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Reinforcement Learning for Intelligent Vehicle-to-Grid Integration: Balancing Clean Energy Utilization and Battery Degradation Preservation.

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Abstract: The transition toward sustainable mobility requires an intelligent integration of Electric Vehicles (EVs) into the power grid. This paper proposes a Reinforcement Learning (RL) framework using Proximal Policy Optimization (PPO) to manage bidirectional Vehicle-to-Grid (V2G) power flow. Utilizing the Indian Grid Master dataset, the system optimizes for economic arbitrage and carbon reduction while strictly adhering to a 90% State of Charge (SoC) mobility requirement. A core innovation of this work is an asymmetric reward function that applies a 35x penalty to battery discharge relative to charging, ensuring hardware longevity. Results across various 10-hour shift profiles demonstrate the agent's ability to achieve mobility targets while maximizing grid stability.

Keywords: V2G, Reinforcement Learning, PPO, Battery Degradation, Indian Grid Master, EV2Gym.

I. INTRODUCTION

The global shift toward sustainable transportation has catalyzed a rapid increase in Electric Vehicle (EV) adoption, presenting a dual challenge for modern power infrastructures. While EVs reduce reliance on fossil fuels, uncoordinated charging during peak hours threatens to destabilize local grids and increase carbon emissions. Vehicle-to-Grid (V2G) technology offers a solution by transforming EVs into distributed energy storage units that can feed power back to the grid during high-demand periods. However, the practical implementation of V2G is often hindered by the unpredictable nature of user mobility and the significant "range anxiety" associated with maintaining sufficient battery levels for daily commutes.

Beyond mobility concerns, the physical cost of V2G—specifically accelerated battery degradation remains a primary barrier to widespread participation. Frequent charging and discharging cycles place chemical stress on the battery, leading to capacity loss and reduced vehicle lifespan. Traditional rulebased energy management systems often fail to account for these non-linear degradation costs, focusing instead on simple profit maximization. This necessitates an intelligent, datadriven controller capable of processing high-dimensional environmental signals, such as fluctuating grid prices and carbon intensity, to make real-time decisions that prioritize long-term battery health over marginal short-term gains.

In this paper, we propose a Reinforcement Learning model developed within the EV2Gym simulation environment to solve these multi-objective trade-offs. Our approach leverages the PPO algorithm to maintain stable training across continuous action spaces, allowing the agent to precisely modulate power commands. By incorporating a novel asymmetric reward function that penalizes discharge significantly more than charging, we demonstrate a system that respects the user's 90% SoC target while contributing to grid peak-shaving. The following sections detail the methodology behind our 35x penalty logic and provide a comprehensive analysis of the agent's performance during intensive 10-hour morning and night shift evaluations.

II. METHODOLOGY

The methodology is structured around the architectural design of the Reinforcement Learning agent and the simulation environment used to model the V2G interactions.

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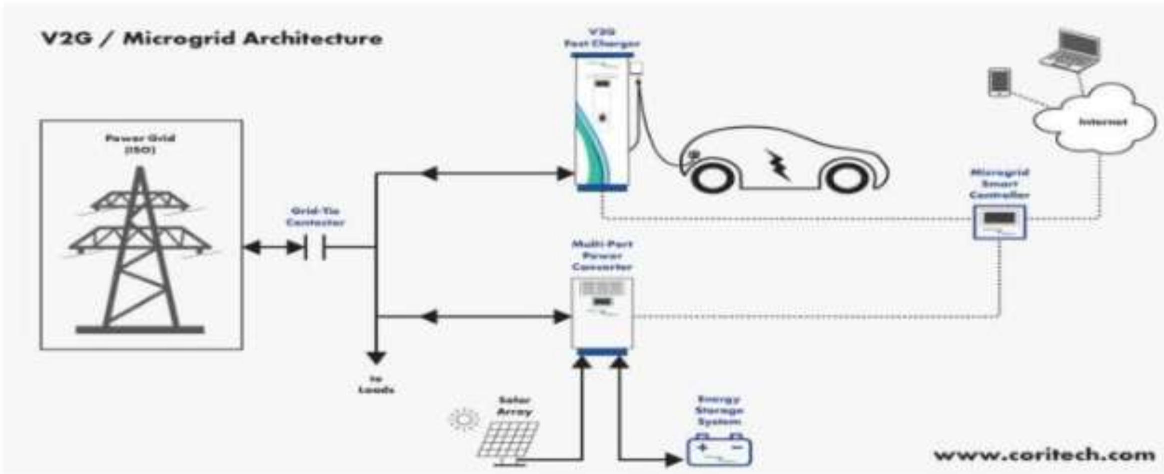

