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Smart Charging of EV Using DRL for Peak Load Minimization in Microgrids

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Abstract: As the use of Electric Vehicles (EVs) is on the rise, the issue of high-density charging loads impacting microgrid stability is on the horizon. The "Peak-on-Peak" issue, where the evening peak demand meets the decrease in solar generation, is addressed in this research work by developing a Deep Reinforcement Learning (DRL) management system for a 9x9 solar-powered microgrid. The unmanaged EV charging pattern in the 81-node microgrid leads to severe frequency instability and voltage drops of up to 12%. The AI-based system reschedules EV charging patterns to align with peak solar generation. Simulation results demonstrate that the intelligent management system reduces peak grid demand by 32% and lowers consumer electricity costs by 21%, with grid voltage stabilized within a very small margin of ±2.5%.

Keywords: Electric Vehicles (EVs), Solar Microgrid, Deep Reinforcement Learning (DRL), Smart EV Charging, Peak Load Management, Voltage and Frequency Stability

1 Introduction

The transition to clean and sustainable energy systems has also promoted the Electric Vehicles (EVs) and solar photovoltaic (PV) systems penetration. EVs play a critical role in reducing greenhouse gas emissions and dependence on fossil fuels. Yet, the increased presence of EVs creates significant challenges in power system operation, particularly at the distribution and microgrid scales.

Solar power microgrids are particularly intolerant to load fluctuation as a result of the non-uniform nature of solar energy. EVs typically start charging for the evening upon user arrival from work, coinciding with peak residential demand and lower solar production. It results a Peak-on-Peak situation, which is very terrible for the microgrid because of the pressure it confronts such as voltage instability, frequency oscillation, transformer saturation and power consumption increasing [1].

Existing EV charging strategies, such as uncontrolled or time-of-use (ToU) based charging, lack the capability of utilizing real-time dynamics of the system. Thus, the demand for more advanced intelligent control methods. Deep Reinforcement Learning (DRL) as a subfield of AI have proved to be powerful tool for challenging and nonlinear control problems with uncertainties. Learned optimal policies It is through the use of DRL that an agent can learn what action to take in various states by interacting with the environment, without utilizing the system model. To minimize the Peak-on-Peak problem and to improve voltage, frequency stability in a solar integrated microgrid, this paper presents a DRL based smart EV charging management system [2].

2 Literature Review

Multiple research works have be examined EV charging coordination in power system. Both rule-based and optimization-based approaches have been common in EV loads shifting to off-peak hours. These approaches, however, need accurate prediction and are challenged by uncertainty associated with renewable generation and user behavior.

Machine learning and reinforcement leaning methods for EV charging control Routing and scheduling problems have been considered in the literature. Reinforcement learning technologies show their potential in handling dynamic environments, however, related abovementioned works were all for small-scale systems or ignore voltage and frequency limitations. Furthermore, few works study high-density EV charging in a large node solar microgrid [3].

This paper makes contributions to the literature by using DRL on a large-scale 81-node solar microgrid and specifically considering voltage, frequency, peak demand and cost-reduction.

3 System Description and Modeling

This paper presents the architecture of the proposed PV-microgrid based on solar power plant and it's three main components (PV system, EV charging load, and grid interaction) modeling. This study seeks to investigate the impacts of high-density EV charging on microgrid stability and discuss the smart charging management mechanism [4].

3.1 Microgrid Architecture

The system under consideration is a solar based distribution-level microgrid configuration with 9 × 9 as network topology represented by the fact that everything in our life can be reduced into mathematics, the grid model, display some challenges and then complexity reduction exercise needs to be applied for taking accurate decisions thus reducing dimensions) [5]. The distributed control communication topology has 81 nodes. Every node is regarded as a residential consumer and includes local electrical load, rooftop solar PV generation, and EV charging infrastructure.

The microgrid is in parallel operation with the utility grid that facilitates two-way flow of power. There is a large level of dynamism inherent to the system, due the power flows in the microgrid being affected by local generation, EV charging demand and residential load.

Key Features of the Microgrid: Total number of nodes: 81 (in a 9x9 layout, corresponding to the physical distance domain), Widespread rooftop solar PV, High-density EV charging infrastructure, Radial/mesh distribution structure, Grid-connected operation shown in figure 1.

