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An Artificial Intelligence Approach for Coordinating Electric Vehicle Charging and Renewable Energy in Power Systems

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Abstract

Electric vehicle (EV) charging from the grid presents significant challenges for the grid due to increased power demand added to the existing base load. This scenario leads to grid instability arising from voltage drops and new peaks generated due to uncontrolled charging. This study proposes an artificial intelligence (AI)-based optimization approach to mitigate the impact of large-scale, uncontrolled charging of EVs. Using real-world datasets of EV charging sessions, we first quantify the impact of EV charging under a baseline "uncontrolled" charging scenario using the IEEE 33-bus test system. We formulate the charging problem as an optimization task with the objective of minimizing energy consumption and peak power demand. A genetic algorithm (GA) and model-predictive control (MPC), combined with solar PV, are employed as charging strategies to solve the optimization problem. Simulation results show that the AI-driven strategy significantly reduced peak power demand by 38.35% and energy consumption by 12.09% with solar PV utilization. A sensitivity analysis of peak power demand reveals that grid stability will be violated with higher charging rates.

Keywords: artificial intelligence; EV charging; genetic algorithm; model-predictive control; peak load shaving; power system; renewable energy; smart grid

1. Introduction

The electrification of the transport sector has moved EVs as new-energy vehicles to the forefront of a global transition that drives sustainable transport, energy systems, and the environment [1]. While EVs offer significant environmental benefits by reducing greenhouse gas emissions, the increasing energy demand from EV charging on the grid imposes a substantial and unpredictable load on the electrical distribution system. This means that peak power demand from the grid due to EV charging is inevitable, which requires a key energy-management system (EMS). Statistics from the International Energy Agency (IEA) indicate that global EV energy consumption in 2024 alone reached 180 TWh. The IEA Global EV Outlook 2025 predicts that this figure will rise substantially by 2030 [2]. Studies have shown that clustering of EV charging activities during evening hours as drivers return home creates new power demand peaks, etc. [3,4], which can worsen when added to the baseload, especially with the use of high-rated EV fast chargers with nonlinear loads [5]. This leads to congestion, grid voltage instability, and power-quality issues, which impact safe grid operations [6,7]. Without intelligent coordination and controlled charging, this new demand profile from EVs threatens to undermine grid reliability, which may require costly infrastructure upgrades that can be avoided.

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To address the problem of new peaks and uncontrolled charging of EVs in power systems, AI combined with smart charging offers many potential solutions. Smart charging, which involves actively controlling the time and rate at which EVs charge their batteries on the grid [8], is one of the most enduring approaches to solving uncontrolled charging. This includes shifting EV charging from peak to off-peak hours. This time-shifting strategy, known as peak-shaving and valley-filling [9], has the potential to flatten the load curve and improve the efficiency and stability of the grid. Furthermore, the intelligent coordination of EV charging with the intermittent output of solar PV [10] allows for smoothing the daily load profile and maximizing RE utilization while reducing the carbon footprint [11]. This study aims to use artificial intelligence algorithms to enhance EV charging, coordination, and control with RE to improve grid stability. To quantify the benefits of this AI-driven strategy in minimizing the uncontrolled charging problem, real-world datasets of EV charging sessions are simulated in a Python environment. This strategy provides significant benefits to power systems with microgrid applications where EVs integrate with RE sources. Figure 1 presents a hierarchical visualization of how AI applications are integrated into power systems, renewable-energy systems, and electric vehicles to enable intelligent power and control. The top layer shows how AI is used to achieve optimized cost and improved tariffs, stability and power quality, user satisfaction, and service reliability. The middle layer is the core AI engine, where intelligent decisions are made for forecasting and prediction of RE generation, energy demand, and pricing. The optimization block shows AI capabilities in energy flow insight, energy storage utilization, and operational schedules. The dynamic scheduling and dispatch generation block shows AI capabilities for dynamic EV charging schedules, energy dispatch from storage, and management of power generation. The bottom layer (system layer), which comprises the physical infrastructure, integrates AI applications to RE sources, smart grid with power-quality management, smart EV charging, and BESS, which AI can charge and discharge dynamically to balance the grid and manage intermittency from RES like solar PV and wind.

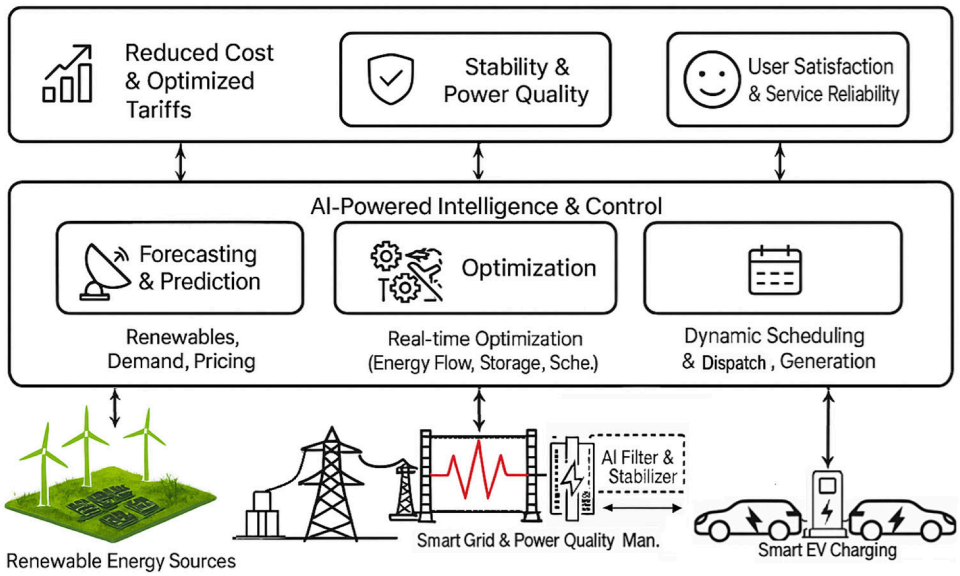


Figure 1. AI orchestrating power systems, renewable energy, and EV applications.

Contribution

The primary contributions of this study are as follows:

1. Bibliometric Analysis: This study provides a quantitative analysis with an in-depth review of the application of AI in coordinating EV charging with renewable-energy integration into the grid. The bibliometric analysis used statistical techniques based

on R programming with R-Studio IDE version 4.5.1 to study, identify patterns, and visualize contributions already made in the domain of AI applications in relation to EVs and renewable-energy integration into the grid.

2. Algorithm Development and Evaluation: We developed and evaluated two AI-based charging strategies, namely a genetic algorithm (GA) and model-predictive control (MPC). The GA and MPC were both integrated with solar PV and evaluated against an uncoordinated baseline. The strategies are assessed for peak power demand reduction and renewable-energy utilization using the IEEE 33-bus test system. Furthermore, we examined their robustness through a sensitivity analysis of grid stability under increasing EV charging rates.

The remaining part of this paper is organized as follows: Section 2 reviews related studies on AI and machine-learning (AIML) applications in EV charging and optimization, in relation to renewable-energy sources and the impact of peak power demand on the grid. At the end of the literature review, a statistical evaluation of related studies is presented using bibliometric analysis to provide insights into AI applications for EV charging and RE integration with the grid. The gaps identified in the reviewed literature are presented. Section 3 deals with the methodology used in this study, including the system model, objective function, and constraints. Section 4 provides the AI-driven strategy, scenario simulations, results, and discussions. Section 5 presents the conclusion of the study along with the findings and recommended future research.

2. Literature Review

Today's power-system distribution networks integrate with distributed energy resources (DERs) [12] to provide energy security. However, these DERs, such as EVs, PV, BESS, wind turbines (WT), combined heat and power, fuel cells, etc., are often at different scales of energy generation and storage. These DERs also have varying EMS, which imposes several operational challenges and technical issues on the power system [13,14]. Distributed microgrids provide a smart strategy that improves grid resilience, reliability, and energy efficiency when RES are integrated into the grid [12].

To enhance microgrid operations and maximize RES utilization, AI with machine learning (AIML) presents the potential to collaboratively optimize EV charging under uncertainty arising from EV state-of-charge and load forecast error [15]. AIML potential extends to and is suitable for predictive analysis, optimal scheduling, and is adaptive to EVs charging in multi-energy microgrid setups [16]. To demonstrate the capabilities of AIML in minimizing the cost of charging EVs and energy consumption from the utility grid, N-Step deep reinforcement learning (DRL) was employed for smart charging [17]. Training the DRL was carried out with datasets of energy consumption, EV demand, and PV power. In [17], part of the objective is to increase RE utilization for EV charging based on the insights provided by the datasets used to determine optimal charging schedules. This led to a 10.9% decrease in electricity consumption from the utility [17].

The effectiveness of an AI-based charging strategy was tested in [18] to flatten the duck curve, which arises due to high solar power supply and utilization during the daytime (which causes electricity demand to dip) and a sharp increase in net electricity demand during evening peak. The study [18] compared four AI models—linear regression, Gaussian mixture regression, random forest regression, and a feedforward fully connected artificial neural network—to predict EV charging, minimize grid energy consumption, and optimize charging schedules. To measure the impact of increased EV penetration on the grid, a sensitivity analysis was conducted, which showed that grid stability will be affected. Average peak demand was reduced to 23.9% using optimal charging based on an AI strategy [18].

A case study [19] that uses edge AI modules integrated with the Open Charge Point Protocol (OCPP) in an EV charging station shows a reduction of 18% in peak energy demand. The AI framework [19], based on federated learning, integrates with edge computing to process data, forecast EV load using LSTM, and coordinate EVs using an adaptive charging algorithm. The uniqueness of federated learning as an ML model is in using multiple devices to train a shared model in a decentralized architecture that ensures privacy and security. This approach [19] minimizes peak load, reduces waiting time for EVs scheduled for charging, improves EV energy demand forecast accuracy, and improves solar PV utilization rate.