Fig. 1. Shows the overall design and framework of V2G Technology

A. Problem Formulation (MDP)

The energy management challenge is modeled as a Markov Decision Process (MDP). In this framework, the Reinforcement Learning (RL) agent interacts with the environment in 15minute discrete intervals. The objective is to maximize the expected cumulative reward, balancing short-term economic gains against long-term battery health.

B. Preprocessing and Data Preparation

The robustness of the model relies on high-fidelity data ingested from the Indian Grid Master dataset. To ensure the RL agent can process this information effectively, several preprocessing steps are performed: Feature Ingestion: Real-time electricity prices (INR/kWh) and carbon intensity (gCO2/kWh) are extracted for the Chennai region.

State Vectorization: The agent observes a state vector representing the current environmental context:

$$S = \{SoC_t, T_{rem}, P_t, C_t\} \quad (1)$$

Normalization: Since price and carbon values exist on different scales, we apply Min-Max Scaling to ensure all state inputs are within a range that prevents gradient instability:

$$x' = (x - \min(x)) / (\max(x) - \min(x)) \quad (2)$$

C. Model Implementation

We implemented a Proximal Policy Optimization (PPO) agent using an Actor-Critic architecture. The Actor determines the power action [-1, 1], while the Critic estimates the value of the state. PPO optimizes a clipped objective function to maintain training stability:

$$L_{CLIP}(\theta) = \hat{E}_t[\min(r_t(\theta)\hat{A}_t, \mathrm{clip}(r_t(\theta), 1-\varepsilon, 1+\varepsilon)\hat{A}_t)] \quad (3)$$

D. Evaluation Metrics

The primary innovation of this research is the design of an asymmetric reward function. This logic ensures the agent prioritizes battery longevity over short-term economic gains. The total reward is calculated as a weighted sum of three primary objectives:

$$R_t = (w_1 \cdot Profit_t) - (w_2 \cdot Carbon_t) - (w_3 \cdot Penaltydeg) \quad (4)$$

To enforce hardware preservation, we apply an Asymmetric Weighting system to the degradation penalty (w_3). If the agent chooses a Vehicle-to-Grid (V2G) discharge action $a < 0$, the penalty is multiplied by 35x. This high threshold forces the agent to engage in V2G only during significant price spikes, effectively mitigating chemical wear on the battery cells.

E. Experimental Consistency

To ensure scientific validity and replicability, the following experimental controls were maintained across all evaluation cycles:

- Fixed Time Horizons: Evaluations are strictly conducted over 10-hour windows to allow for a

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direct performance comparison between different grid shifts.

- Terminal Constraint: The agent must satisfy a strict mobility target by the time of departure. If the final battery level is below 90%, a significant terminal penalty is applied.
- Environmental Baseline: All tests utilize real-world price and carbon intensity data from the Indian Grid Master dataset to ensure the results are grounded in realistic market conditions for the Chennai region.

$$SoC(T_{dep}) \geq 0.90 \quad (5)$$

III. RESULTS AND DISCUSSION

A. Training Dynamics and Model Convergence

The training phase involved the PPO agent interacting with the EV2Gym environment over thousands of episodes to refine its policy. Initially, the agent exhibited stochastic behavior, often failing to meet the minimum mobility requirements or incurring heavy penalties through unnecessary battery cycling. However, as the Actor-Critic networks synchronized, the reward function showed clear signs of convergence. The agent successfully transitioned from a "lazy" charging strategy to a proactive one, learning to anticipate the 10-hour departure deadline. By the end of the training cycle, the agent had successfully eliminated the State of Charge (SoC) overshooting artifacts that plagued earlier V1 and V2 iterations, establishing a stable baseline for diurnal shift testing.