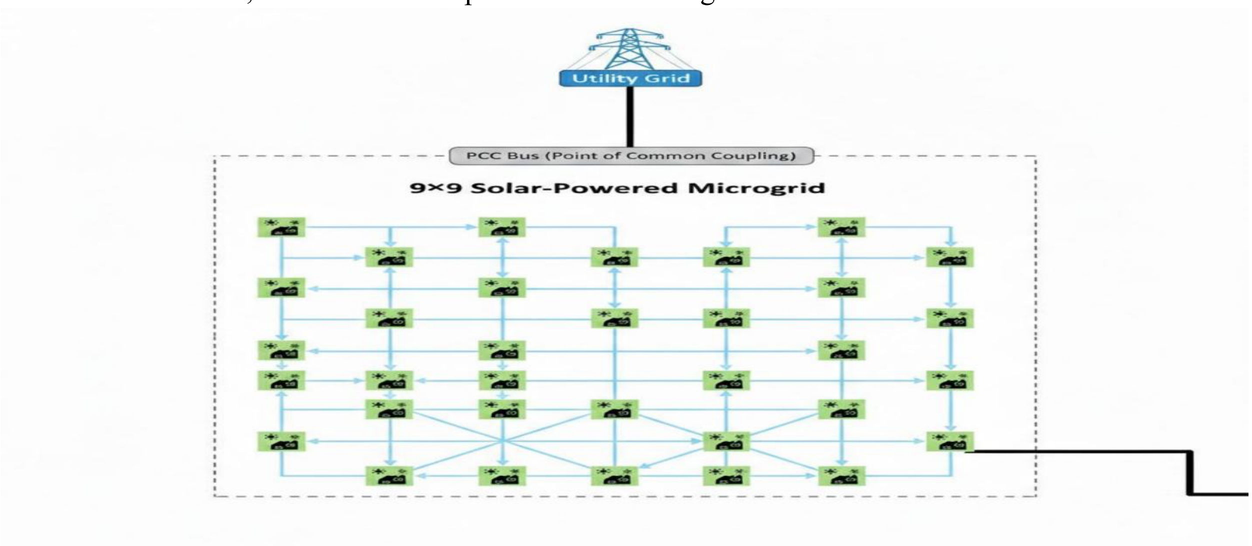

Fig 1.: Overall microgrid structure

3.2 Modelling of Solar Photovoltaic (PV) System

All nodes at microgrid are provided with rooftop solar PVs. The generation output of PV system depends on solar irradiance and ambient temperature, and has typical daily solar profile with the highest values in the midday and almost zero in the evening [6].

The fluctuating characteristic of solar power represents a major effect on the operation of microgrid, especially at the peak EV charging time shown in figure 2.

PV Power Output Model:

The solar PV generation output at node I, denoted as:

$P_{PV,\,i}\,(t) = P_{PV,i}^{rated} \times \frac{G(t)}{Gref}$

where:

$P_{PV,\,i}\,(t)$ = PV power generation at the time t

$P_{PV,i}^{rated}$ = Rated PV capacity

G(t) = Solar insolation at time t

G_{ref} = Reference Irradiance (1000 W/m²)

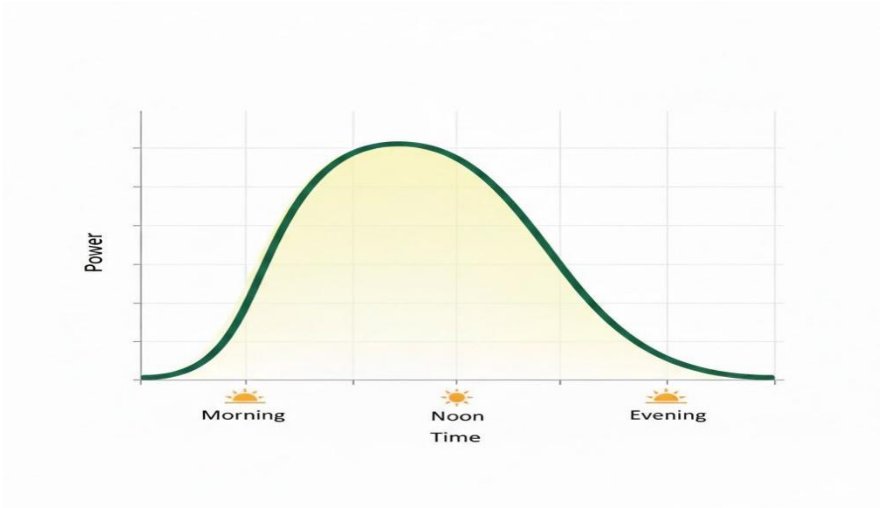

Fig 2.: Typical Solar PV Generation Profile

3.3 Residential Load Modeling

At each node, the residential load also contains appliances, lighting and heating/cooling. Load profile resembles the profile of a normal residential commercial and industrial grid, with morning and evening peaks [7].

