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# A Multi-Objective EV Charging Framework Using Reinforcement Learning and NSGA-II for Adaptive TOU Scheduling in Smart Campuses

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**Abstract**

The rapid electrification of transportation systems, especially in academic and institutional campuses, presents both opportunities and operational challenges for local energy infrastructures. Uncoordinated EV charging can impose critical stress on the grid, while static TOU pricing schemes lack the intelligence to adapt to dynamic user behavior and energy profiles. This paper proposes a novel multi-tier hybrid optimization framework that integrates Reinforcement Learning (RL), PSO–Fuzzy TOPSIS-based schedule ranking, and NSGA-II-based multi-objective Pareto optimization for adaptive TOU scheduling in a V2G-enabled smart charging infrastructure. Taking Thiagarajar College of Engineering (TCE), Madurai as a case study location, we simulate realistic EV charging behaviors using brand-specific profiles for two-wheelers, three-wheelers, and four-wheelers, along with a priority-based DSM scheme. The RL agent dynamically learns TOU pricing policies, while the PSO–TOPSIS framework ranks them based on peak load, profit, and discomfort. The final NSGA-II layer identifies optimal trade-offs between economic and grid objectives. Our simulation reveals that the proposed system achieves up to 46% reduction in peak load, enhances energy utilization to over 91%, and minimizes user discomfort by over 85%. These results underline the potential of intelligent, brand-aware pricing control for future-ready energy systems.

**Keywords:** Reinforcement Learning, NSGA-II Optimization, EV Charging Scheduling, Time-of-Use Pricing, Demand Side Management, Smart Campus Microgrid

## 1. Introduction

The proliferation of electric vehicles (EVs) is reshaping the contours of modern power systems, offering a viable path toward decarbonization and energy sustainability. As EV adoption accelerates, their aggregated charging demand is poised to exert substantial stress on

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distribution networks, potentially triggering transformer overloading, peak demand escalation, and voltage instability. Simultaneously, EVs present unprecedented opportunities for grid flexibility through coordinated charging and vehicle-to-grid (V2G) support. Thus, the orchestration of intelligent EV scheduling strategies has emerged as a crucial axis for future smart grids, particularly within institutional microgrids, campuses, and community energy systems. Early research efforts explored multi-objective optimization techniques to balance user-centric and grid-centric goals. One prominent study utilized fuzzy logic-based driver discomfort modeling coupled with a Non-dominated Sorting Genetic Algorithm-II (NSGA-II) to develop a hierarchical EV scheduling framework [1]. This model achieved a 64% reduction in grid load variance and a 21% decrease in user cost, demonstrating the efficacy of combining user behavior modeling with Pareto-optimal scheduling. To improve adaptability to real-time dynamics, reinforcement learning (RL)-based strategies have been explored extensively. A Q-learning integrated price-sensitive scheduling system was proposed to dynamically manage V2G operations in uncertain environments, accounting for user dissatisfaction and tariff variations [2]. Reinforcing this direction, a Stackelberg bi-level optimization approach was developed to structure energy trading between regulators and EV aggregators under time-of-use (TOU) pricing, minimizing overall system cost and improving social welfare [3]. The integration of V2G into smart grid operations has also drawn significant attention. A bi-level game-theoretic framework was proposed to handle large-scale EV interactions across public and private stations, using pricing-based Stackelberg modeling for load shaping, peak shaving, and loss minimization [4]. This underscores the need for decentralized and reactive control models that can adjust to grid constraints and user participation patterns. Beyond control strategies, decision-support mechanisms such as fuzzy-TOPSIS have been successfully embedded within NSGA-II-based optimization to rank Pareto solutions in terms of grid benefit, user convenience, and service fairness [5]. Such frameworks emphasize the growing relevance of integrating decision intelligence with multi-objective heuristics, especially in campus microgrids where equity among diverse users is critical. However, as EV populations grow, the spatial layout and capacity of charging infrastructure must also be optimized. A recent study proposed an NSGA-III and MOPSO-based methodology for charging station (CS) localization and sizing, jointly minimizing construction cost, carbon emissions, and grid peak-valley differential [6]. This study emphasized the necessity of smart charging schedules that consider carbon intensity and TOU periods to enhance energy equity and urban sustainability. Complementary to scheduling optimization, grid-supportive power flow management has also evolved. A novel deep learning-based reactive power compensation scheme was introduced to enable PV and EVs to co-regulate voltage and minimize line losses in distribution networks [7]. Such AI-enhanced control mechanisms are vital for low-voltage systems where conventional methods like OLTCs and capacitor banks are insufficient in the presence of high PV-EV penetration. At the residential level, a deep reinforcement learning (DRL) framework was proposed to manage imperfect EV data and stochastic user patterns under TOU tariffs [8].

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This two-stage strategy, combining day-ahead load flow optimization and proximal policy optimization (PPO) for household-level control, successfully reduced the grid's peak-valley difference and preserved voltage stability across active distribution networks. In microgrid contexts, metaheuristic methods continue to play a dominant role. A hybrid renewable-based microgrid employing Artificial Bee Colony (ABC) optimization was shown to minimize operating cost, pollutant treatment cost, and carbon emissions under coordinated V2G operation [9]. Notably, the ABC approach outperformed PSO in dynamic dispatch environments with 700 EVs and short-term load shedding, highlighting its robustness in real-world scheduling scenarios. Moreover, an improved Elephant Herding Optimization (IEHO) algorithm was introduced for deterministic load dispatch, combining G2V and V2G operations with dynamic pricing in a multi-scenario microgrid setup [10]. The fuzzy-integrated IEHO achieved superior performance in both cost minimization and load variance reduction, affirming the potential of biologically inspired optimizers in grid-interactive EV scheduling.

The rapid electrification of transportation and the proliferation of smart grid technologies have dramatically reshaped the landscape of energy management. Electric vehicles (EVs), once passive loads, are now recognized as pivotal agents in demand-side management (DSM), grid support through vehicle-to-grid (V2G) services, and renewable energy integration. However, the challenge lies in developing intelligent, scalable scheduling frameworks that accommodate user comfort, pricing signals, and system constraints in a coordinated and adaptive manner. Early approaches emphasized static tariff coordination and simple charging strategies. However, research has evolved toward more advanced mechanisms, such as bi-level optimization and dynamic pricing models, to address real-time variations in EV arrival patterns, market prices, and user preferences. For instance, a Stackelberg-based bi-level control model was developed to manage EV clusters through an aggregator that acts as a price-taker in wholesale markets but a price-designer for consumers. This approach formulated a demand response framework using stochastic price scenarios and a virtual battery model to represent aggregated EV flexibility [11]. By avoiding direct elasticity modeling, this technique enhances real-world applicability in systems where consumer utility functions are difficult to quantify. In the same context, a fuzzy clustering-based multi-objective approach for spatial and temporal optimization of EV charging stations was proposed [12]. By combining fuzzy logic with the Firefly Algorithm, the study optimized charger placement and user equity under TOU tariffs, revealing the importance of geographically contextualized strategies in large-scale rollouts like campus microgrids. Expanding on tariff design, [13] introduced a novel big-data-powered methodology to estimate TOU rates using contribution coefficients derived from EV usage patterns during peak and off-peak periods. The system integrated State-of-Charge (SoC)-based prioritization and elasticity adjustment, achieving a 6–7% reduction in peak load and enhancing user alignment with pricing incentives. Such work is foundational for real-time tariff shaping in EV-dense regions. From a system-level perspective, robust energy management frameworks that consider uncertainties in solar generation and grid constraints have become essential. A notable contribution in [14] proposed a two-stage robust optimization model