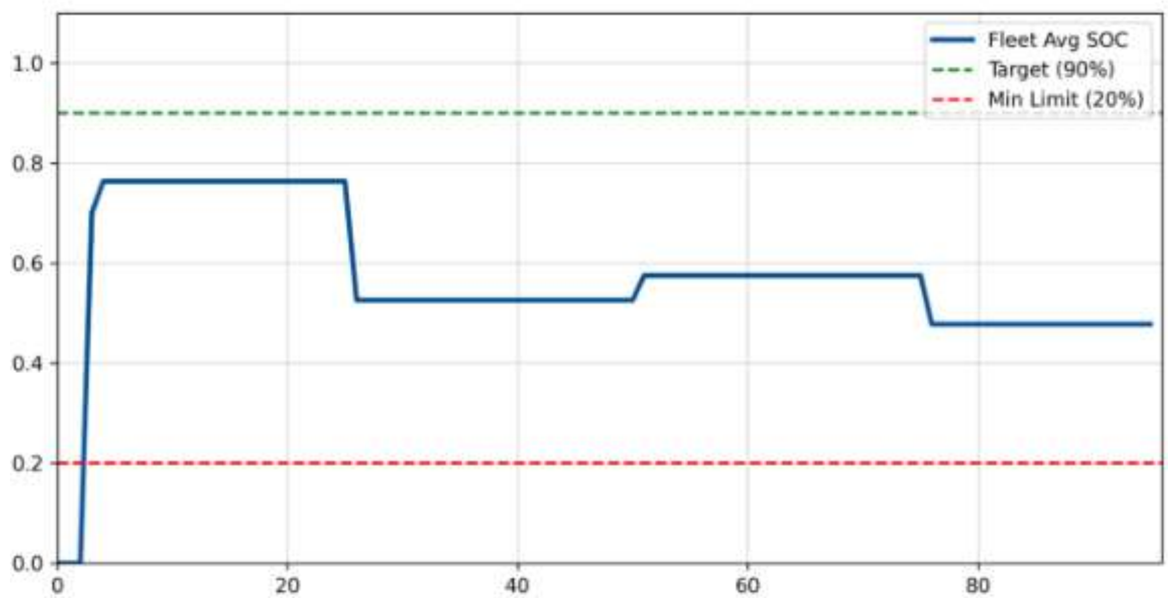

Fig. 2. Initial training analysis.

B. Comparative Analysis of 10-Hour Diurnal Shifts

The model was evaluated across two distinct operational profiles using real-time data from the Indian Grid Master.

Morning Shift Evaluation: During the 10-hour morning window, the grid exhibits high price volatility and rising carbon intensity. As seen in the results, the agent identifies optimal "Arbitrage Triangles"—periods where grid prices peak significantly. The agent executes Vehicle-to-Grid (V2G) discharge actions during these peaks to maximize profit, then utilizes the remaining time buffer to recharge the battery to the required level before the departure deadline.