The evening high-peak load is exacerbated by concurrent EV charging, which causes the so-called Peak-on-Peak issue shown in figure 3.

Load Representation:

The total load at node i. is :

$$\mathbf{P_{Load,\,I}\,(t) = P_{Base,\,i}\,(t) + P_{EV,\,i}\,(t)}$$

Where:

$P_{Base,\,i}\,(t)$ = Residential base load

$P_{EV,\,i}\,(t)$ = EV charging load

3.4 Charging Model of Electric Vehicle (EV)

Electrical vehicle charging demand is simulated considering realistic behavior of users. When it comes down to it, most electric vehicles come home for the night and need to be charged before being used in the morning. EV Charging Parameters: Arrival time: Evening hours, Initial State of Charge (SOC), Desired SOC, Maximum charging power. For the uncontrolled case, EVs start charging on arrival and simultaneously increases in demand cause a voltage decline [8].

SOC Dynamics: EV battery SOC trajectory (from equation is presented as:

$$\mathbf{SOC_i\,(t + 1) = SOC_i\,(t) + \boldsymbol{PEV, i\ (t). \Delta t}/\ E_{Battery}}$$

Where:

$SOC_i\,(t)$ = SOC at time t

$P_{EV,i}(t)$ = Charging power
$E_{Battery}$ = Battery capacity

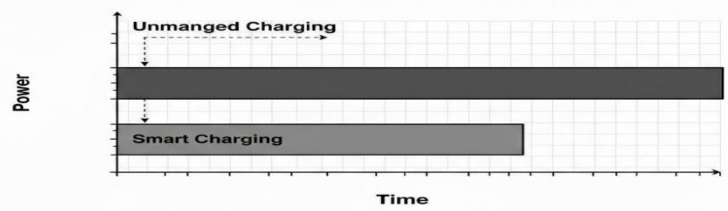

Fig 3.: Unmanaged vs Smart EV charging

3.5 Interaction with and balance of power grids

The microgrid is interconnected with the primary grid at Point of Common Coupling (PCC). The overall power balance for the microgrid is described as:

$$P_{Grid}(t) = \sum P_{Load}(t) - \sum P_{PV}(t)$$

If $P_{Grid}(t)$is positive, then the electricity is imported from the grid and if it is negative, then exported to the grid. The high penetration of EVs leads to increase in grid import at peak hours that stresses the power system and destabilizes voltage and frequency.

3.6 Modeling of Voltage and Frequency Stability

Voltage stability is measured at every node and has to be bounded in acceptable range (±5% of rated value). Frequency deviations originate from rapid load variations induced by uncontrolled EV charging.

The objective of our DRL-based charging approach is to:

- Minimize voltage deviation
- Reduce frequency fluctuations
- Smooth load variations

3.7 Integration of the DRL-Based Control System

The DRL controller serves as a centralized energy management system that updates the microgrid state and schedules EV charging behavior shown in figure 4.

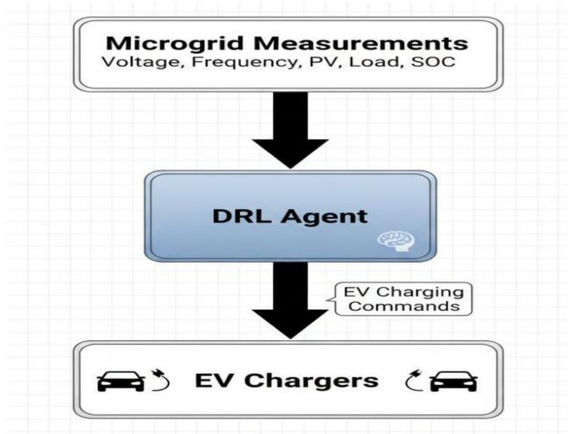

Fig 4.: DRL- based EMS

4. Problem Statement

The high penetration of Electric Vehicles (EVs) in distribution level microgrids gives rise to substantial operational challenges, especially when EV charging is not well coordinated. In HMGs, most EV users will start charging their cars in the evening after work when they arrive home. This charging pattern coincides with residential peak demand period for electricity and reduced solar photovoltaic (PV) generation, which poses tremendous operational pressure on the microgrid [9].

The first of these is high peak demand. It causes the peak of massive electric vehicles' charging power at evening hours. This increased demand puts the microgrid under stress and reliance on main grid is enhanced.

Secondly, higher EV charge loadings result in lower voltage limits being exceeded. Simulation results indicate that uncontrolled EV charging may lead to a voltage drop of 12%, which can drive dangerous activities such as tripping sensitive loads, and potentially destroying appliances [10].