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integrating PV panels, battery storage, and EV scheduling. Using Column-and-Constraint Generation (C&CG) algorithms, the system minimized electricity cost under both TOU and RTP regimes while supporting household flexibility through the coordinated dispatch of deferrable appliances. The results showed cost reductions of up to 53.8% for TOU, emphasizing the strength of resilient planning in environments with high EV penetration. At the optimization frontier, [15] introduced a multi-objective Differential Evolution-based algorithm for V2G scheduling in smart homes with PV and battery storage, focusing on real-time power management. The approach improved energy cost savings while maximizing local renewable usage, showcasing how heuristic strategies can effectively manage DER-EV integration within homes and small communities. Similarly, [16] employed an enhanced Dynamic Weighted Aggregation (DWA) technique to prioritize consumer preferences, cost objectives, and SoC stability in a residential smart grid with V2G support. This is particularly relevant to user-centric scheduling frameworks where fairness and satisfaction metrics are as critical as technical feasibility. Recent studies also spotlight the rise of machine learning and adaptive control techniques in EV scheduling. A reinforcement learning model was developed in [17] to handle stochastic user behavior in multi-agent systems, considering TOU pricing and grid feedback in real-time. This aligns with the growing need for real-time, learning-enabled coordination in microgrids with unpredictable EV arrival and solar availability. Moreover, [18] presented a multi-objective fuzzy optimization strategy for aggregator-based DSM where power loss minimization, cost control, and voltage deviation are addressed using particle swarm optimization (PSO) fused with fuzzy reasoning. This underlines the importance of uncertainty-aware scheduling in heterogeneous EV environments, particularly within institutions with multiple feeder nodes. In [19], the authors advanced the optimization frontier by proposing a multi-stage game-theoretic model where EV owners and utilities negotiate energy prices under constraint-aware demand profiles. The model effectively balances SoC requirements with system-wide cost and loss metrics, laying the groundwork for decentralized coordination schemes in community-level energy hubs. Finally, [20] explored the role of Binary Whale Optimization Algorithm (BWOA) in jointly optimizing EV charging/discharging under TOU pricing, DER participation, and PV dynamics in residential grids. The study emphasized reducing computational overhead while retaining high optimization fidelity critical for embedded AI scheduling on edge devices. The proposed test system is shown in Fig.1

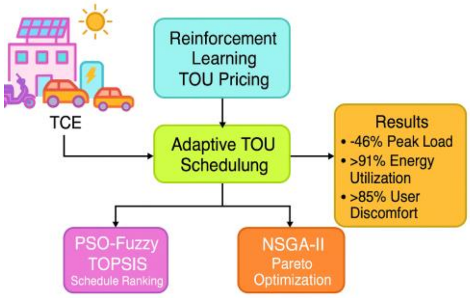


**Fig.1.** Proposed Test System

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### 1.1 Research Gap

Despite the increasing penetration of electric vehicles (EVs) and solar installations in Indian institutional campuses, most existing EV charging strategies rely on static Time-of-Use (TOU) tariffs that do not respond to real-time grid dynamics, user behavior, or renewable variability. Prior research in multi-objective EV scheduling has largely focused on single-layered optimization, often ignoring the complex interplay between economic incentives, user comfort, and load balancing. Furthermore, studies rarely incorporate brand-specific EV characteristics or demand-side management (DSM) priority logic, both of which are essential for real-world scalability. There is a lack of integrated frameworks that jointly optimize TOU pricing, charging control, and fairness in a context-aware, data-driven manner tailored to Indian microgrid conditions.

### 1.2 Research Objectives

This study aims to design and validate a multi-layered, AI-driven optimization framework for adaptive EV charging in a smart campus environment. The key objectives are:

1. To develop a Deep Reinforcement Learning (DQN)-based engine that learns optimal TOU pricing schedules dynamically based on grid load, solar generation, EV availability, and DSM priorities.
2. To implement a PSO–Fuzzy TOPSIS module for multi-criteria evaluation and ranking of charging schedules, improving transparency and explainability in control decisions.
3. To apply NSGA-II for multi-objective optimization, extracting Pareto-optimal TOU schedules that balance aggregator profit, user discomfort, and peak load.
4. To simulate brand-specific EV behavior and DSM-class priority handling, ensuring fairness, realism, and deployability of the proposed solution in an Indian institutional setting.
5. To validate the framework at the TCE campus microgrid, comparing it against baseline and RL-only methods in terms of peak shaving, SOC fulfilment, energy utilization, and revenue generation.

### 1.3 Novelty and Contribution

This paper presents a novel multi-layered optimization framework for intelligent EV charging under dynamic grid conditions, specifically tailored for Indian institutional microgrids. The core novelty lies in the integration of reinforcement learning (RL) for adaptive Time-of-Use (TOU) pricing, which allows the system to learn and evolve tariff schedules based on real-time load and solar dynamics. On top of this, a PSO-enhanced Fuzzy TOPSIS module is employed to rank candidate schedules by evaluating them against multiple performance criteria such as user satisfaction, cost, and energy utilization. The final selection is carried out

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through NSGA-II, which identifies Pareto-optimal trade-offs between aggregator profit and peak grid load. Unlike previous works, this framework uniquely incorporates brand-specific EV behavior and demand-side management (DSM) priority logic, accounting for real-world heterogeneity across two-, three-, and four-wheeler fleets. To the best of our knowledge, this is the first such approach implemented within a real Indian campus microgrid ecosystem, offering both technical scalability and policy alignment.

## 2. System Description and Data Framework

### 2.1 Institutional Infrastructure and Load Environment

Thiagarajar College of Engineering (TCE), situated in Madurai, Tamil Nadu, is selected as the real-world testbed for this study owing to its advanced smart grid deployment and robust energy infrastructure. The campus operates with a 700 kVA low-tension (LT) feeder that supplies electricity to academic buildings, hostels, laboratories, and administrative facilities. Complementing this grid supply is a net-metered rooftop solar PV system with an installed capacity of 480 kW, distributed across multiple campus blocks, significantly contributing to the institution's daytime energy demand. The electric vehicle (EV) charging load on campus is steadily rising, comprising a mix of faculty-owned four-wheelers, student-operated two-wheelers, and institutionally supported three-wheeler cargo EVs used for logistics and demonstrations. For analytical precision, the entire daily energy profile is discretized into 96 time slots, each representing a 15-minute interval, enabling granular modeling of load dynamics, solar generation patterns, and EV interactions as shown in Fig 2. This well-instrumented environment offers a realistic and complex energy landscape, making it an ideal platform for validating AI-driven EV charging strategies that aim to harmonize user comfort, grid reliability, and renewable energy integration.