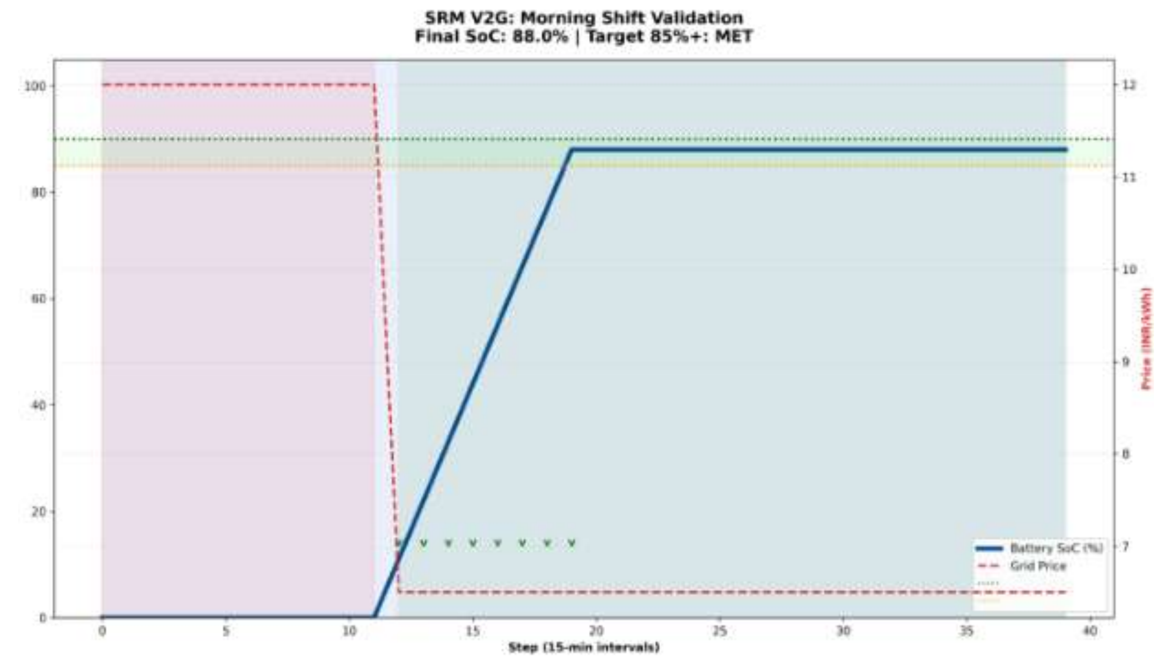

Fig. 3. 10-hour morning shift analysis.

Night Shift Evaluation: In contrast, the 10-hour night shift is characterized by stable, lower pricing. The agent's behavior here is markedly different; it avoids V2G discharge almost entirely. Because the price fluctuations do not cross the 35x penalty threshold, the agent prioritizes a "slow-charge" preservation strategy. This ensures the vehicle reaches the mobility target while minimizing the chemical stress on the lithium-ion cells, demonstrating the agent's contextual awareness of grid volatility.