AI-driven hybrid models incorporate ANN for control and coordination [20] in a microgrid setup with RES, the hydrogen cycle, and EVs for energy storage. Using the Non-dominated Sorting Genetic Algorithm (NSGA) to optimize the microgrid (solar PV and wind turbine included), 62.6% of energy demand was delivered while 60% of the energy generated was stored. Part of the objective includes optimizing RE grid integration, the hydrogen cycle, and regulating V2G [20].

Advanced energy-management strategies based on an AI framework [21], which implements five different deep reinforcement-learning (RL) algorithms, were used to optimize the EV charging schedule in a microgrid consisting of solar PV. With the objective of minimizing energy demand from the grid-tied EV charging station, the problem in [21] was formulated as a Markov Decision Process [MDP]. The approach in [21] improved solar PV utilization and minimized grid energy for charging-station operators and EV users. An AI-based solution for energy management of EV charging, control, and allocation of energy resources was employed in [22] to optimize EV energy consumption. The study [22] employed the multi-verse optimizer, social spider algorithm (SSA), and gray wolf optimizer (GWO). To improve the optimization process while training the ML models [22], the optimization algorithms of stochastic gradient descent (SGD), adaptive gradient (AdaGrad) algorithm, and adaptive moment (Adam) algorithm were used. The study in [23] emphasizes the significant benefits of using AI and ML models to achieve predictions and energy optimization. Using an IoT architecture [23] that integrates with EVs, charging stations, and user applications, datasets were analyzed, and predictions were made to forecast battery life and optimal charging cycles using support vector machine (SVM) and neural network (NN).

From the perspective of securing EV charging infrastructure and a microgrid integrated with RE sources, the authors in [24] developed an AI smart grid framework and analyzed 3395 EV charging sessions using NN and clustering algorithms. The study [24] focused on effective ways to mitigate cyber-physical attacks that could affect grid operations and EV charging. It provides significant contributions to secure grid stability and sustainability vis-à-vis large-scale charging of EVs and RE integration. EV charging stations based on a microgrid with solar PV and BESS provide energy security and stability to the grid [25] using an AI-based adaptive controller. In [25], ANN-based V2G and G2V provide power management and control for EVs and charging stations in residential sectors. Power-quality issues related to voltage overshoot were minimized from 9.6% to 0% [25].

Using blockchain with adaptive artificial intelligence, the authors [26] developed "IntelliGrid AI", a smart-home EMS. It uses deep learning with an advanced Q-learning algorithm to secure energy transactions, balance energy supply and demand, and optimize power flow vis-à-vis EVs, the home, BESS, and PV. This approach [26] reduced energy cost by 20% while providing grid security, stability, and energy efficiency.

The EVs ecosystem augmented with AI continues to drive a future grid that will remain smart, sustainable, secure, and resilient. These AI-powered capabilities with blockchain architecture secure energy transactions on grid-tied EV infrastructure [27] to provide stability and security to grid assets. Moreover, the energy-trading platform secures bidirectional

charging with AI-powered EMS [27]. The EMS is applied for predictive maintenance of high-energy-density solid-state batteries, grid load balancing, scalability, and minimizing energy consumption and cost. Energy minimization was quantified [27] by analyzing and comparing three prominent blockchain consensus mechanisms (proof-of-work, proof-of-stake, and practical Byzantine fault tolerance).

In [28], hybrid algorithms were used to minimize grid energy losses (improve cost) and voltage variations (power-quality issues) caused by added load from EVs and charging stations coupled to the grid. To achieve the objective, GA with self-adaptive multi-population elitist JAYA was used to optimize the allocation of charging stations with EVs on IEEE radial distribution systems. Simulation tests on the IEEE 33-bus system showed a 6.33% reduction in energy losses and 22.5% with the IEEE 69-bus system [28].

EMS based on a numerical model and ANN was used to manage power flow in a grid-connected solar PV and BESS [29], while considering the uncertainties introduced by PV sources and EVs. Part of the objective [29] is to increase the utilization of RE in EV charging stations to minimize high energy consumption from the grid. The EMS strategy [29] uses AI-powered optimization with hybrid ML models of ANFIS (adaptive neuro-fuzzy inference system), which combines the strengths of ANN and fuzzy inference systems, and feedforward ANN. Reactive power optimization based on DRL was used [30] to address uncertainties introduced to the grid from EV charging, WT, and PV. The study in [30] developed an optimization model with three layers. The first layer implements a type of recurrent neural network (RNN) called bidirectional long short-term memory (LSTM). It uses two LSTMs to process a sequence of historical charging data in forward and backward directions, while using an adaptive boosting algorithm to predict future datasets of EV load demand. The second layer is used to convert the reactive power problem into an MDP model. This model uses DRL agents to learn the problem space and enables real-time autonomous control to achieve grid voltage stability, reduce power losses, and control the intermittency from RE power supplied. To overcome the limitations of overestimation bias in Q-values from the RL process based on the MDP framework, the third layer implements a double deep Q-network (DDQN), a type of deep Q-network (DQN) algorithm designed to address the limitation using two neural networks. The two NNs are used iteratively to improve the Q-value by first doing a network evaluation using the first NN, while the second NN is used as the target network. This process provides stable control for the grid.

2.1. Bibliometric Analysis

This review examines existing research efforts from 2015 to 2025 that are focused on AI techniques and their application to coordinate, control, and manage EV charging with renewable-energy integration on the grid. A comprehensive literature review was conducted using the Scopus scholarly database. The keywords include AI coordinating EVs and RE, AI and machine learning for EV charging and optimization with RES. A statistical evaluation of 122 documents was made using bibliometric analysis (Figure 2) based on R programming with R-Studio IDE. The analysis found relevant publications and provided insight into AI-related optimization studies with research focus areas in EV charging and RE coordination. The overall structure of Figure 2 is based on nodes (circles), edges (lines), and clusters (colors). Looking at the network map of Figure 2, it can be observed that nodes are of different sizes, which often indicates how important the keywords are within the surveyed datasets and the frequency of their occurrence. The edges connecting keywords show relationships. Thicker lines show stronger relationships between keywords, the significance of the keywords, and how often they are used. The clusters with different colors show how the keywords are grouped into diverse thematic areas of research, and their interdisciplinary significance across domains. Based on these definitions, the insights

drawn from this structure using the key thematic clusters based on colors and prominent nodes are given as follows. The blue clusters are central to the survey and have the largest number of nodes, which indicates they are the core focus. Prominent keywords include electric vehicles, charging (batteries), artificial intelligence, renewable energy, electric power transmission network, energy management, energy efficiency, vehicle-to-grid, and smart grid. This cluster (blue) shows how EVs are integrated into the grid, how they are powered, and managed with AI optimization across different aspects. The red clusters on the top right have prominent keywords including battery-management systems, storage systems, state of charge, digital storage, and decision-making. The focus here is on battery technology and how they are managed to provide crucial support to EV operations and for grid support. The state of charge and digital storage highlight one of the key functions of the red cluster in providing battery monitoring and data that are used in making informed decisions. The purple cluster has keywords including machine learning, deep learning, reinforcement learning, learning systems, and learning algorithms. This cluster highlights the significance of advanced AI techniques that are applied to all aspects of the blue clusters and other clusters on the network, especially in optimizing charging, energy management, and predictive analytics. With keywords including renewable-energy sources, electric power distribution, energy policy, EVs, and charging infrastructure, the green cluster focuses on the broader energy landscape and infrastructure support for EVs and RES. The orange cluster has microgrid as a keyword, which signifies the specific interest in localized energy systems and the role of microgrids in supporting EV charging, RE energy management, and grid stability.

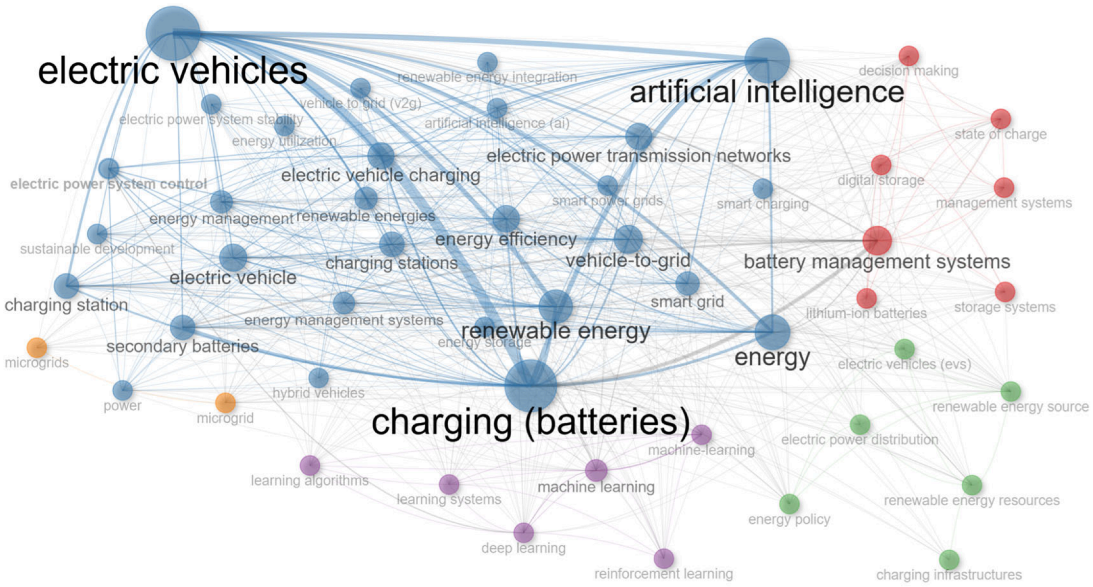


Figure 2. Bibliometric analysis of AI techniques coordinating EV charging and RE applications.