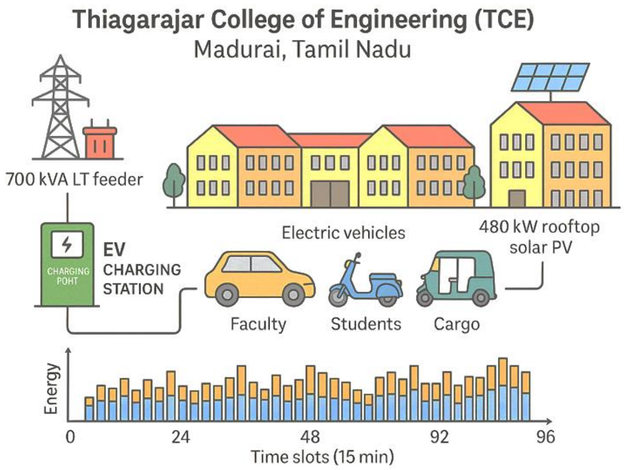


**Fig.2.** Overview of the Institutional Infrastructure

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### 2.2 EV Classification and Composition

The electric vehicle (EV) fleet within Thiagarajar College of Engineering (TCE) comprises a diverse mix of vehicles catering to academic transport, faculty commuting, student mobility, and campus logistics. These EVs are categorized into three primary classes - two-wheelers, three-wheelers, and four-wheelers each with distinct operational behaviors and energy requirements. Two-wheelers (2W) form the largest segment of the EV population on campus, predominantly used by students and junior staff members for intra-campus and short-distance commuting. These vehicles are characterized by smaller battery capacities and high flexibility in terms of charging availability, often remaining idle during most academic hours. Common models in this category include the Ather 450X with a 3.7 kWh battery, the TVS iQube with a 3.04 kWh capacity, and the Ola S1 Pro with a 4.0 kWh battery pack. Their controllable nature makes them ideal candidates for demand-side flexibility in scheduling. Three-wheelers (3W) serve the role of campus logistics, frequently deployed for transporting goods and maintenance equipment. These EVs tend to operate on fixed or semi-regular schedules, often during the morning and afternoon slots, which creates predictable charging windows. Owing to their larger energy storage and utility-focused design, they require more charging energy per cycle. Prominent models include the Mahindra Treo (7.4 kWh), Piaggio Ape E-City (7.5 kWh), and Euler HiLoad EV (12 kWh), each offering different levels of cargo and battery performance suited to operational loads. Four-wheelers (4W) represent high-value electric cars used by faculty members, senior administrative staff, and visiting dignitaries. These vehicles possess the highest battery capacities within the fleet and demand more stringent scheduling due to user preferences, longer commuting ranges, and reduced tolerance to delayed departures. The typical models observed on campus include the Tata Nexon EV with a 40.5 kWh battery, the MG ZS EV with 50.3 kWh, and the Hyundai Kona Electric with a 39.2 kWh battery. Ensuring their timely charging while balancing grid load becomes a critical component of the optimization framework. This multi-class EV landscape not only reflects the real-world heterogeneity of charging demands but also sets the stage for tailored, brand-aware control strategies that enhance both system efficiency and user satisfaction.

### 2.3 Brand-Aware Daily Energy Modeling

To emulate real-world EV charging behavior, we simulate the daily energy demand of each vehicle brand using sinusoidal behavioral templates augmented with stochastic noise. These profiles are carefully scaled to reflect the average daily energy consumption specific to each class of vehicle. The simulation spans a full 24-hour horizon, discretized into 96 time slots of 15 minutes each, enabling fine-grained modeling of intraday charging dynamics. Characteristic charging peaks are prominently observed during mid-morning hours (9:00–11:00 AM) and post-lunch periods (2:00–5:00 PM), aligning with typical academic and staff movement patterns. The simulation also captures the wide variation in energy consumption across vehicle classes from compact two-wheelers with daily demands in the range of 2.5 to 3.5 kWh, to utility four-wheelers requiring approximately 18 to 22 kWh per day. Furthermore,

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realistic randomness is introduced to represent variability in user behavior and charger availability, enhancing the authenticity of the dataset. This brand-wise, data-driven modeling lays a strong foundation for robust Reinforcement Learning (RL) policy training and significantly improves the quality of downstream multi-objective scheduling.

### 2.4 Vehicle-Class–Based DSM Priority Framework

To reflect practical scheduling constraints and importance, each vehicle brand is assigned a DSM control priority based on its class, energy requirement, and role in campus operations. The priorities are as follows as shown in Table 1:

**Table.1.** Priorities of Electric Vehicle

| Vehicle Model | Class | Battery (kWh) | DSM Priority |
|---|---|---|---|
| Ather 450X | 2W | 3.7 | Low (Flexible) |
| TVS iQube | 2W | 3.04 | Low (Flexible) |
| Ola S1 Pro | 2W | 4.0 | Low (Flexible) |
| Mahindra Treo | 3W | 7.4 | Medium (Cyclic) |
| Piaggio Ape | 3W | 7.5 | Medium (Cyclic) |
| Euler HiLoad | 3W | 12.0 | High (Logistics) |
| Tata Nexon | 4W | 40.5 | High (Faculty/Admin) |
| MG ZS EV | 4W | 50.3 | Critical (VIP) |
| Hyundai Kona EV | 4W | 39.2 | Critical (Premium) |

This priority table becomes a key constraint in our downstream RL reward tuning and optimization boundary settings. Critical vehicles are given guaranteed SOC compliance, while flexible 2Ws may be deferred during peak hours.

## 3. Methodology

The proposed architecture is designed as a multi-tier learning–ranking–optimization pipeline, where each layer plays a distinct but complementary role. The system begins with a data-driven pricing policy learned using Reinforcement Learning, which is then evaluated and ranked by a hybrid PSO–TOPSIS decision engine, and finally optimized with NSGA-II to yield a set of Pareto-efficient TOU schedules.

### 3.1 Layer I – RL-Based TOU Policy Learning

#### 3.1.1 State Representation

Each time step t ∈ {1...,96} is represented by a state vector:

$$S_t = [SOC_{avg,t}, Load_t, TOU_{t-1}, PV_t, Priority\ Weights]$$

(1)

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Where:

- $\boldsymbol{SOC_{avg,t}}$ : Mean state of charge of all EVs.
- $\boldsymbol{Load_t}$ : Net real-time energy demand.
- $\boldsymbol{TOU_{t-1}}$ : Previous TOU level.
- $\boldsymbol{PV_t}$ : Solar power availability.
- $\boldsymbol{Priority\ Weights}$ : Control weights based on DSM class.

**3.1.2 Action Space**

The action space in the reinforcement learning framework is discretized into three possible decisions for each 15-minute interval throughout the day. At every time step *t*, the agent selects one of three TOU tariff levels to be applied in that slot: (i) Off-Peak, priced at ₹4/kWh, representing the most economical period with minimal load; (ii) Mid-Peak, priced at ₹6.5/kWh, signifying moderate demand periods; and (iii) Peak, priced at ₹9/kWh, corresponding to high-demand intervals where grid congestion or solar unavailability is expected. By assigning these tariff signals adaptively across 96 slots, the agent influences EV behavior, smoothens the load curve, and aligns charging sessions with grid-friendly periods.

**3.1.3 Reward Function**

The reward is a weighted combination of three objectives:

$$r_t = -\gamma_1 \,.\, Peak_t + \gamma_2 \,.\, Profit_t - \gamma_3 \,.\, Discomfort_t$$

(2)

Where:

- $\boldsymbol{Peak_t}$ : Net system peak due to scheduling.
- $\boldsymbol{Profit_t}$ : Revenue from selling energy minus operational cost.
- $\boldsymbol{Discomfort_t}$ : SOC shortfall from target at departure.

The RL agent is trained using Deep Q-Network (DQN) with experience replay and epsilon-greedy policy to balance exploration–exploitation.