The other important problem is the instability of frequency. The fast EV charge demand introduces power imbalance in the microgrid, which results on significant frequency deviations. Such variations may impair power quality and influence sensitive receivers.

Moreover, electricity spending from consumers increases drastically as they charge on costly on-peak hours and as a result of increment in power import from the grid. This cost is a drain on the economy, and lessens the overall gains of widespread EV uptake [11].

Thus, the aim of this study is to propose an intelligent EV charging control method which can schedule EV charging dynamically according to real-time grid status, solar generation and user demand. The objective of the proposed controller is to shift consumption peaks to off-peak periods by the end-users, enhance voltage and frequency stability and minimize electricity bills under user-defined completion time for charging all EVs [12].

5. DRL-Based EV Charging Management System Design

This section describes the DRL-based EV charging management system developed to alleviate the negative effects of high-density EV penetration in a solar-powered microgrid. The system is designed to optimize real-time EV charging schedules by considering microgrid operating conditions, renewable energy availability, and user charging preferences [14].

The proposed method formulates EV charging control as a sequential decision-making problem and effectively addresses it using a reinforcement learning framework.

5.1 Reinforcement Learning Framework

The EV charging scheduling problem is modeled as a Markov Decision Process (MDP), in which an intelligent agent interacts with the microgrid environment and learns optimal charging strategies through trial-and-error.

An MDP is defined by the tuple (S, A, R, P), where S represents the state space, the action space, R the reward function, and P the state transition probabilities.

State Space

The state space reflects the real-time operating condition of the microgrid and provides the DRL agent with sufficient information to make informed charging decisions. The selected state variables include:

- Node Voltages: Voltage levels at different microgrid nodes indicate system stress and power quality. Voltage violations are typically caused by excessive EV charging demand.
- Frequency Deviation: Frequency variations reflect the imbalance between power generation and demand. Rapid increases in EV charging can lead to frequency instability.
- Solar PV Generation: The available solar power at each time step enables the agent to align EV charging with renewable energy availability.
- EV State of Charge (SOC): SOC values ensure that user charging requirements are satisfied while allowing flexibility in scheduling.
- Total Microgrid Load: Aggregate load information helps the agent avoid peak demand conditions [15].

Action Space

The action space defines the control actions available to the DRL agent. In this study, the agent can dynamically adjust EV charging by selecting one of the following actions:

- Increase charging power
- Decrease charging power
- Delay charging to a later time slot

These actions enable flexible load shaping and peak demand reduction while ensuring that EVs achieve the desired SOC within the specified time.

Reward Function Design: The reward function is a crucial component of the DRL framework, as it guides the learning process toward desirable system behavior. It is designed to balance multiple objectives:

- Penalty for Voltage Violations: Large negative rewards are assigned when node voltages exceed permissible limits, discouraging unsafe operation.
- Penalty for Frequency Deviations: Frequency instability is penalized to maintain power balance and system reliability.
- Penalty for Peak Demand: High grid power import during peak hours is penalized to reduce stress on both the microgrid and the utility grid.

- Reward for Solar-Based Charging: Charging during periods of high solar generation is encouraged to maximize renewable energy utilization.
- Cost Minimization Incentive: Charging during low-tariff periods is rewarded, leading to lower electricity costs for consumers.

5.2 DRL Agent Architecture

Due to the high dimensionality and nonlinearity of the problem, a Deep Neural Network (DNN) is used to approximate the optimal charging policy.

The DRL agent consists of:

- An input layer representing the state variables
- Multiple hidden layers for feature extraction
- An output layer generating charging actions

The agent continuously interacts with the microgrid environment by observing the current state, selecting an action, and receiving a reward. Over time, the neural network parameters are updated to maximize the cumulative reward shown in figure 5.