The strong presence and connectivity between AI, EVs, charging (batteries), and RE show that AI is a critical research area that will advance the EV ecosystem vis-à-vis energy systems. Based on this evidence, Table 1 is presented as a summary of the AI techniques with machine-learning applications in the literature reviewed. Table 2 compares the AI and ML techniques used in the literature reviewed with the study presented in this manuscript. Table 2 compares the significance and contributions of this study in terms of the scalability and robustness of the applications. It also compares the complexity of the algorithms used in terms of computational resources and time required for training and evaluation. When it comes to large-scale integration of EVs with RE sources tied to the grid, a crucial aspect of any AI and ML applications is the adaptability to future expansion, which is also a key

component assessed in Table 2. This study recognizes that no single algorithm is best for all problems. Hence, the applicability of the techniques to handle conflicting objectives was also assessed using Table 2. This is very significant for multi-objective optimization; for example, minimizing the cost of EV charging on the grid should be carefully balanced with maximizing the quality of RE or its efficiency for grid stability and security.

Table 1. Summary of AI techniques in the literature review for EV charging.

Ref.	AI Technique	Objective	EV	RE	ES	Computational Process and Algorithm	Demand Shift to Off-Grid	Grid Impact (Sensitivity Analysis)
[15]	LSTM	V2G optimization, grid load management	✓	×	×	Monte Carlo, ILP	not considered	not considered
[17]	Deep NN, DRL	increase RE utilization, reduce energy cost, and peak demand	✓	✓	×	Deep Q-network	considered	not considered
[18]	LR, GMR, RF, FFANN	predict EV energy demand, flatten duck curve, scheduling	✓	×	×	LR, GMR, RF, FFANN	not considered	considered
[19]	Federated learning, LSTM	Forecast EVs, reduce peak load, PV utilization	✓	✓	×	LSTM, edge computing	considered	not considered
[20]	ANN	Regulate V2G, hydrogen cycle, optimize RE and EMS	✓	✓	✓	Sobol algorithm, Genetic algorithm (NSGA)	considered	considered
[21]	DRL,	Minimize grid energy use, optimize EVCS	✓	✓	×	MDP, Truncated Quantile Critics	considered	not considered
[22]	Social spider optim, Gray wolf optim,	Min energy consumption	✓	✓	×	Multi-verse optimizer, SGD, AdaGrad, Adam	not considered	not considered
[23]	SVM, ANN	Predict battery life, charging patterns, optimize energy	✓	×	×	Kernel functions	not considered	not considered
[24]	ANN	Monitor EV charging, secure grid assets, detect anomaly	✓	✓	×	Clustering algorithm	not considered	considered
[25]	ANN	Energy security, stabilize the grid, energy management	✓	✓	✓	Adaptive controller,	considered	not considered
[26]	Deep learning,	Optimize energy flow,	✓	✓	✓	Q-learning, blockchain, MDP	considered	not considered
[27]	DNN	Min charging cost, grid load balance, BMS	✓	✓	✓	Practical Byzantine fault tolerance, proof of work	considered	considered
[28]	GA, SAMPE-JAYA	Minimize energy loss, improve power quality	✓	×	×	Metaheuristic JAYA algorithm, GA	considered	considered
[29]	ANN	Energy management, PV utilization, grid stability	✓	✓	✓	ANFIS, NN, MPPT	considered	not considered
[30]	DRL, LSTM, DDQN	EV load forecast, Energy management	✓	✓	×	Adaptive boosting, MDP, Deep Q-Network	not considered	considered

Note—RE: renewable energy, ES: energy storage, ILP: improved linear programming, LR: linear regression, RF: random forest, GMR: Gaussian mixture, FFANN: feedforward ANN, BMS: battery-management system, DNN: deep neural net.

Table 2. Comparative analysis of artificial intelligence techniques.

AI Technique	Multi-Objective Optimization	Computational Cost	Scalability	Robustness	Adaptability
Linear Regression	Poor: mostly used in single-objective optimization	Low to medium: for small-to-moderate data size, efficient for large datasets	High: scales efficiently with large datasets using gradient descent, etc.	Low: sensitive to outliers and assumptions	Low; except when paired with hybrid models

Table 2. *Cont.*

AI Technique	Multi-Objective Optimization	Computational Cost	Scalability	Robustness	Adaptability
Gaussian Mixture Regression	Limited: in handling uncertainty	Medium to High: increases with dimensionality and expectation maximization	Medium: moderately scalable with distributed computation	Medium: sensitive to initial parameter conditions	Medium: parameterization of weights allows adaptation
Random Forest	Limited: capacity for solving MOO	Medium to High: due to multiple decision trees and dimensionality	High: works well with high-dimensional data	High: robust to overfitting noise, outliers, missing data	Medium: easy to tune with few parameters
Artificial Neural Network	Moderate: often used as powerful predictors	Medium to High: can be computationally intensive	High: with large dimensional and unstructured data	Medium: sensitive to hyperparameters, outliers	Medium: adapts to nonlinear relationships
Long Short-Term Memory	Moderate: sequential nature of LSTM adds complexity to MOO	High: due to complex architecture, slower training	Limited: due to sequential processing	High: reliable for dynamic, volatile environments	High: for sequential and temporal data
Deep Neural Network	Moderate: handles Pareto-optimal solutions and high dimensionality	High to very high: due to complex architecture	High: parallel processing and highly scalable for large data	Variable: medium to high based on DNN architecture	High: adaptable to high dimensionality
Reinforcement Learning	Limited: due to scalarization issues, struggles with trade-offs	Low: efficient for small discrete state/action pairs using Q-tables	Low: suffers from the curse of dimensionality	Low to medium: degrades with complex scenarios	Medium: struggles with dynamic environments
Deep RL, Double Deep Q-Network	High: flexible in balancing trade offs	High to very high: trains intricate DNN, DQN. Uses high resources	High: manages high-dimensional states and actions	High: hyperparameter tuning effect, overestimation issues	Very High: adaptable to dynamic environments
Federated Learning	Limited: across decentralized clients	Medium: with decentralization, can be complex with aggregation	High: scales with large number of devices	Medium: model performance issues due to non-IID	High: certain algorithm needed to curb non-IID
Model-Predictive Control	High: formulate MOO within the cost function and weighted objective	High: for complex systems with long prediction horizons	Medium: limited for high-dimensional data	High: robust to inaccuracies and accounts for uncertainties	High: receding horizon principle makes it adapt
Genetic Algorithm	Very High: suits Pareto front, i.e., NSGA algorithms used for optimal trade-offs	High: involves evaluating a large population over many generations	Medium: population size can be adjusted by parallelization	High: handles noisy objective functions	High: adapts without structural changes
Gray Wolf Optimization	Very High: uses Pareto dominance or leader-selection system to find trade-offs	Low to medium: based on the curse of dimensionality	Medium: performance scales linearly with dimensionality	Medium: optimal balance for exploration and exploitation	Medium: structures allow for hybridization
Social Spider Algorithm	High: approximates Pareto-optimal sets, balances convergence with diversity	Medium to High: based on population and dimensionality	Medium: scales with higher objectives	Medium: robust against local optima due to global search	Medium: good diversity, hybridization with ML

Table 2. *Cont.*

AI Technique	Multi-Objective Optimization	Computational Cost	Scalability	Robustness	Adaptability
Self-Adaptive Multi-Population JAYA	Very High: due to self-adaptive mechanism and multi-population	Medium to High: based on fitness function, sub-population, data size	Medium: solves large-scale optimization problems	High: very robust	High: very adaptable
Hybrid Genetic Algorithm with Model-Predictive Control	Very High: enables tuning weights for multi-objectives	Med-High: scales with prediction horizon and model complexity	High: surrogate models boost scalability, i.e., NN, RF	High: offsets uncertainties, explores multiple controls	Very High: for nonlinear systems, discount factor
Hybrid GA-MPC (This study: Kene et al.)	Maximum: GA finds global MOO trade-offs, which MPC tracks locally	Balanced: GA runs slowly offline while MPC runs instantly in real time	Very High: GA handles macro grid scale, MPC handles local scale	Very High: handles inaccuracies with real-time feedback	Very High: adapts to high-dimensional EV/SPV

Table 2. Comparative analysis of AI techniques from literature reviewed, including the Genetic Algorithm and Model-Predictive Control used in this study. Note: Linear Regression is included as a classical statistical baseline frequently used alongside or as a benchmark for the AI/ML techniques.

2.2. Research Gaps

The following are some of the identified gaps in the literature review:

1. *Multi-Objective Optimization (MOO)*: In the literature review, techniques like DRL [17,21] most of the time optimize a single, complex reward function, which makes explicit trade-offs difficult in the optimization process. In [20], NGSA-II was applied for MOO; it focuses on a specific microgrid setup and did not explicitly combine long-term planning with the real-time objective of minimizing a 24-h peak demand for multi-conflicting objectives, e.g., peak-shaving vs. maximizing solar PV self-consumption, minimizing energy cost vs. increasing EV aggregation for ancillary services.
    - *Hybrid GA-MPC strategy*: The combination of genetic algorithm and model-predictive control for this study is well-suited for MOO. At the GA level, a fitness function is defined that simultaneously evaluates peak power demand, EV energy consumption, and RE energy (PV) utilization based on a ToU. As opposed to [20], this study explicitly combines the optimal partitioning of large-scale EV charging.
    - *At the MPC* level, real-time scheduling is taken as a target under a baseline of uncontrolled charging. Using a real-time objective function, it prioritizes grid stability. Part of this process used highly resolved models of EV energy-consumption profiles at 10 min to 15 min resolution over a 24-h period to assess the impact of uncontrolled charging of EVs on the grid using the IEEE 33-bus system as a test case for evaluation.
2. *Computational Cost*: In [19], federated learning and LSTM require high computational cost. With large-scale datasets, global optimization methods such as GA [20] and complex training algorithms like DRL [17,21] are computationally expensive. This makes it intractable and infeasible to apply these global optimization methods in optimization problems with large-scale EVs, which can introduce dimensionality as they incorporate grid constraints and often require power-flow simulations within the optimization process. In the literature review, techniques like DRL [17,21] also optimize, most of the time, a single complex reward function.