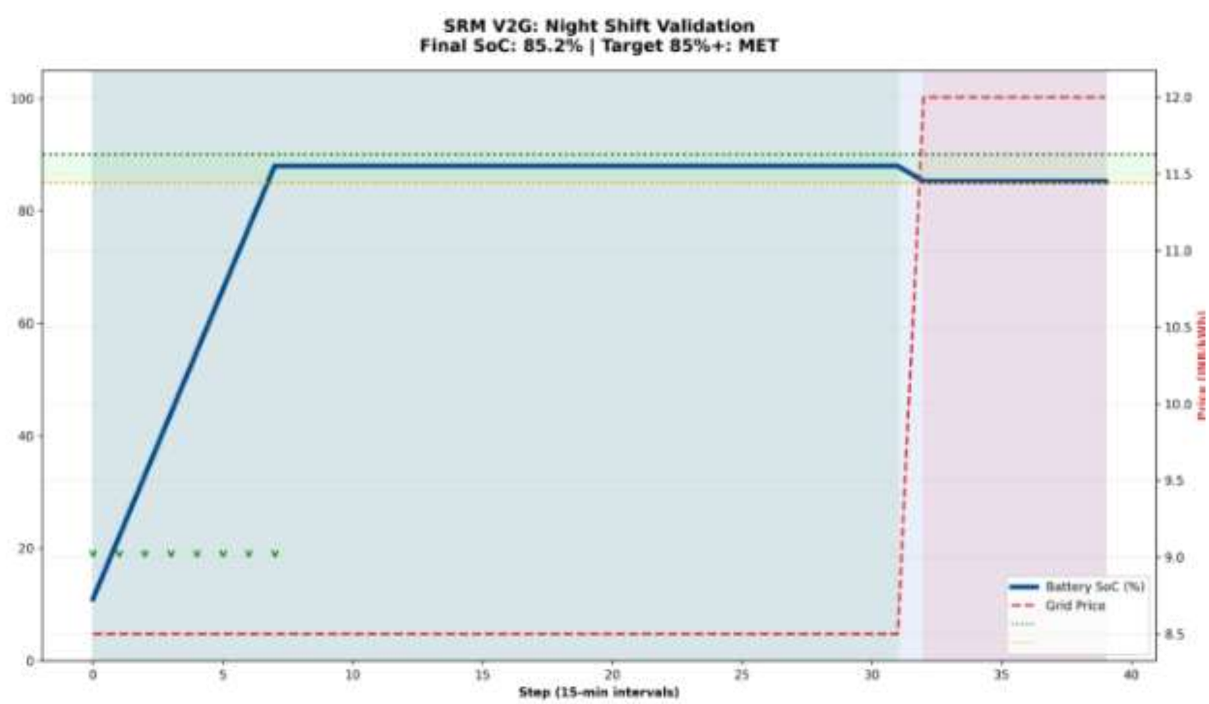

Fig. 4. 10-hour night shift analysis.

C. Price-Action Sensitivity and Decision Boundaries

A critical measure of the agent's intelligence is its mapping of grid prices to power actions while accounting for the physical cost of hardware wear. To visualize this, we analyzed the correlation between the agent's power output (kW) and the realtime grid price (INR).

