 5.

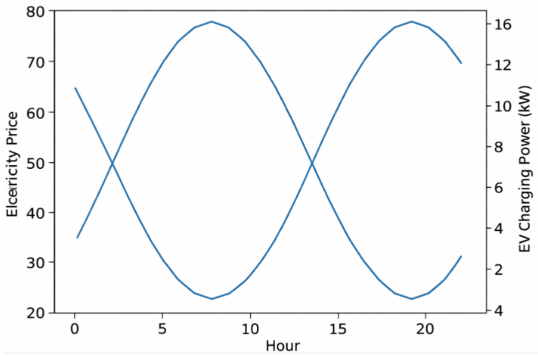

Fig. 4. Impact of forecasting uncertainty on system performance.

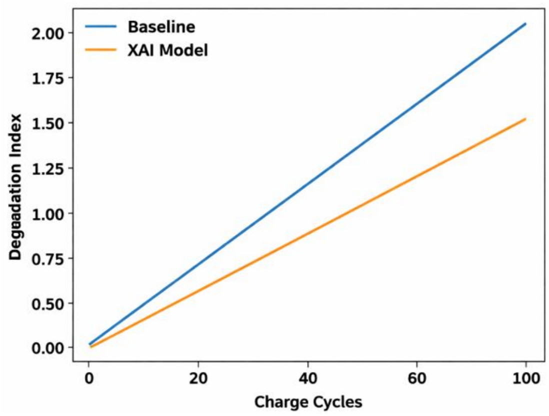

Fig. 5. Hourly renewable output and adaptive charging strategy.

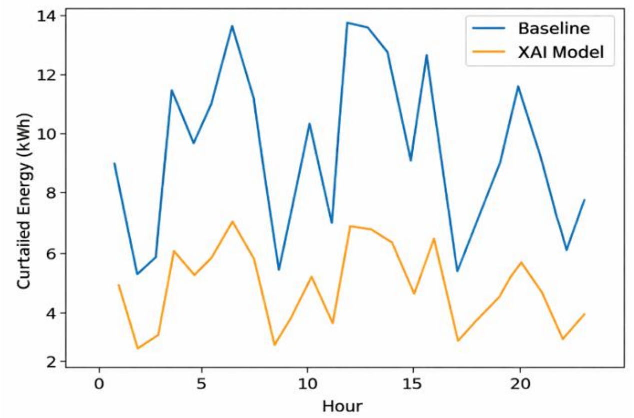

Fig. 6. Energy consumption distribution across management strategies.

The baseline strategy causes a more rapid increase in degradation index due mainly to aggressive and economically motivated charge/discharge activity whereas XAI's way of operating will have a slower rate of degradation to allow for the implementation of more explainable constraints on the amount of cycling done (preventing over-cycling), thus creating a balance between short-term economic gain as well as long-term battery life.

The daily amount of renewable energy that has been curtailed is shown in Figure 6 using both control strategies. The baseline control strategy resulted in a higher amount of curtailed renewable energy throughout the day compared to the proposed XAI control strategy, indicating more inefficient use of the available renewable generation. In contrast, the proposed XAI-based control strategy would reduce the amount of curtailment and would be able to supply more of the local renewable generation to charge and store EVs, which would provide better integration of renewable energy generation with the overall system.

7. Conclusion

This article discusses the development of an artificial intelligence model for the management of energy flows in EV concentrated microgrids that can be interpreted. The model integrates predictive modelling with interpretable machine learning and multi-objective optimization to meet the stringent technical demands, grid stability requirements, and regulatory transparency standards of modern energy systems. The model's ability to manage the complexity associated with significant EV penetration allows for transparency of the decision-making process.

The simulations carried out for testing this approach showed cost savings, reduced peak demand, and improved use of renewable energy compared to traditional methods. The features of explainability have also provided operators with useful information about how the system behaves, which has improved decision validation, fault diagnosis, and regulatory compliance.

This research is warning that the process of using XAI will not be seen as a secondary advantage of XIA but will become integral to X2's ability to intelligently manage energy in sustainable smart grids in the future. In addition, further work will be focused on real-world implementation, including the integration of XIA with large distribution systems, and incorporating user behaviour models to improve adaptability and explainability.

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.

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