- *Hybrid GA-MPC* strategy: Can run offline, day-ahead, to minimize the impact on real-time operations and to reduce computational cost. Moreover, at the GA level, the best schedule for EV charging can be determined based on energy forecasts, and EV loads can be shifted from peak to off-peak periods to ensure grid stability.
- Solving smaller optimization problems over a short time horizon of 10 min to 15 min for a day-ahead can be solved with MPC as a suitable method. This process significantly reduces computational demand, unlike re-running a full 24-h global optimization of GA or DRL at every time step. With this, real-time or near-real-time control is feasible.

3. *Scalability*: In the literature review, some studies [17,25] used a smaller number of EVs for evaluation. The curse of dimensionality has a significant impact on the scaling of global optimization algorithms like GA and DRL in policy search. The primary reason is the growing number of dimensions (features or parameters), which also increases the search space exponentially, thereby causing the search samples (useful information) to become highly inadequate. For instance, when GA or DRL directly searches for the parameters of a control policy as it tries to scale directly to large-scale EV datasets, the machine-learning models encounter poor performance in the process of analyzing the datasets in high-dimensional spaces where numerous local minima exist, making it impossible to find the global optimum. It is for this reason that the algorithms are unable to find and optimize the parameters of the control policy. Moreover, the curse of dimensionality (search space) adds to the scalability issues by increasing communication overhead and computational complexity among many factors. With large-scale coordination of EVs, central DRL methods struggle in this regard. While decentralized DRL scales well as it learns and acts independently based on local observations, it can result in suboptimal performance due to a lack of overall coordination.
    - *Hybrid GA-MPC strategy*: This hybrid approach decouples the two functions of the GA and MPC by exploiting their unique strength based on the hierarchical structure. In this approach, the GA handles nonlinear optimization problems that do not require real-time operation and are not subject to real-time constraints. This minimizes computational intensity that otherwise would be required in real-time control. This method enables the GA to perform global optimization as it decouples from the MPC. On the other hand, the MPC's constant real-time feedback and adaptability to unpredictable scenarios or variability make it robust to large-scale systems. As an example, in a large-scale EV charging problem, MPC operates on real-time constraints of voltage limits, charging rates, etc., using a short prediction horizon to perform local optimization like minute-by-minute EV coordination, scheduling, and energy management.
4. *Robustness in Handling Constraints or Failures*: With real-world optimization problems, prediction accuracies are crucial to ensure that grid constraints are not violated to maintain grid stability. As an example, with day-ahead schedules as seen in [19], where LSTM was used as a load prediction model for EV charging demand, the power demand was forecasted at 18%; whereas this study reported 38.35% for GA–PV and 30% for MPC–PV. In this case [19], the LSTM model architecture has inherent vulnerabilities related to performance and training challenges, thereby leading to prediction errors. To further explain this scenario, let us imagine a case where actual EV load demand with RE solar PV generation differs significantly from the predicted values. The precalculated schedules will violate grid constraints, cause power imbalance, and potentially lead to grid instability. Essentially, when schedules are precalculated in EV charging scenarios, part of the objectives is to achieve a balance between the supply

and demand to maintain the operational limits set by aggregators and grid operators. While some AI approaches used in the literature reviewed [18,20,26,30] tried to ensure robust operations, there are inevitable errors within their training distribution that lead to unpredictable failures.

- *Feedback Mechanism of the hybrid GA-MPC strategy*: the MPC incorporates a feedback policy at every time step of the iteration, where it measures the actual state of the grid, e.g., voltage levels, load capacity, and energy demand, and compares this to the predictions made. Based on the difference between the actual and predicted values, corrections are made accordingly.
- *Constraints Handling*: the MPC explicitly incorporates operational constraints (voltage limits, line limits, transformer limits, charging power, etc.) into its optimization problem at every time step to ensure the constraints are maintained within the limits of the most current information. However, the GA in the hybrid approach handles constraints using penalties, which in most cases does not guarantee feasibility where predictions are inaccurate.

5. *Adaptability in Handling Uncertainties*: Adaptive algorithms employ specific mechanisms that are centered around feedback loops and dynamic structure adjustments. These help them to modify their behavior with a changing environment or in response to new information. In the literature review [19,25], adaptive algorithms are mentioned, but the mechanisms were not detailed. With DRL agents, they can be adaptable when trained on sufficient variability, but retraining or online adaptation becomes complex.

    - *Rolling Horizon in MPC*: One of the core strengths at the MPC level of the hybrid approach is the rolling horizon (or the receding horizon control). What this control strategy does is use a prediction horizon to forecast a system's future state or behavior over a finite horizon to determine the required optimal control inputs to a system. Therefore, at every time step, the MPC controller optimizes its control sequence over a future horizon but only applies the first step of the optimal sequence before re-optimizing. This key feature in MPC makes it adaptable to changes and constraints in real-time environments with uncertainties. For instance, with uncontrolled charging or an unexpected EV plug-in to the grid, or during a sudden drop in PV power generation, the MPC instantly integrates this new information into its next optimization cycle and adjusts the charging rates of controllable EVs or dispatches power from BESS accordingly to address the current system state.
    - *Updates on Predictions*: The MPC at each time step updates its plan on the most recent measurements and predictions. This may be for load curtailment, PV power supply, EV dispatch for ancillary services, or for other coordination purposes. With updates on its predictions, the MPC becomes increasingly adaptable to current and future system states and is suitable for real-world applications in large-scale system optimization. This inherent feedback mechanism in the MPC control strategy allows it to respond to uncertainties, unpredictable variations, and deviations between the predicted system behavior and the actual system behavior at every time step of the horizon. Furthermore, the continuous updates on predictions within the MPC feedback system allow it to handle model mismatch.

This study directly addresses Gaps 1–3 above in the following ways: it formulates an explicit multi-objective fitness function combining peak demand, energy consumption, and PV utilization (Gap 1); it decouples day-ahead GA optimization from real-time MPC control to reduce computational burden (Gap 2); and it evaluates scalability via the sensitivity anal-

ysis in Section 4.3.3 (Gap 3). Gaps 4 and 5 (robustness to prediction error and adaptability in uncertainty) are addressed qualitatively through the MPC feedback mechanism but are not independently benchmarked against failure cases in this study, which is noted as a direction for future work.

3. Methodology

In this section, the system architecture of AI coordinating EVs and RE solar PV is presented. It starts with the system description and components of the referenced IEEE 33-bus distribution system, followed by the problem formulation, objective functions with constraints, the optimization goal, and the EV charging datasets.

3.1. System Description and Components

The structure of the system that this study investigates is shown in Figure 3. It is based on the IEEE 33 radial distribution system with EVs charging from the grid, and combines solar PV modules and BESS to minimize the power drawn from the grid by EVs. This approach reduces the cost of power infrastructure upgrades while delivering efficient power conversion with AC–DC converters. The direction of power flow from different energy sources is indicated with arrows as seen in Figure 3. The integration of BESS and RES, where solar PV power can be stored and supplied to charge EVs, helps to create an efficient and sustainable charging ecosystem. Moreover, BESS with PV integration mitigates uncontrolled charging impact on the electric grid. The benefits of this integration are outlined in the following examples:

- *Energy Arbitrage and Load Shifting*: With AI-powered intelligence and control [31], BESS, solar PV, and EVs can be coordinated based on a ToU strategy. During off-peak periods (9 p.m.–5 a.m.) when solar PV power is not available, the grid power (GP) can be supplied to charge the BESS to optimize operational cost. Likewise, GP can be supplied for EV charging during off-peak periods when the cost of electricity is low. Conversely, EV charging can benefit immensely from using the power discharged from the BESS (PBESS) during morning peak periods (6 a.m.–9 a.m.) and evening peak periods (4 p.m.–9 p.m.) when energy demand and electricity prices are high. EV charging can also benefit from solar PV power supply during the period (5 a.m.–7 p.m.) when solar power is available. This strategy is cost-effective as it reduces grid operational costs.
- *Peak-Shaving*: Employing BESS and solar PV power for charging EVs during peak periods helps to shave energy demand from the grid while also reducing large-scale, uncontrolled charging impact [32]. Hence, demand peaks, voltage fluctuations, harmonic distortions from nonlinear loads, and transformer overload are mitigated. This control strategy is further enhanced with AI-powered intelligence and EMS.
- *Frequency and Voltage Control*: Rapid frequency response and voltage control are key components for grid stability. Advancements in power electronics make it possible for grid-forming inverters to provide rapid frequency and voltage adjustments within milliseconds when deviations occur [33,34]. This response time is faster than traditional synchronous generators. Unlike traditional inverters, grid-forming inverters have advanced power electronic converters that make them act like synchronous machines. With these capabilities, grid-forming inverters perform condition monitoring and determine when grid frequency or voltage changes suddenly. When grid-forming inverters interface BESS and solar PV with the electric grid, they create and control frequency and voltage that are used to stabilize the grid when sudden changes occur, thereby acting like traditional power plants. The integration of the BESS and solar PV with grid-forming inverters makes the grid more resilient, enables microgrids that can

operate in island modes (independently), and provides black start capabilities for a quick grid recovery [35].

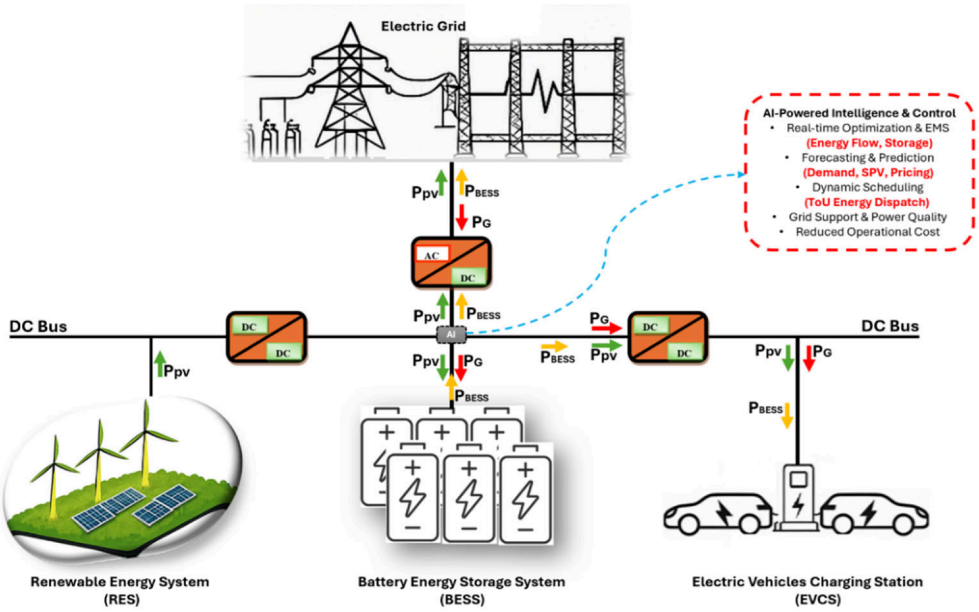


Figure 3. System architecture: AI coordinating grid, PV, BESS, and EVs charging operation.