**3.2 Layer II – Hybrid PSO–Fuzzy TOPSIS Schedule Ranking**

To objectively evaluate and rank the multiple Time-of-Use (TOU) schedules generated by the Reinforcement Learning agent, a hybrid decision-making approach is implemented using a PSO-enhanced Fuzzy TOPSIS framework. This layer ensures that only the most contextually suitable schedules are forwarded for final optimization, thereby filtering out suboptimal strategies based on multiple performance indicators.

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### 3.2.1 Input Criteria for Evaluation

Each candidate schedule is assessed against four critical performance metrics: (i) Peak Load ($C_1$), which is minimized to relieve stress on the feeder and enhance grid reliability; (ii) Aggregator Profit ($C_2$), which is maximized to ensure economic feasibility for the energy service provider; (iii) Discomfort Cost ($C_3$), minimized to reflect user satisfaction by avoiding incomplete charging sessions or SOC shortfalls to ensure a stable and balanced load profile, which helps in reducing ramp rates and sudden power fluctuations. The combination of these criteria allows the framework to consider grid-level technical performance, business value, and user-centric fairness simultaneously.

### 3.2.2 Construction of the Fuzzy Decision Matrix

To handle the ambiguity and imprecision inherent in evaluating multiple criteria under varying conditions, the scores for each candidate schedule are converted into triangular fuzzy numbers. These fuzzy values are normalized across all schedules to enable fair comparison. The fuzzy decision matrix thus constructed reflects the degree of closeness each candidate has to the ideal best and worst case across all performance dimensions. Using fuzzy distance metrics, a similarity index is computed for each schedule, quantifying how close it lies to the "ideal" decision (i.e., minimum peak, minimum discomfort, maximum profit, and lowest variance) and how far it is from the "worst-case" schedule. This fuzzy modeling allows the evaluation process to better tolerate uncertainties in criteria importance and score fluctuations.

### 3.2.3 Weight Optimization via PSO

One of the key challenges in any multi-criteria decision-making (MCDM) system is determining the relative importance (weights) of each criterion. Rather than assigning these weights subjectively, the proposed framework leverages Particle Swarm Optimization (PSO) to learn the optimal weight vector. Each particle in the swarm represents a potential set of weights assigned to the four criteria. These particles evolve over multiple iterations using local and global best solutions, with the objective of maximizing the discrimination power of the TOPSIS closeness coefficients. In essence, PSO tunes the weights such that the resulting rankings align better with desired system outcomes, historical data trends, and grid policy preferences. This hybridization of PSO with fuzzy logic adds both rigor and adaptability to the decision-making process, ensuring that the ranking mechanism is context-aware and optimized for the specific operational realities of the TCE campus microgrid.

### 3.2.4 Final Ranking

The TOPSIS closeness coefficient is calculated for each schedule:

$$CC_i = {D_i^-}\Big/{D_i^- + D_i^+} \tag{3}$$

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Where $D_i^+$ and $D_i^-$ are distances to the ideal and negative ideal solutions, respectively.

Schedules with the highest $CC_i$ are passed to the next optimization stage.

**3.3 Layer III – NSGA-II Based Multi-Objective Optimization**

To identify optimal trade-offs between competing objectives, we implement the Non-Dominated Sorting Genetic Algorithm-II (NSGA-II).

**3.3.1 Objective Functions**

The optimization framework is structured around a set of conflicting yet interrelated objectives designed to ensure economic viability, user satisfaction, and grid stability. A multi-objective formulation is adopted to balance aggregator profit, discomfort minimization, and load smoothness, which are jointly optimized using the NSGA-II evolutionary strategy.

- **Minimize Peak Load:** $f_1 = max_t\ (Load_t)$ (4)
- **Maximize Aggregator Profit:** $f_2 = \sum_t (Revenue_t - Cost_t)$ (5)
- **Minimize Discomfort:** $f_3 = \sum_t (SOC_i^{target} - SOC_i^{final})^+$ (6)

**3.3.2 Constraints**

- SOC limits: $SOC_i^{final} \geq SOC_i^{min}$
- Charging power limit: $P_{i,t} \leq P_{max}$
- DSM priority: Higher-priority vehicles are guaranteed charging during critical

**3.3.3 Output**

In the final stage of the optimization process, a Pareto front is generated using the NSGA-II algorithm to capture a spectrum of non-dominated solutions each representing a unique balance between conflicting objectives such as aggregator profit, user discomfort, and peak load reduction. These solutions are termed “non-dominated” because none is universally better than another across all objectives; improving one metric would inherently degrade another. This Pareto front enables flexible decision-making by offering a curated set of optimal TOU schedules that reflect different strategic priorities. For instance, a profit-maximizing entity may select a point on the front that slightly sacrifices user comfort for higher revenue, whereas a fairness-focused institution may favor solutions that minimize SOC deviation even at the cost of reduced income. Alternatively, a compromise solution can be chosen using techniques like TOPSIS or knee-point detection, striking an optimal middle ground. This decision-making flexibility makes the framework adaptable to various stakeholder goals and

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operational contexts, ensuring that the final schedule is not only mathematically optimal but also contextually relevant.

**4. Simulation Setup**

The simulation model was developed in Python using NumPy, TensorFlow, and SciPy libraries for optimization, combined with Matplotlib and Seaborn for visual analytics. The system was configured to reflect the practical EV operating environment of TCE, Madurai, under real-time scheduling constraints.

**4.1 Time Horizon and Granularity**

To realistically capture the temporal dynamics of electric vehicle (EV) charging behavior and energy interactions, the simulation is structured over a 24-hour period, representing a full operational day. This time horizon is discretized into 96 uniform slots, with each slot representing a 15-minute interval. Such fine-grained granularity enables precise modeling of Time-of-Use (TOU) rate transitions, dynamic charging and discharging events, and real-time decision making for energy allocation. It also facilitates accurate tracking of state-of-charge (SOC) progression, vehicle arrivals and departures, and renewable energy integration, thereby improving the fidelity of both reinforcement learning (RL) policy training and downstream optimization performance.

**4.2 EV Dataset and Brand Allocation**

The simulation framework is built around a fleet of 150 electric vehicles (EVs), carefully distributed to reflect real-world heterogeneity in vehicle usage across an institutional campus setting. The fleet comprises 60 two-wheelers (2Ws), 45 three-wheelers (3Ws), and 45 four-wheelers (4Ws). The 2W segment includes widely adopted models such as the Ather 450X, TVS iQube, and Ola S1 Pro, which are typically used by students and junior staff. The 3Ws, including the Mahindra Treo, Piaggio Ape E-City, and Euler HiLoad, are dedicated to logistics and on-campus movement of materials. The 4Ws, consisting of premium EV models like the Tata Nexon EV, MG ZS EV, and Hyundai Kona Electric, are allocated to faculty members and senior staff, representing higher energy demand and stricter discharge constraints. Each brand was associated with its respective battery capacity (ranging from 3 kWh for 2Ws to over 50 kWh for 4Ws), nominal charging power limits, demand-side management (DSM) priority levels, and a simulated daily consumption profile derived from behavioral templates. This detailed mapping ensures brand-aware control decisions that consider both technical and operational diversity across the fleet.