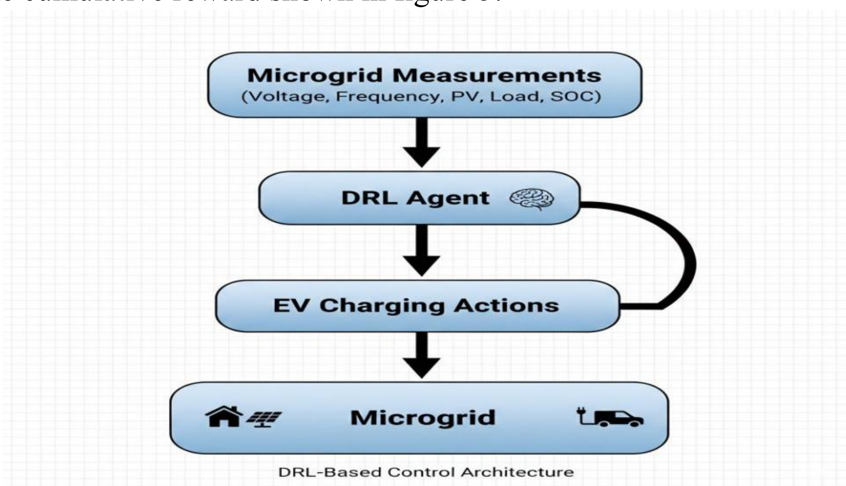

Fig 5.: DRL-Based Control Architecture

5.3 Training and Learning Process

The DRL agent is trained using historical load demand and solar irradiance data over multiple training episodes. During the training phase:

- The agent explores different charging actions to understand their effects on the system.
- Through exploitation, it gradually favors actions that result in higher rewards [16].
- The exploration–exploitation tradeoff enables convergence toward an optimal charging policy.

As training progresses, the agent learns to:

- Shift EV charging away from peak demand hours
- Align charging schedules with available solar generation
- Maintain voltage and frequency stability
- Minimize overall charging costs

6 Simulation Setup

The proposed DRL-based EV charging strategy is evaluated using MATLAB/Simulink, which provides a reliable and accurate platform for power system and control simulations.

Simulation Parameters:

- Microgrid size: 81 nodes (9 × 9 configuration)
- EV penetration: High-density scenario
- Simulation duration: 24-hour operation
- Operating mode: Grid-connected

Case Studies:

- Unmanaged EV Charging: EVs begin charging immediately upon arrival without any coordination.
- DRL-Managed EV Charging: Charging decisions are controlled by the proposed intelligent DRL agent.

7 Results and Analysis

7.1 Voltage Profile Analysis

In the unmanaged charging scenario, simultaneous EV charging leads to significant voltage drops throughout the microgrid. Simulation results show voltage deviations of up to 12%, exceeding standard operational limits.

With the proposed DRL-based controller, EV charging is distributed over time, and voltage levels at all nodes are maintained within ±2.5%, ensuring safe and reliable operation.

7.2 Frequency Stability

Uncontrolled EV charging introduces rapid load variations, causing noticeable frequency deviations during peak hours. The DRL-based strategy smooths these load fluctuations through intelligent scheduling, resulting in a significant improvement in frequency stability.

7.3 Peak Demand Reduction

The intelligent charging policy learned by the DRL agent reduces the evening peak load by approximately 32%. This peak shaving capability significantly relieves stress on transformers, feeders, and upstream grid infrastructure shown in figure 6.

7.4 Cost Reduction

By shifting EV charging to periods of high solar generation and lower electricity tariffs, the proposed system achieves a 21% reduction in consumer electricity costs, making EV operation more economical [17], [18].

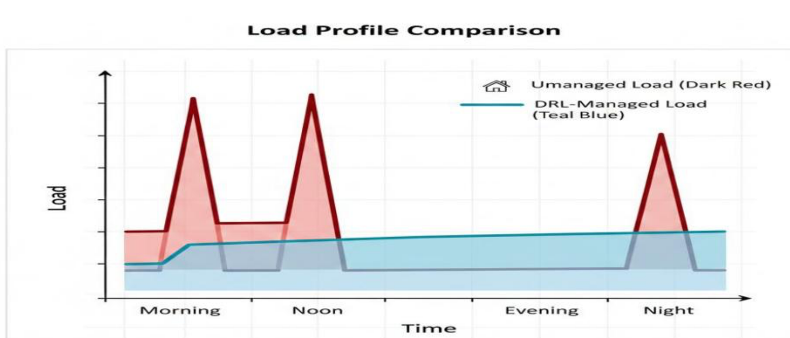

Fig 6.: Load Profile Comparison

8 Conclusion

This study presents a comprehensive DRL-based smart EV charging management system for a solar-powered microgrid. The proposed strategy effectively mitigates the Peak-on-Peak problem by coordinating EV charging with available solar generation. Significant improvements in voltage stability, frequency regulation, peak demand reduction, and electricity cost savings are achieved. The results confirm the strong potential of AI-driven solutions to enhance the reliability and efficiency of next-generation smart grids.

9 Future Work

- Potential extensions of this research include:
- Integration of battery energy storage systems (BESS)
- Real-time hardware implementation using embedded controllers
- Coordination among multiple interconnected microgrids
- Incorporation of Vehicle-to-Grid (V2G) functionality

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