3.1.1. Solar PV Components

The output power of the solar PV component of the system illustrated in Figure 3 is based on the number of PV panels NPVPanels and the nominal power P_{PV}^{nom} (i.e., rated capacity (kW) or power) of the PV panels. This expression is given as Equation (1).

$$P_{PV}(t) = NPV_{panels} \cdot P_{PV}^{nom} \quad (1)$$

However, the solar PV nominal power P_{PV}^{nom} is often determined by many factors, which include solar irradiance power, the temperature coefficient, which shows the extent to which the nominal power will vary based on the solar PV cell temperature; and the efficiency of the PV inverter also contributes to the output power of the solar PV system since it considers the conversion losses from DC to AC. Hence, the nominal power P_{PV}^{nom} is modeled and given as Equation (2).

$$P_{PV}^{nom} = \left(\frac{G_i(t)}{G_{STC}}\right) \cdot [1 + \gamma \cdot (T_c(t) - T_{STC})] \cdot \eta_{PV} \quad (2)$$

where:

P_{PV} (t) = solar PV power output for a given time (t)
NPV_{panels} = the number of PV panels
P_{PV}^{nom} = solar PV nominal power or rated capacity (kW) of PV at STC
$G_i(t)$ = incident irradiance for a given time (t)
G_{STC} = irradiance at standard test condition (STC) referenced at 1000 W/m^2
γ = temperature coefficient ($-0.3/°C$ to $-0.5/°C$) for max. power correction
$T_c(t)$ = actual operating temperature of the solar PV cell at a given time (t)
T_{STC} = solar PV cell temperature under STC referenced at 25 °C
η_{PV} = PV inverter efficiency.

The constraint on the solar PV system that limits the amount of power that can be delivered to charge EVs, BESS, and to maintain grid stability is given as Equation (3).

$$P_{PV}^{min}(t) \leq P_{PV}(t) \leq P_{PV}^{max}(t) \quad (3)$$

At any given time (t), the sum of the power drawn by EVs, BESS, and the grid should not exceed the maximum solar PV power P_{PV}^{max}.

3.1.2. BESS Component

For the BESS, operational limits are placed on the minimum state-of-charge SoC_{BESS}^{min}, which is around 20% to prevent deep discharge, while a maximum state-of-charge around 90% is imposed to prevent excessive charging. The constraint for the BESS SoC is expressed as Equation (4).

$$SoC_{BESS}^{min}(t) \leq SoC_{BESS}(t) \leq SoC_{BESS}^{max}(t) \quad (4)$$

Constraints are also placed on the BESS minimum and maximum allowable power levels during BESS charging (P_{BESS}^{ch}) when power is absorbed from PV or the grid and discharging (P_{BESS}^{dis}) when BESS supplies power for charging EVs, or for grid stability. The constraint is expressed as Equation (5).

$$P_{BESS}(t) = \begin{cases} P_{BESS}^{dis}(t);\ 0 \leq P_{BESS}^{dis}(t) \leq P_{BESS}^{dis(max)}(t) \\ P_{BESS}^{ch}(t);\ 0 \leq P_{BESS}^{ch}(t) \leq P_{BESS}^{ch(max)}(t) \end{cases} \quad (5)$$

The BESS discharge constraints $P_{BESS}^{dis}(t); 0 \leq P_{BESS}^{dis}(t) \leq P_{BESS}^{dis(max)}(t)$ explain the limits on the power levels required to satisfy any load demand. Discharge power $P_{BESS}^{dis}(t)$ at any given time must remain a positive power value to supply any load and should not exceed the maximum allowable power supply to ensure safe operating conditions.

Similarly, during the charging phase, the BESS must have a negative power value to allow power absorption where $P_{BESS}^{ch}(t)$ indicates charging power received by the BESS at any given time. The lower limit of the $P_{BESS}^{ch}(t)$ ensures that the BESS does not discharge power during charging operations and maintains a maximum power $P_{BESS}^{ch(max)}$ that can be absorbed by BESS.

The general equation that defines the limits placed on the BESS power output (discharging) or input (charging) is expressed as Equation (6).

$$-P_{BESS}^{min(maxch)}(t) \leq P_{BESS}(t) \leq P_{BESS}^{maxdis}(t) \quad (6)$$

In this case, Equation (6) defines $P_{BESS}(t)$ as a power value on the BESS with two upper limits. The limit $-P_{BESS}^{min(maxch)}(t)$ is the minimum instantaneous power with a negative power value that indicates the BESS is charging (absorbing power). Furthermore, $-P_{BESS}^{min(maxch)}(t)$ represents the maximum charging power that can be absorbed by the BESS. Meanwhile, $P_{BESS}^{maxdis}(t)$ is defined as a positive power, indicating the BESS is discharging power to a load, which must not exceed the maximum instantaneous power $P_{BESS}^{maxdis}(t)$.

3.1.3. EV Component

Similar to the BESS, limits must be placed on EV charging to protect EV batteries from deep discharge or overcharging. The constraint in Equation (7) defines the limits for the EV battery state-of-charge at any given time.

$$SoC_{EV}^{min}(t) \leq SoC_{EV}(t) \leq SoC_{EV}^{max}(t) \quad (7)$$

A constraint is placed on the energy required by EVs, which is defined based on EV battery SoC, EV nominal battery capacity, and the efficiency of the EV charger.

$$E_{EV}^{req}(t) = \frac{SoC_{EV}^{req}(t) \cdot C_{EV}^{nom}(t)}{\eta} \quad (8)$$

In Equation (8), a limit is placed on the power required by the EV charger or the EV charging station (EVCS) to supply the required energy. This constraint is defined as the charging rate in Equation (9).

$$0 \leq P_{EV}(t) \leq P_{EV}^{max}(t) \quad (9)$$

3.1.4. Grid Constraints

EVs charging on the grid have a potential impact on the magnitude of line currents. To put this in perspective, an increase in the number of EVs charging on the grid increases the current (I) on the feeder lines, thereby causing thermal overload on electrical conductors and equipment. This impact can be mitigated by placing a limit on the IEEE 33-bus feeder lines. This constraint is defined as Equation (10).

$$|I_{line}(j)| \leq I_{line}^{max}(j); \forall j = 1 \ldots 32 \text{ feeder lines} \quad (10)$$

The term $|I_{line}(j)|$ expresses the magnitude of the current (I) flowing in the j^{th} feeder line, which must be less than the thermal limit of the system. Meanwhile, the term $I_{line}^{max}(j)$ places a maximum current on the j^{th} feeder line. The term $\forall j$ applies to all 32 feeder lines on the IEEE 33-bus system.

In relation to the resistance (R) of feeder line conductors on the IEEE 33-bus system, the increase in current (I) causes the line conductors to overheat, which reduces the overall system efficiency. This phenomenon increases the active power loss (P_{loss}) on individual feeder lines, which is expressed as Equation (11).

$$P_{loss}(t) \propto I^2R, \text{ or } P_{loss}(t) = I^2R \quad (11)$$

The power loss on the IEEE 33-bus feeder lines is given as Equation (12). This constraint captures the total active power loss on the grid to maintain the thermal limit

$$P_{loss}^{total} = \sum I_{line}(j)^2 \times R_j \leq P_{loss}^{max} \quad (12)$$

where the term P_{loss}^{total} indicates the total active power loss across the IEEE 33-bus feeder lines. Meanwhile, the term $\sum I_{line}(j)^2 \times R_j$ defines the sum of individual power loss P_{loss} as heat, which is directly proportional to the square of the current (I^2) and resistance (R) of individual (j) feeder line. The last term P_{loss}^{max} is an indication of the maximum power loss that is acceptable on the grid, which is typically between 5 and 10%.

The voltage magnitude limits for individual buses on the grid are given as Equation (13). The terms V^{min} and V^{max} in Equation (13) are calculated based on power-flow equations and have values corresponding to 0.95 p.u. and 1.05 p.u., respectively.

$$V^{min} \leq V_j(t) \leq V^{max} \quad (13)$$

To ensure the grid transformer capacity is not exceeded, a constraint is provided as Equation (14) to limit overload and maintain stability.

$$P_{gTx}^{max}(t) \geq P_{Base}(t) + \sum_{i=1}^{N} P_{EV,i}(t) \quad (14)$$

Equation (14) shows that the sum of power consumption at any given time (t) including baseload P_{Base} and all EVs charging on the grid must be less than or equal to the grid transformer rated maximum power P_{gTx}^{max}. In other words, Equation (14) shows that the grid transformer power should be limited by the constraint, which ensures total grid load power consumption $\left(P_{gLoad}^{total}\right)$ at time (t) stays below the available maximum grid power (P_{g}^{max}) shown as Equation (15).

$$P_{gLoad}^{total}(t) \leq P_{g}^{max}(t) \tag{15}$$

where P_{gLoad}^{total} represents the total grid load power, which includes baseload power (P_{Base}), EV charger power (P_{EV}), and BESS power (P_{BESS}) demand.