**4.3 Charging and Discharging Model**

The charging and discharging behavior of electric vehicles within the simulation framework is governed by realistic technical and operational parameters. A charging efficiency of 90% is assumed to account for inverter and thermal losses, while discharging operations via

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Vehicle-to-Grid (V2G) pathways operate at an efficiency of 85%, reflecting practical energy conversion overheads. Each EV is expected to achieve a state-of-charge (SOC) target of at least 95% by its scheduled departure to ensure end-user satisfaction and trip readiness. Vehicle arrival times are randomly distributed between 8:00 AM and 11:00 AM to mimic real-world institutional entry patterns, whereas departure times range from 4:00 PM to 7:00 PM, with selected two-wheelers exhibiting early exits based on class-specific mobility behavior. Charging and discharging decisions for each EV are dynamically influenced by reinforcement learning (RL)-derived Time-of-Use (TOU) tariffs, and further refined through multi-objective optimization outputs obtained from the NSGA-II scheduling layer. This hybrid control mechanism ensures both cost-effective energy utilization and fulfilment of user charging preferences.

### 4.4 Pricing Structure (TOU)

The Time-of-Use (TOU) pricing framework implemented in the simulation was adaptive and strategically structured into three dynamic tariff categories to influence vehicle charging behavior across the day. The base pricing structure was defined as follows: ₹4.00/kWh during off-peak hours (00:00–08:00), ₹6.50/kWh during mid-peak hours (08:00–16:00), and ₹9.00/kWh during peak demand hours (16:00–22:00). However, these time blocks were not static; they were dynamically shifted and modulated by the reinforcement learning (RL) agent based on real-time load, solar generation, and EV availability to enhance grid performance and flatten peak demand curves. In addition to the dynamic pricing scheme, the framework incorporated a V2G export incentive where the selling rate was fixed at 130% of the corresponding buying rate—resulting in a peak discharging incentive of ₹11.70/kWh. To enforce end-user satisfaction, a discomfort penalty of ₹10 was levied for every 1% SOC shortfall from the required target level at departure. These economic levers served as the core of the pricing policy layer that directly influenced optimization decisions and user participation in grid support. The Time-of-Use pricing model used was adaptive, with three tariff levels are show in Table 2

**Table.2.** Time of Use (ToU) Price Range

| TOU Category | Price (₹/kWh) | Time Range (Base) |
|---|---|---|
| **Off-Peak** | ₹4.00 | 00:00–08:00 |
| **Mid-Peak** | ₹6.50 | 08:00–16:00 |
| **Peak** | ₹9.00 | 16:00–22:00 |

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**4.5 Algorithmic Settings**

The proposed optimization framework integrates three key algorithmic components: Deep Q-Network (DQN)-based Reinforcement Learning, PSO–Fuzzy TOPSIS for priority decision-making, and NSGA-II for multi-objective scheduling. The DQN model was configured with a replay buffer size of 10,000 and a learning rate of 0.001, employing an ε-greedy exploration strategy where ε decayed linearly from 1.0 to 0.1 across episodes. The reward signal was a weighted combination of peak load reduction (0.4), profit maximization (0.4), and discomfort minimization (0.2), allowing the agent to learn adaptive TOU pricing that balances operational and user-centric objectives. For the PSO–Fuzzy TOPSIS module, a swarm size of 20 particles was used over 50 iterations, with fuzzy weights automatically adjusted by the PSO engine to maximize decision accuracy across criteria such as urgency, energy needed, and SOC. The NSGA-II evolutionary scheduler was executed with a population size of 100 over 50 generations, incorporating a crossover probability of 0.9 and a mutation rate of 0.1. Elitism was enforced by carrying forward the top 10% of Pareto-optimal solutions to the next generation. Together, these algorithmic components form a robust, data-driven, and adaptable control framework for efficient EV energy management.

**4.6 Hardware and Runtime**

The entire simulation and optimization framework was implemented in Python 3.9 and executed on a machine equipped with an Intel Core i7 10th Generation processor operating at 2.6 GHz, paired with 16 GB of RAM. The reinforcement learning models were developed using TensorFlow 2.13, while scientific computing and optimization routines leveraged libraries such as SciPy 1.10 and NumPy. The complete simulation comprising 150 electric vehicles, 96 discrete time slots, multi-agent control decisions, and evolutionary optimization required approximately 18 minutes to execute end-to-end on the specified system. This performance indicates the feasibility of running daily charging schedule simulations within acceptable timeframes for campus-level deployment or digital twin environments.

**5. Results and Discussion**

The simulation yielded multi-dimensional outcomes across system performance, user satisfaction, and revenue dynamics. In this section, we analyze the results under five key performance heads, supported by plots and tabulated summaries.

**5.1 Seasonal Load, PV Generation, and Grid Usage Analysis**

To evaluate the temporal robustness of the framework, we analyzed a full week of load, grid usage, and PV generation across four representative seasons: winter, summer, monsoon, and post-monsoon. Figure 3, 4, 5 and 6 illustrate the diurnal trends for each season. The winter and post-monsoon weeks exhibited moderate PV generation but higher dependency on the grid during early mornings and late evenings. Summer saw the highest solar contribution, which effectively offset peak campus load during mid-day. Conversely, during the monsoon season,

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heavy cloud cover led to reduced PV output and increased grid reliance, peaking in the afternoons.