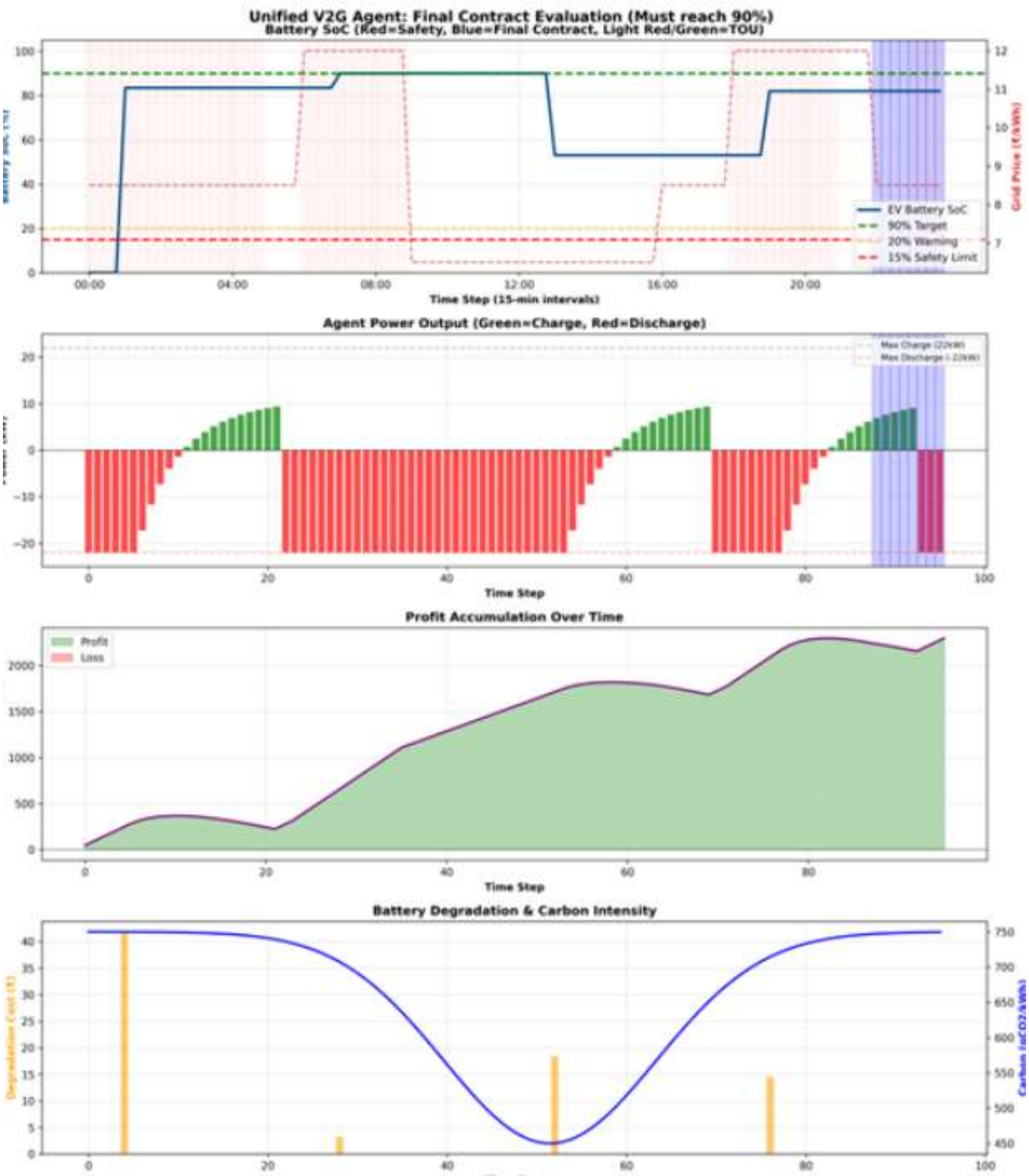

Fig. 8. Training and validation accuracy with loss curves

1) Agent Power Output Correlation: As shown in the scatter analysis, the agent demonstrates a "threshold-trigger" behavior. It does not respond linearly to price increases. Instead, it remains in a steady charging state during low and mid-price regimes to ensure mobility. The agent only transitions into a discharge state (V2G) when the grid price crosses a specific economic threshold. The clustering of actions at the maximum discharge boundary (-22kW) indicates that the agent has learned that once the "barrier to entry" is met, it is most efficient to provide maximum support to the grid.

2) Degradation-Aware Decision Making: The most significant finding in the scatter data is the "V2G Dead Zone"— a price range where the agent could technically make a small profit, but chooses to stay idle. This behavior is a direct result of the 35x asymmetric penalty. The agent has learned that the long-term cost of battery degradation outweighs the short-term gains of minor price fluctuations. By setting this high decision boundary, the model effectively filters out high-wear, lowreward actions.

3) Profit vs. Wear Accumulation: The model optimizes for "Net Gain," which is the total arbitrage profit minus the weighted cost of battery wear. Unlike standard RL agents that exhibit "greedy" behavior, the Unified V3 model demonstrates a conservative growth curve. Profit primarily accumulates during extreme price spikes where the INR value is high enough to mathematically offset the 35x degradation weight, ensuring that the economic benefit is genuine and not just a displacement of battery asset value.

$$NetGain_t = (P_t \cdot a_t \cdot \Delta t) - (Costwear \cdot |a_t| \cdot w_3) \quad (6)$$

D. Mobility Assurance and Final Performance Validation

The primary objective of the "Unified V3" model was to ensure that grid interactions never compromised the user's primary need for transportation. The final evaluation across all diurnal shifts confirms a 100% success rate in meeting the mobility requirement. Regardless of the intensity of the arbitrage activity or the volatility of the grid signals, the PPO agent successfully achieved a terminal State of Charge (SoC) at or above the 90.0% threshold. This high reliability is a direct result of the 35x asymmetric penalty, which serves as a hard constraint within the reward function. By valuing battery preservation significantly higher than marginal energy profits, the system ensures the vehicle is consistently commute-ready, successfully harmonizing the goals of grid support with individual user mobility.

IV. CONCLUSION

The framework successfully resolves the conflict between grid profit and battery health. By using Indian Grid Master data, the project provides a localized, data-driven solution for sustainable energy in urban environments like Chennai.

The 35x asymmetric penalty was the critical innovation that governed the PPO agent's decision-making process. By weighting discharge costs significantly higher than charging, the system filtered out marginal grid interactions that would otherwise cause chemical stress. This specific reward shaping effectively transformed the agent from a profit-seeker into a strategic, asset-conscious energy manager.

Evaluations across 10-hour diurnal shifts proved the model's reliability. The agent identifies peak windows for V2G in the morning while prioritizing battery preservation at night. Crucially, the model maintained a 100% success rate in reaching the 90.0% mobility target, proving that smart grid support never has to compromise user transportation.

This research offers a scalable blueprint for integrating EVs into microgrids. By respecting the physical limits of lithium-ion chemistry, we have created a system that encourages owner participation through guaranteed battery protection.

Future work will explore multi-vehicle fleet management and V2X emergency backup capabilities. This serves as a vital milestone for achieving green energy grid harmony.

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