3.1.5. Power Balance

Based on Figure 3 and the equations provided thereafter, the flow of power on the grid can be described by a power balance equation given in Equation (16).

$$\sum P_g + \sum P_{PV} + \sum P_{BESS,dis} = \sum P_{Base} + \sum P_{EV} + \sum P_{BESS,ch} + \sum P_{loss}^{total} \tag{16}$$

Equation (16) shows that the total power delivered by the grid, including power generated by the solar PV and BESS, must be equal to the total power demand by the baseload, power demand to charge EVs and BESS, and the total active power loss across the grid.

3.1.6. Problem Formulation and Optimization Goal

The optimization problem for large-scale EV charging from the grid is formulated as a day-ahead optimal scheduling problem. This charging problem is solved hourly over a 24-h period, given as time (T). Within this optimization horizon, the objective function (provided as Equation (17)) is to minimize the total power demand to avoid grid overload and power-quality issues.

$$\text{minF} = \sum_{t=1}^{T}(P_{Base} + P_{EV} + P_{BESS,ch}) + \lambda_{loss}\sum_{t=1}^{T} P_{loss}^{total} \tag{17}$$

The penalty cost (λ_{loss}) added to Equation (17) is a weighting factor projected to penalize high power demand and encourage peak-shaving.

3.2. Real-World EV Charging Datasets

Real-world charging session datasets are mostly not available due to licensing issues, data privacy issues, and clauses in signed agreements that prohibit public access. To demonstrate the impact of large-scale charging of EVs on the grid, this study used datasets from the study conducted in [36]. These datasets are available from a public charging station in Spain and published under the terms of the "Creative Commons Attribution License", which permits unrestricted use, distribution, and reproduction. For this study, 32,688 datasets were collected from different EV chargers, including CHAdeMO, Mennekes, Combo 2, and Schuko. Out of these datasets, only 10,896 datasets were useful for the simulations, while 21,792 were excluded due to missing timestamps, duplicate records, and sessions shorter than 30 s, which may be due to connection errors. There were 2724 charging sessions utilized to establish uncontrolled EVs energy consumption and the impact of peak power demand when large-scale charging takes place on the grid. The rating of the EV chargers is provided in Table 3. In preparing the datasets, it was necessary to do data screening, which ensures that relevant and useful charging session data were used. This process involved the removal of charging sessions with invalid data points, missing

values, outliers, and duplicate data points, as opposed to linear scaling normalization pre-processing, given as Equation (18).

$$x' = \frac{x' - x_{min}}{x_{max} - x_{min}} \quad (18)$$

The Z-score normalization technique was adopted to process the nonlinear EV charging datasets. One of the advantages of the Z-score normalization technique over the min–max linear scaling technique represented by Equation (18) is the robustness to outliers. With Z-score, the datasets were normalized using the mean and standard deviation. This process reduces overfitting and improves the performance, training efficiency, and generalization capabilities of the machine-learning model used in this study. The Z-score equation used is given as Equation (19).

$$x' = \frac{x - \mu}{\sigma} \quad (19)$$

where $x^{'}$ is the normalized data and should have a mean or average score of zero and a standard deviation of one; x is the original data, while μ and σ are the mean and standard deviation values of the datasets.

Table 3. EV charger types used in this study.

Charger Type	Rating	Charging Level	Current Type
CHAdeMO	44 kW	Level 3	DC
Combo	44 kW	Level 2 and 3	AC and DC
Mennekes	43 kW	Level 2	AC
Schuko	3 kW	Level 1	AC

3.3. GA-MPC Coupling

The GA and MPC operate in a hierarchical, sequential architecture. The GA runs offline, for a day-ahead horizon, and outputs an optimal 24-h charging schedule in 15-min time steps that minimizes the fitness function of Section 4.1; this schedule becomes the reference trajectory for the MPC layer. At each real-time time step, the MPC receives state variables (e.g., EV/BESS SoC, actual PV output, base load) and resolves a short-horizon, 15-min time-step optimization that tracks the GA reference while enforcing the real-time constraints of Equations (3)–(15). Only the first control action of each MPC solution is implemented before the next re-optimization. Deviations between the GA reference and the MPC's realized dispatch are handled first on a rolling window (intraday), where MPC absorbs short-term deviations locally by adjusting the remaining EV charging profiles within the bounds set by the GA. Secondly, on a day-to-day basis, deviations are fed back to the GA for the next day's run to update battery SoC initial states, grid constraints, and forecasting models.

4. Simulations, Results, and Discussions

This section discusses the charging strategies, including GA and MPC integrated with solar PV, which were used in this study. These two strategies demonstrate how controlled charging of EVs is used to minimize the cost of grid energy consumption and optimize power demand. Based on three scenarios, simulation experiments are carried out, followed by results and discussions to explain how the charging strategies minimize the objective function.

4.1. Genetic Algorithm

GA has numerous advantages when compared with traditional methods of optimization. These include the suitability for solving nonlinear optimization problems, the ability

to handle complex objective functions, and adaptability to real-world optimization problems like EV charging on a large scale [37]. To optimize EV charging in this study, GA is used to generate an optimal charging schedule that minimizes the high cost of energy consumption, power demand, and peak load. The GA optimizes this scheduling process by initializing a population of scheduling solutions (chromosomes) based on optimal charging times for individual EVs. The next stage is a fitness function (a weighted combination of Equation (17)), which the GA uses to evaluate the population of scheduling solutions and to determine the extent to which the scheduling solution meets the objective function. This is carried out by creating a fitness score assigned to each chromosome, where a higher score shows how good a particular solution is in balancing energy use with power demand for EVs to minimize cost. The GA then enters a selection stage to choose the solutions that fit the criteria for the objective function; then, the chosen solutions will serve as parents for the next generation. In the selection process, the GA uses different selection methods, i.e., roulette wheel selection, tournament selection, and rank selection. A study conducted in [38] shows that tournament selection was used to achieve optimal selection of EV charging stations based on a scheduling model. Hence, this study used the tournament method, which yielded good results. Next is the crossover, which involves a combinatorial process where genetic information exchange (e.g., charging characteristics) takes place between two parent chromosomes to create offspring (new solutions). A mutation process is introduced to the offspring solutions, which explores the probability of obtaining a global optimal solution. An example is when EV charging parameters (e.g., ToU charging) are changed to achieve cost minimization. After the mutation process, a test for convergence is initiated to know if an acceptable offspring solution is attained. The GA continually iterates the process of fitness, selection, crossover, and mutation until it reaches a termination criterion where an optimal solution is reached [39]. These criteria include ending the GA when an optimal fitness score is attained for the EV charging schedule. The application of GA in EV charging and optimization has significantly improved grid energy consumption with smart charging strategies that enhance energy management. The GA process, as already outlined in this section, is depicted in Figure 4. Key parameters defined for the GA are a population size of 200 to ensure enough unique schedules to test different peaks, 1000 generations to ensure the schedules converge and stabilize, a 0.1 (10%) mutation rate to prevent stagnation and allow GA to constantly test new charging windows, and a crossover rate of 0.8 (80%) to ensure GA is mating schedules frequently enough to combine the best charging patterns from different parents. Because this study works with discrete power levels over time, the chromosome-encoding scheme used is real-valued (floating-point) matrix encoding. This differs from the binary encoding, which introduces unnecessary quantization errors and inflates chromosome length, which slows down convergence within the MPC execution window.

4.2. Model-Predictive Control

The application of MPC to optimize EV charging demand incorporates an advanced control method [40], which uses a model controller with the receding horizon strategy to solve a finite-time optimization problem. As an example, the MPC combines this strategy with the model controller to manage EV power demand from the grid with solar PV utilization to minimize the cost of peak demand while respecting constraints [41]. The first step of the MPC optimal control for this study is a state initialization, which comprises measuring the current state of charge (SoC) of individual EV batteries, solar PV power generation, and BESS capacity at a given time (t). The second step is prediction horizon and constraint optimization, where the MPC makes decisions based on a future prediction of EV power demand, solar PV supply, and the grid capacity to adapt EV loads in addition to

existing baseloads. At this stage, a prediction horizon over a period of 24 h is defined with 15-min sampling time steps, whereby the current state is measured, and predictions are made for future control actions. The next step is the implementation of receding horizon, where the first step of the control action is taken (e.g., adjust charging schedules, charge EVs with PV) to minimize the cost related to power demand and supply from the grid. At this stage, a receding horizon or prediction window is established for the next action at time step (t + 1). Subsequently, the MPC enters a stage where the process is repeated with continuous learning at every time step, with an update and feedback system to solve the optimization problem. The MPC process as outlined above is depicted in Figure 5.

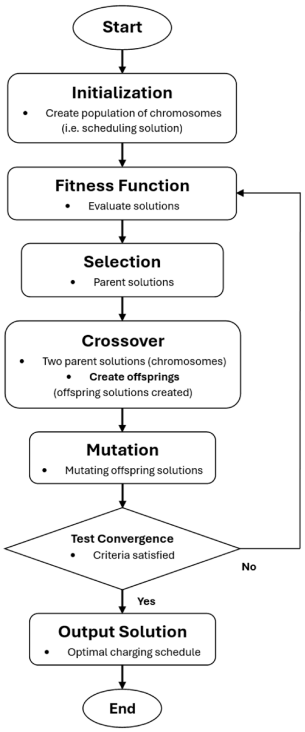


Figure 4. Genetic algorithm process.