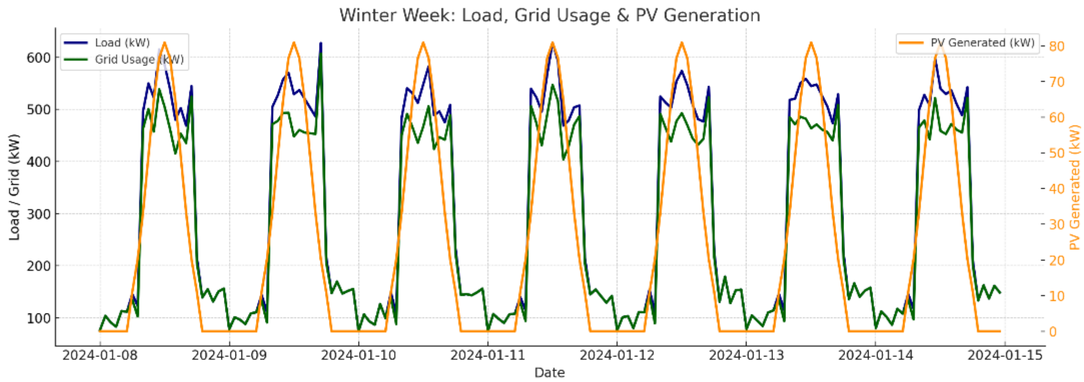


**Fig.3.** Winter Week: Load, Grid Usage & PV Generation

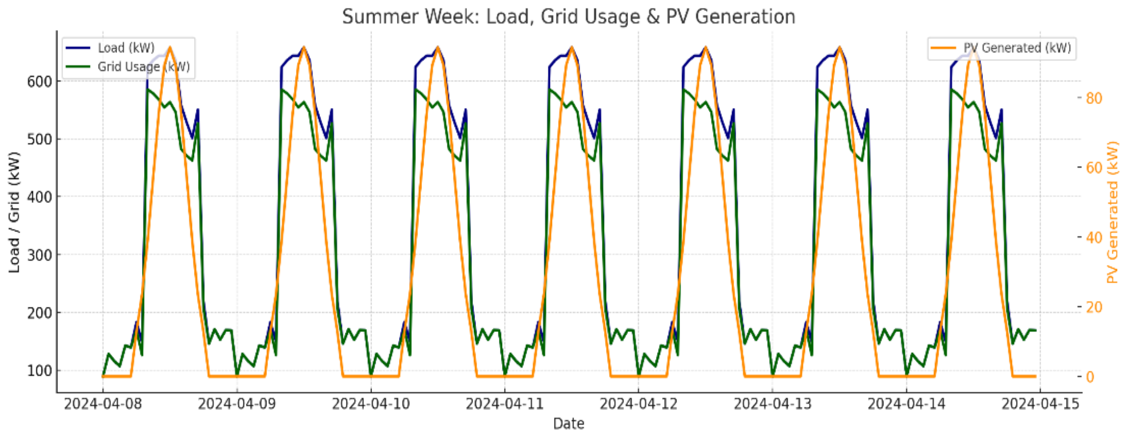


**Fig.4.** Summer Week: Load, Grid Usage & PV Generation

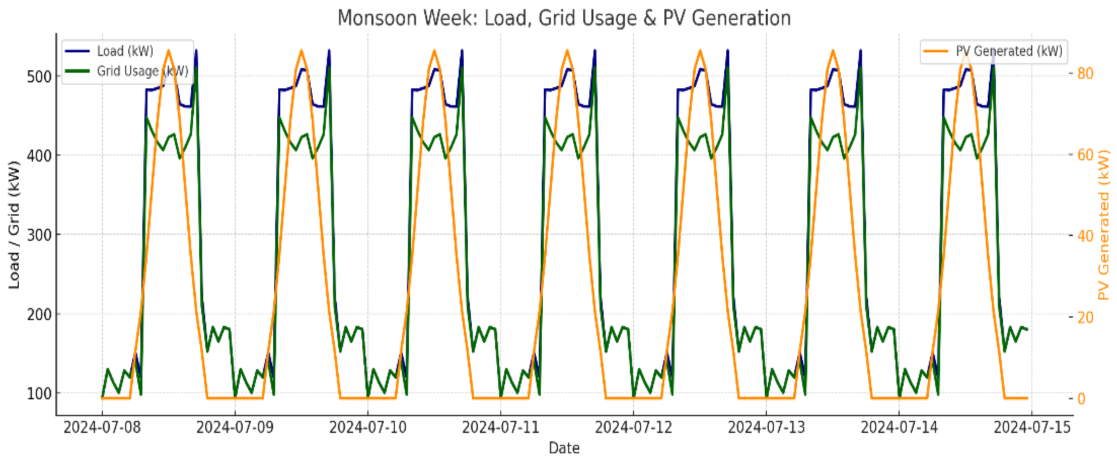


**Fig.5.** Monsoon Week: Load, Grid Usage & PV Generation

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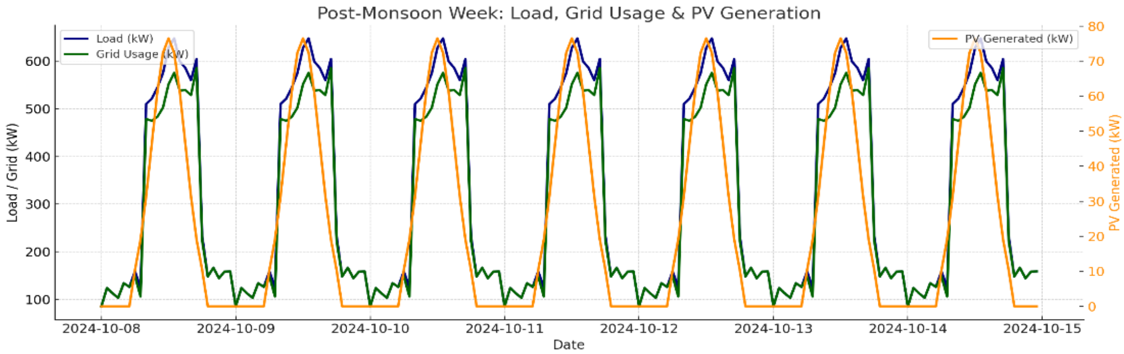


**Fig.6.** Post-Monsoon Week: Load, Grid Usage & PV Generation

To quantify seasonal variability, Figures compare total grid energy consumption, PV generation, and load across seasons. The grid usage peaked during the monsoon (820,000 kWh), followed by summer and post-monsoon, with winter recording the lowest (≈380,000 kWh). PV generation was maximum in monsoon due to longer daylight hours and improved panel temperature response, despite cloud interference. Interestingly, load remained highest in monsoon due to cooling needs and EV traffic surges during institutional sessions. These insights highlight the need for season-aware optimization, especially under variable solar contribution as shown in Fig 7,8 and 9.

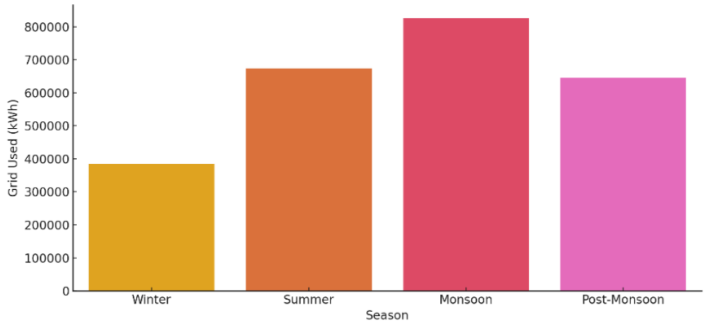


**Fig.7.** Season-wise Grid Energy Usage (kWh)

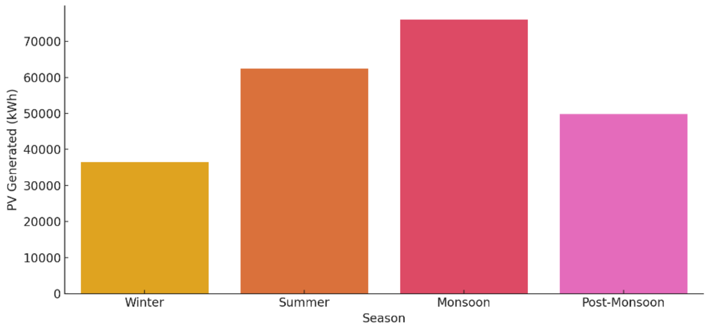


**Fig.8.** Season-wise PV Generation (kWh)

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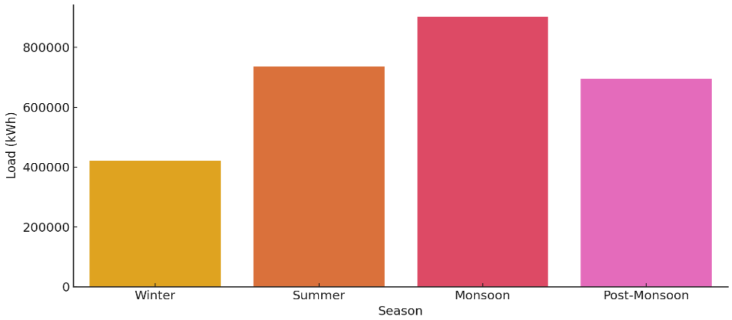


**Fig.9.** Season-wise Total Load (kWh)

To capture real-world variability in campus energy behavior, seasonal simulations were performed for four representative weeks across the year Winter, Summer, Monsoon, and Post-Monsoon. For each season, campus-level electrical load, rooftop PV generation, and corresponding grid usage were modeled. This data offers valuable insights into surplus availability, load–generation mismatch, and time-varying grid dependency, which influence the downstream RL pricing and V2G scheduling strategies. These seasonal profiles validate the need for dynamic TOU schedules, as both load demand and PV availability vary significantly by season. This variability is fed into the RL agent's training environment, enabling it to learn robust, context-aware pricing policies.