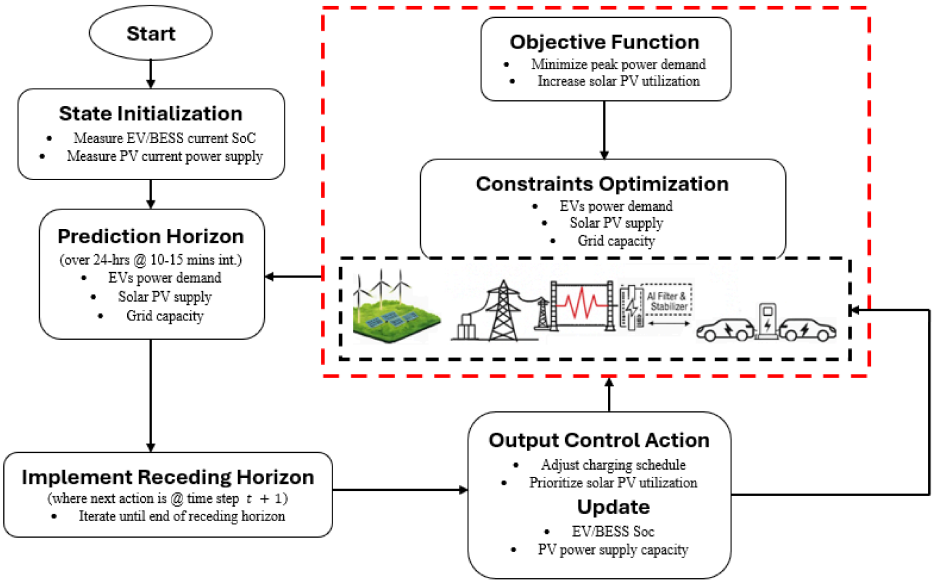


Figure 5. Model-predictive control process.

4.3. Simulation Scenarios with GA and MPC-Optimized Charging

In this subsection, three experiments are performed using computer-aided simulations with Python programming version 3.13.5, 64-bit, June 2015, to demonstrate how GA and MPC with solar PV optimize EV charging from the grid when compared with the uncontrolled charging scenario. The IEEE 33-bus radial distribution system was used to represent the grid to establish a baseline for comparing the uncontrolled charging scenario with the GA–PV and MPC–PV charging strategies.

The three scenarios that were selected to build a coherent evaluation narrative are as follows: Scenario 1 establishes the baseline energy-consumption impact of uncontrolled EV charging and measures how much the proposed GA–PV and MPC–PV strategies reduce it; Scenario 2 tests the same strategies against the grid stability critical metric of instantaneous peak power demand, since energy savings and peak-shaving do not necessarily align; and Scenario 3 stress-tests the uncontrolled baseline itself under increasing charger power ratings, to show why coordinated charging (Scenarios 1–2) becomes more, not less, necessary as fast-charging adoption grows. The parameters of the grid are provided in Table 4.

Table 4. Grid parameters of the IEEE 33-Bus.

No. of Buses	Number of Lines	Base (MVA)	Base (kV)	Nominal Capacity (kW)
33	32	10	12.66	3715

4.3.1. Scenario 1: Uncontrolled EV Energy Consumption

Typical uncontrolled charging means that an EV arrives at a charging station without being monitored for its energy requirement, initial SoC, and the desired SoC before departing. However, controlled charging has the potential to limit instability in grid operations by monitoring power supply, energy demand, and EVs SoC. Figure 6 shows three scenarios where uncontrolled energy consumption by EVs is compared with controlled strategies of GA and MPC with solar PV to minimize EV energy demand from the grid.

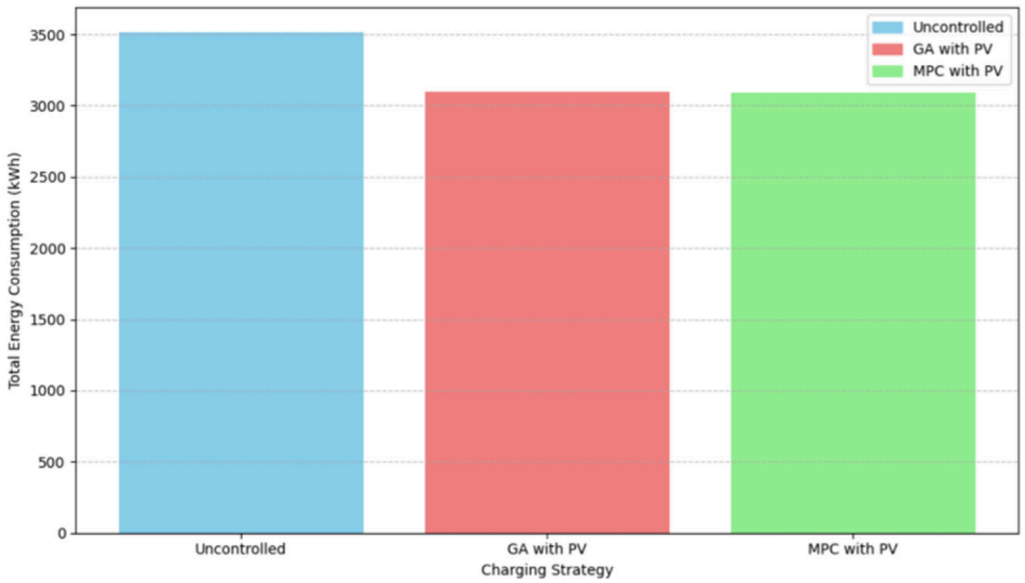


Figure 6. Comparing uncontrolled EV energy consumption with controlled strategies of GA–PV and MPC–PV.

From Figure 6, energy consumption for uncontrolled charging is given as 3512.75 kWh. With the controlled charging strategy of GA–PV, the total energy consumed is given as

3098.24 kWh, which translates to an 11.80% reduction. For the MPC–PV strategy, the total energy consumption was reduced to 3088.21 kWh, which is a 12.09% reduction.

4.3.2. Scenario 2: Peak Energy Demand

This scenario looks at how the charging strategies of GA–PV and MPC–PV can be used to lower peak power demand when large-scale charging operations take place on the grid. In Figure 7, the power drawn from the grid with uncontrolled EV charging is given as 281.46 kW. Using the GA–PV and MPC–PV strategies, the power drawn from the grid was minimized to 173.53 kW and 197.06 kW, respectively. This translates to a reduction of 38.35% and 30% using the charging strategies. This was achieved based on time-of-use (ToU) charging strategies, which consider shifting EV charging to solar PV power and to off-peak periods when electricity cost is low. Both the GA–PV and MPC–PV flatten the power demand from EVs, as indicated in Figure 7.

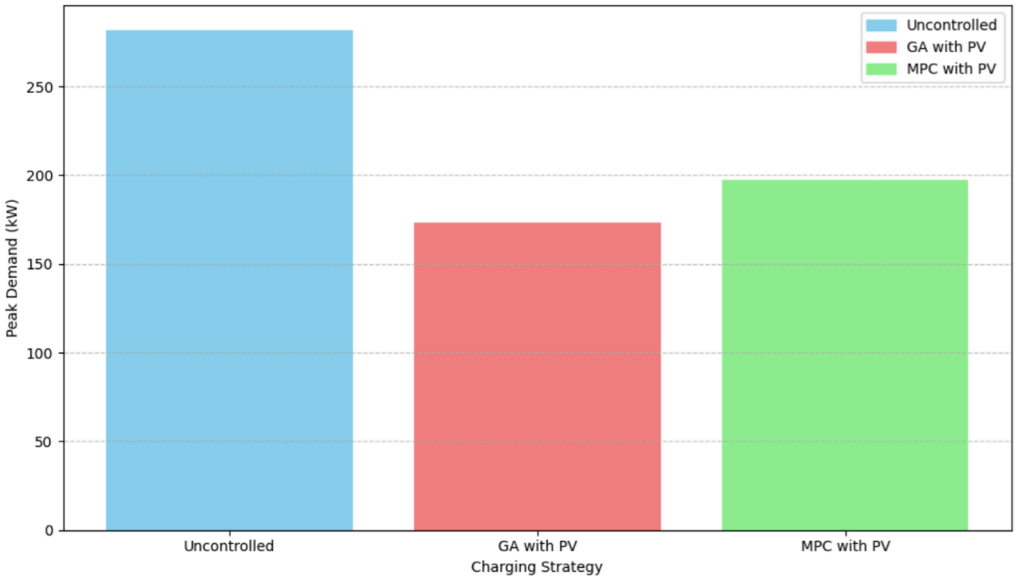


Figure 7. Minimizing peak power demand using GA–PV and MPC–PV strategies.

4.3.3. Scenario 3: Sensitivity of Peak Power Demand to EV Charging Rate

This scenario isolates the effect of individual EV charger power rating on grid peak demand, holding the charging strategy fixed at the uncontrolled baseline. In charging scenarios where high-powered chargers like the CHAdeMO, Mennekes, and Combo 2 are used, the impact on grid stability is quite significant. Because uncontrolled charging of EVs on a large scale already impacts the grid, an increase in the charging rates exacerbates the impact. Using varying EV charging rates, this sensitivity analysis and experiment demonstrate that uncontrolled charging of EVs coupled with higher charging rates would increase peak power demand and negatively impact the grid. In Figure 8, four different charging rates of 3 kW, 7 kW, 10 kW, and 15 kW were plotted against peak power demand using uncontrolled charging scenarios. By increasing the charging rate, peak power demand grew from 199.82 kW at 3 kW to 521.46 kW at 15 kW. This experiment shows that higher peak demands are inevitable, especially with uncontrolled charging and high charging rates. Moreover, this sensitivity analysis also shows an increase in instantaneous power drawn from the grid, which can result in power-quality issues.

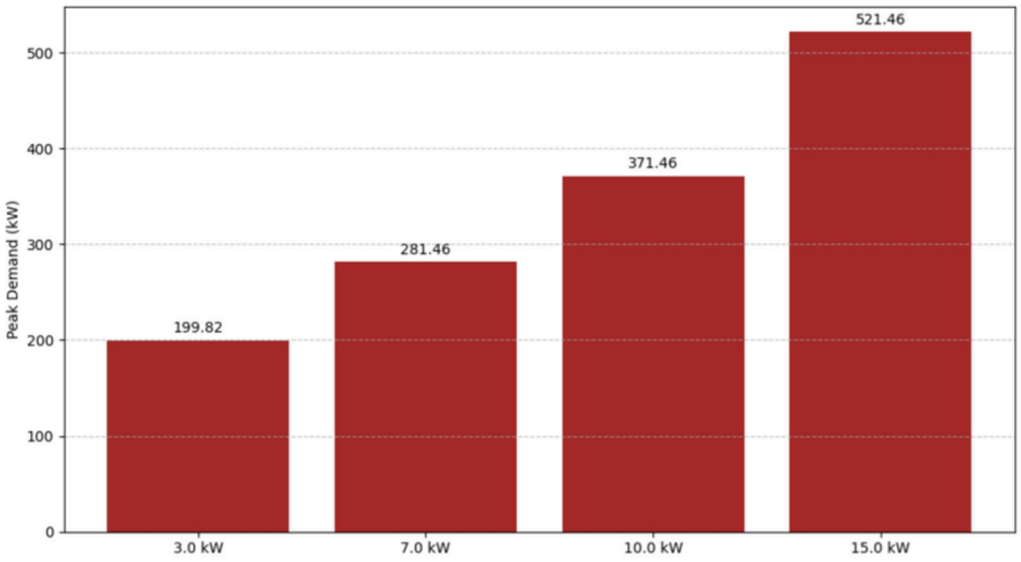


Figure 8. Effect of increasing charging rate on peak power demand for uncontrolled charging.

4.3.4. Statistical Analysis: Influence of EV Charging Strategy on the Optimization Process

In this section, we present the statistical analysis in Table 5 for a small subset of data (7 days of energy consumption) to evaluate the charging strategies. Using ANOVA (analysis of variance), we compare uncontrolled charging with the GA–PV and MPC–PV strategies to determine the extent to which these methods reduced energy consumption.

Table 5. Statistical analysis to evaluate the charging strategies (GA–PV and MPC–PV).

Strategy	Count	Mean (kWh)	Std (kWh)	25% (kWh)	50% (kWh)	75% (kWh)	Max (kWh)
Uncontrolled Charging	7	25.78	6.69	21.70	24.10	30.50	35.70
GA–PV	7	20.14	5.12	17.60	19.30	22.80	28.60
MPC–PV	7	16.42	4.41	13.90	15.40	18.20	23.90

- Uncontrolled Charging: Table 5 shows that the uncontrolled charging scenario has the highest mean energy consumption and the highest standard deviation.
- GA–PV: The genetic algorithm strategy reduced the mean energy consumption and has a lower standard deviation when compared to uncontrolled charging.
- MPC–PV: The model-predictive control strategy achieves the best result for reduced energy consumption and has the lowest standard deviation.
- 95% Confidence Interval (CI): For the mean energy consumption, uncontrolled charging has CI (21.72, 29.84), GA–PV (16.92, 23.36), and MPC–PV (13.79, 19.04). These intervals show that, with 95% confidence, the true mean daily energy consumption for MPC–PV is significantly lower than those of GA–PV and uncontrolled charging.
- One-Way ANOVA: Using analysis of variance, the F-statistic is 13.56, while the p-value is <0.001. Since the p-value from the one-way ANOVA is less than 0.05 (i.e., at 5%), we conclude that statistical significance exists between the mean energy consumption evaluated in all three scenarios.

These results show that the GA–PV and the MPC–PV significantly reduced energy consumption when compared to the uncontrolled charging scenario. MPC–PV shows the best optimization results and a definite performance gain for reduced energy consumption.

4.4. Model Comparison

In this section, Table 6 is provided to compare the implementation of this study's algorithms with others in the literature reviewed. While a direct apple-for-apple benchmark was outside this study's scope, the reported reductions in peak power demand and energy consumption are broadly consistent with the literature. The closest comparison from Table 6 is the GA-based coordination [28], which used the same IEEE 33-bus system to achieve 6.33% energy-loss reduction. Compared to this study's 38.35% peak-demand and 12.09% energy-consumption reductions. Our study recognizes that differences in dataset, EV population, and metric definition do prevent precise benchmarking.

Table 6. Key comparison of implemented models.

Ref	Study	Method	Test System	Reported Metric
[28]	GA + SAMPE-JAYA for CS/V2G allocation	GA	IEEE 33-bus and 69-bus	6.33% energy-loss reduction (33-bus), 22.5% (69-bus)
[18]	LR/GMR/RF/FFANN charging optimization	ML ensemble	Not stated as IEEE 33-bus	23.9% average peak-demand reduction
[19]	Federated learning + LSTM, edge/OCPP	DRL	EV charging stations	18% peak-demand reduction
[17]	N-step DRL	DRL	Simulated microgrid	10.9% electricity consumption decrease
This study: Kene et al.	AI coordinating EV charging and RE: Hybrid GA-MPC	Hybrid GA-MPC	IEEE 33-bus	38.35% peak-demand reduction and 12.09% energy-consumption reduction

5. Conclusions

This study presented an artificial intelligence approach based on a genetic algorithm, with model-predictive control combined with solar PV to coordinate EV charging. The simulation results, which were based on different scenarios, demonstrated a significant reduction in peak power demand and improved energy consumption with solar PV utilization. The major findings from this study based on the optimization strategy used are as follows:

5.1. Genetic Algorithm Combined with Solar PV

- Long-term scheduling: Where gradient-based methods would perform less optimally, in this study, the GA–PV strategy converged to feasible day-ahead schedules despite the non-convex coupling between SPV intermittency and EV demand, achieving 38.35% peak-demand reduction as seen under Section 4.3.2.
- Optimal Sizing: Employing GA was useful in minimizing the cost of energy as it balances the solar PV power supply with the demands of EV energy consumption. For municipal utility operators and energy managers, this aspect of optimal sizing is a useful strategy in their energy economics because it reduces capital expenditure while successfully minimizing the levelized cost of energy (LCOE).
- EV Battery Health: The GA–PV application has the capacity to optimize EV battery depth-of-discharge (DoD). This is an advantage as it extends battery life.

5.2. Model-Predictive Control Combined with Solar PV

- Buffering Intermittency: Solar PV ramping is inevitable due to weather changes and the natural occurrence of daily sunrise and sunset. As a result, solar PV power generation increases and decreases drastically over a short period, causing instability in grid performance. The application of MPC helps utility and energy managers

balance a sudden surge or drop in power generation by adjusting EV charging rates in seconds. This reduces the impact of rapid solar ramping on the grid and helps to maintain frequency stability.

- Resilient to Prediction Error with Feedback Mechanism: A significant function in the application of MPC is the ability to re-optimize at every time step. This gives MPC robustness against errors in solar PV predictions, as compared with strategies that are executed without real-time feedback mechanisms to adjust performance.

Regarding the overall application of GA and MPC combined with solar PV, the integration creates a multilayer optimization framework that minimizes EV energy consumption directly from the grid while maximizing solar PV utilization. The outcome of the GA and MPC with solar PV is summarized as follows:

- Based on Scenario 1 with uncontrolled EV energy consumption, the simulation results in Figure 6 show that the MPC–PV charging strategy had a better optimization result with a 12.09% reduction in energy consumption, when compared with the 11.80% from the GA–PV strategy. The statistical analysis in Table 5 further confirms this.
- In Figure 7, under the peak power demand of Scenario 2. The GA–PV charging strategy had a better result with lower power demand. GA–PV reduced peak power demand by 38.35%, while the MPC–PV had only a 30% reduction.
- With Scenario 3, the objective here was to determine the impact of high charging rates from EV chargers on the stability of the grid. The simulation from the sensitivity analysis in Figure 8 shows that a higher charging rate will increase peak power demand and lead to grid instability.
- Table 5 provides empirical evidence that uncontrolled charging will impact the grid due to uncontrolled energy consumption. However, the statistical analysis shows that significant energy reduction can be realized using GA–PV and MPC–PV charging strategies, where the MPC algorithm showed performance gains over the GA.

6. Future Research Directions

- Multi-objective trade-off mapping: This study optimizes a single weighted objective (Equation (17)); future work should apply NSGA-II to generate an explicit Pareto front between EV charging speed and grid voltage stability, enabling operators to select operating points rather than a single weighted compromise.
- Robust MPC under degraded forecasts: The MPC formulation here assumes reasonably accurate SPV predictions; future work should develop chance-constrained or robust MPC variants that maintain grid safety guarantees when PV forecast confidence falls below 50%.
- Adaptive GA hyperparameters: The GA mutation and crossover rates are fixed in this study (0.1 and 0.8); future work should apply reinforcement learning to tune these online in response to seasonal solar variability, improving convergence without manual retuning.
- Physics-informed control for V2G/G2V: Future work should apply physics-informed neural networks (PINNs) to enforce AC optimal power-flow constraints directly within real-time V2G/G2V control, reducing reliance on linearized approximations.
- Open EV charging data standards: Because this study's 33% data-usability rate (Section 3.2) reflects a broader field-wide data-quality problem, future policy work should promote standardized, open EV charging datasets to improve reproducibility and generalizability across studies.
- Pairwise Comparisons: Because ANOVA tests are based on a single p-value, this is a limitation, as it does not say where a specific difference exists in the data. A pairwise comparison is highly suggested; for example, Tukey's HSD (Honestly Significant

Difference) can be used as a post hoc test, which must be conducted after running the ANOVA. This will protect against false-positive results (i.e., control false alarms) that may arise where ANOVA may show significant variance, whereas Tukey's post hoc test has the capacity to isolate individual pairs, quantify the specific performance gains, and determine if MPC–PV actually has a significant difference from the GA–PV optimization algorithm for the scenarios analyzed.

7. Recommendations

Practical recommendations for charging-station operators: Based on the findings of this study, charging-station operators combining grid and PV supply should:

- Prioritize scheduling EV charging within solar PV availability hours (05:00–19:00) before drawing from the grid, as indicated in Section 3.1, where we discussed the ToU strategy.
- It is beneficial to reserve GA-based application for day-ahead scheduling, sizing, and long-term capacity planning. This study demonstrates the value of this approach with stronger peak-shaving performance at 38.35%.
- MPC-based real-time control should be used where PV forecast uncertainty or unplanned EV arrivals are significant. This demonstrated robustness to prediction error is provided in Section 2.2 of this study.
- Charging-rate limits should be treated as an active control lever. Using the sensitivity analysis demonstrated in Scenario 3 of this study, we have been able to show that peak power demand doubles from 3 kW to 15 kW under uncontrolled charging. We recommend that maximum charging power per session should be controlled, using this as a low-complexity mitigation strategy, even without full GA and MPC deployment.

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