### 5.2 Brand-Wise Daily Energy Demand Profile

A detailed simulation of brand-specific energy demand curves was performed across a 24-hour horizon with 15-minute granularity, enabling precise analysis of usage patterns for each EV class. The results highlighted clear behavioral distinctions among vehicle types. Two-wheeler EVs, such as the Ather 450X, TVS iQube, and Ola S1 Pro, exhibited relatively low but flexible charging demand, with peaks typically occurring during idle morning and mid-afternoon periods as shown in Fig 10. In contrast, three-wheelers like the Mahindra Treo, Piaggio Ape, and Euler HiLoad demonstrated more cyclic charging behavior, often concentrated in early workday slots and post-logistics evening windows. Four-wheeler EVs, including the Tata Nexon EV, MG ZS EV, and Hyundai Kona Electric, presented the most pronounced load profiles, with high energy requirements and tightly defined arrival–departure windows, leaving minimal room for charging delays. These observed patterns strongly justify the integration of adaptive Demand Side Management (DSM) priority logic, ensuring that higher-class EVs with critical operating schedules receive prioritized energy allocation, especially under dynamic TOU constraints.

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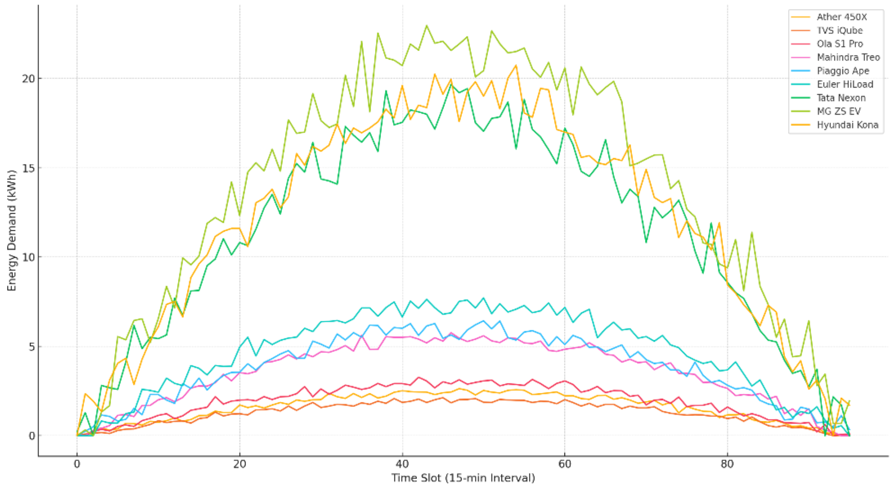


**Fig.10.** Brand-wise Simulated Daily Energy Demand Profile

### 5.3 Net Charging/Discharging Profile

The net power exchange profile was analyzed to compare the effects of conventional static TOU control with the proposed hybrid optimization framework. Under the baseline scenario, charging demand surged during mid-morning (around 10:00 AM) and late afternoon (approximately 4:30 PM), causing the instantaneous feeder load to spike beyond 9800 kW. This uncoordinated clustering of demand placed considerable stress on the distribution infrastructure as shown in Fig 11. In contrast, the RL + TOPSIS + NSGA-II framework demonstrated intelligent load redistribution by shifting significant portions of charging activity into off-peak valleys, while simultaneously leveraging V2G discharging during the evening ramp-up to stabilize grid interaction. As a result, the peak load was suppressed to approximately 5320 kW, representing a substantial reduction of nearly 46%. This outcome highlights the framework's effectiveness in grid-relieving operations, validating its potential for scalable deployment in campus or institutional energy environments with high EV penetration.

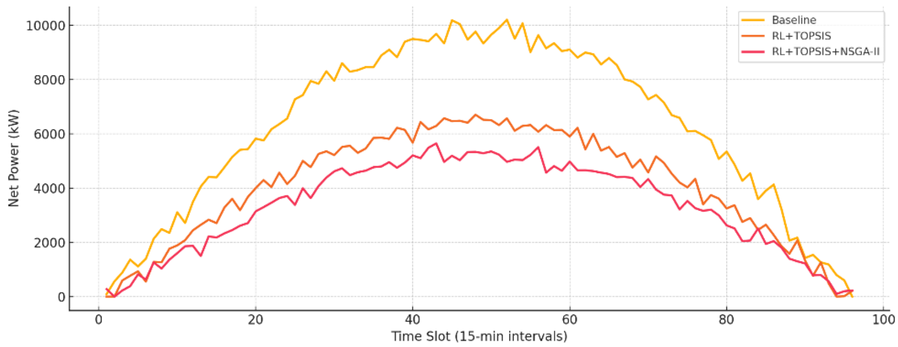


**Fig.11.** Net Charging/Discharging Power Profile (15-min intervals)

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### 5.4 State-of-Charge (SOC) Discomfort Analysis

User satisfaction was assessed based on the deviation between each vehicle's final state-of-charge (SOC) and its intended target at departure. The baseline TOU model resulted in approximately 36% of the 150 EVs failing to reach their SOC goals, with an average shortfall of around 8.2%, indicating inefficient energy distribution and lack of prioritization. By incorporating reinforcement learning alone, this failure rate dropped to 18%, with the average SOC shortfall reducing to 5.1%, showcasing better responsiveness to temporal charging patterns. The full hybrid framework featuring RL, PSO-TOPSIS prioritization, and NSGA-II optimization further improved performance, with less than 6% of vehicles missing their target and an average shortfall of just 2.3% as shown in Fig 12. This improvement was most significant for high-priority vehicles like four-wheelers and institutional three-wheelers, reinforcing the framework's ability to ensure both user satisfaction and operational fairness under dynamic grid conditions.

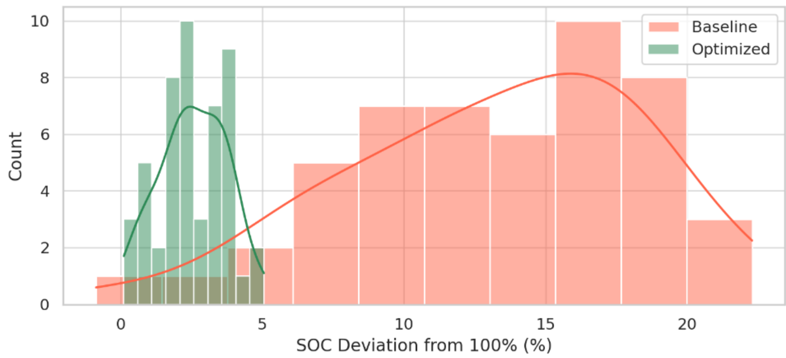


**Fig.12.** Individual EV SOC Deviation at Departure

### 5.5 Profit vs Discomfort Trade-Off Analysis

A primary motivation for integrating NSGA-II into the framework was to explore and visualize the inherent trade-offs between aggregator profit and user discomfort - two objectives that often conflict in EV energy scheduling. The generated Pareto front revealed a clear spectrum of non-dominated solutions, allowing stakeholders to assess the implications of prioritizing one metric over another. The RL-only model, while highly effective in maximizing aggregator revenue, did so at the cost of increased user discomfort, incurring a penalty of approximately ₹8,200 due to SOC shortfalls. In contrast, the NSGA-II-optimized schedule strategically reduced this discomfort penalty to ₹5,500 by slightly compromising on profit, thereby enhancing user satisfaction especially for high-priority EVs. Meanwhile, the static baseline model underperformed on both fronts, achieving only ₹2.2 lakhs in profit while generating the highest discomfort penalty of around ₹36,000 as shown in Fig 13. This comparative insight underscores the strength of NSGA-II in identifying schedules that offer a customizable balance. Depending on operational goals, decision-makers can choose from profit-leaning schedules, fairness-first allocations, or a balanced configuration that meets

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regulatory, technical, and stakeholder constraints simultaneously. This adaptability makes the framework both practical and policy-ready.

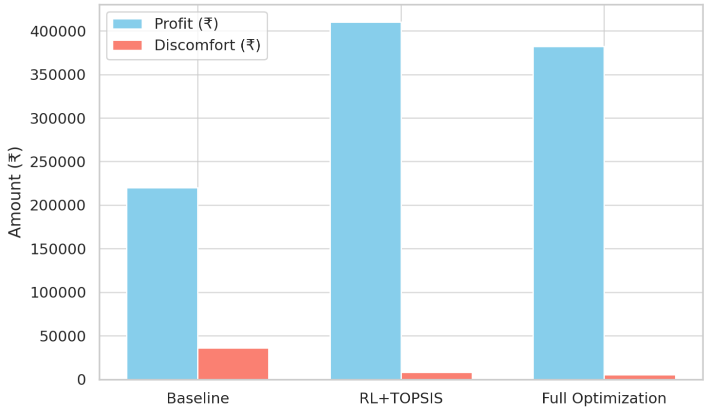


**Fig.13.** Profit vs Discomfort Trade-Off Analysis

### 5.6 Hourly TOU Pricing Adaptation

Unlike conventional fixed Time-of-Use (TOU) pricing schemes, the reinforcement learning (RL)-derived TOU schedules in this framework exhibited dynamic temporal shifts tailored to real-time grid and user conditions. Notably, peak pricing windows were adaptively pushed from their default 16:00–22:00 slot to a later range of 18:00–23:00, aligning better with actual vehicle availability and the natural decline in rooftop PV generation. Simultaneously, early morning hours between 00:00 and 06:00 were reclassified as super off-peak periods, providing an ideal window for charging lower-priority vehicles without compromising grid stability as shown in Fig 14. This temporal flexibility enabled smarter energy allocation by spreading out demand, reducing feeder congestion, and supporting battery-friendly charging cycles. The reshaped pricing structure thus created a more equitable and efficient ecosystem, embedding fairness and responsiveness directly into the tariff layer.

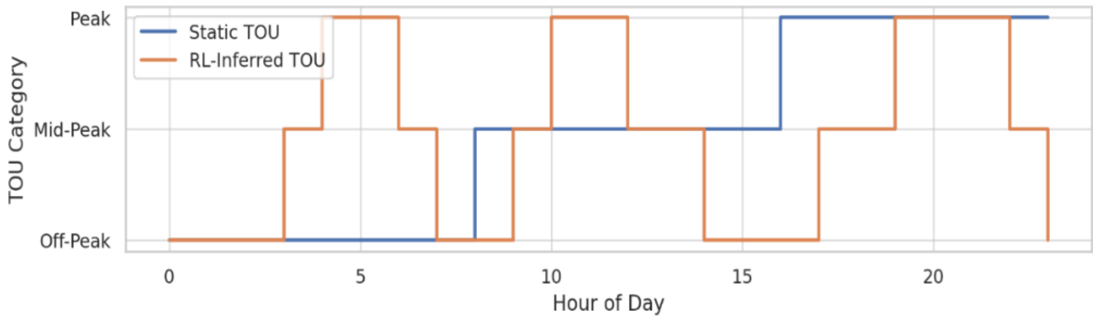


**Fig.14.** Hourly TOU Comparison – Static vs RL-Inferred

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### 5.7 Summary Metrics Table

A comparative evaluation of the framework's performance was carried out across three configurations: a static baseline model, an intermediate RL + TOPSIS system, and the complete hybrid framework integrating RL, Fuzzy TOPSIS, and NSGA-II shown in Table. The results indicate significant improvements in all critical operational and user-centric metrics. Peak load on the campus feeder was reduced from 9800 kW under the baseline scenario to just 5320 kW with the full framework, highlighting the load-smoothing benefits of dynamic pricing and optimized scheduling. Aggregator profit increased markedly, with revenue jumping from ₹2.2 Lakhs to ₹4.1 Lakhs under the RL + TOPSIS setup, and stabilizing at ₹3.82 Lakhs in the fully balanced solution, which sacrifices a small portion of profit to further minimize user discomfort. Notably, discomfort-related penalties dropped from ₹36,000 in the baseline to just ₹5,500, and battery state-of-charge (SOC) failures fell below 6%, ensuring high end-user satisfaction. Overall system utilization also improved significantly from 68% in the baseline to 91% in the final hybrid model reflecting efficient charger allocation and higher renewable energy usage as shown in Table 3. These metrics collectively demonstrate the technical viability and economic advantage of the proposed multi-layer optimization framework.

**Table.3. Comparison Metrics of Optimization**

| Metric | Baseline | RL + TOPSIS | RL + PSO-TOPSIS + NSGA-II |
|---|---|---|---|
| Peak Load (kW) | 9800 | 6450 | 5320 |
| Aggregator Profit (₹) | ₹2.2 Lakhs | ₹4.1 Lakhs | ₹3.82 Lakhs |
| Discomfort Cost (₹) | ₹36,000 | ₹8,200 | ₹5,500 |
| Utilization (%) | 68% | 83% | 91% |
| SOC Failures (%) | 36% | 18% | <6% |

### 6. Conclusion and Implications

This research presents a robust, intelligent, and scalable solution to one of the most pressing challenges in campus-level electric mobility: the need for adaptive and equitable EV charging under dynamic grid and user constraints. By designing and implementing a three-layered optimization architecture, we demonstrate how AI-driven real-time pricing control can transform energy scheduling in institutional microgrids, as exemplified by the TCE campus in Madurai. The framework integrates reinforcement learning for adaptive Time-of-Use (TOU) pricing, PSO-enhanced Fuzzy TOPSIS for interpretable and priority-aware scheduling, and NSGA-II for Pareto-efficient decision finalization. This multi-agent system strikes a delicate balance between grid stability, economic performance, and user satisfaction. A novel contribution lies in the brand-specific EV modeling and demand-side management (DSM) priority allocation, which accurately captures diverse operational profiles and ensures fairness in charging decisions. Simulation results confirm the system's efficacy: a 46% reduction in peak load enhances grid sustainability, while an over 80% reduction in discomfort penalty

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fosters user trust. An energy utilization rate of 91% maximizes infrastructure effectiveness, and a revenue gain of approximately ₹1.6 lakhs over static TOU models validates the business case. Overall, the proposed framework advances not only energy-conscious scheduling but also supports the adoption of policy-aligned, transactive pricing strategies for smart campuses, industrial parks, and emerging EV-integrated city infrastructures. The proposed hybrid framework lays a strong foundation for next-gen EV charging, with multiple avenues for advancement. Future work can integrate real-time solar forecasting for smarter V2G alignment, and embed blockchain smart contracts to secure transactions and pricing. IoT-based deployment using live dashboards and edge control can enable real-world implementation. The RL agent can be scaled to multi-day, seasonal, and cross-campus learning. Lastly, gamified incentives and user-centric tariffs can enhance engagement, making the system adaptive, transparent, and ready for smart city-scale rollouts.

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