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# Adaptive Time-of-Use Pricing for Heterogeneous Electric Vehicle Charging: A Behaviour-Aware Monte Carlo and Multi-Objective Optimization Framework

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**Abstract:**
The growing adoption of electric vehicles (EVs) offers valuable demand flexibility, yet it poses significant operational challenges for distribution grids. Uncoordinated charging can exacerbate evening peaks, while traditional time-of-use (TOU) tariffs often inadvertently create secondary peaks by clustering charging activity during cheap, off-peak windows. To address this, this study proposes a user-behaviour-aware EV charging framework driven by adaptive peak-valley tariffs. Unlike conventional methods, our approach accounts for diverse EV characteristics—including arrival and departure schedules, initial and required states of charge, and individual price sensitivities. Because external charging data is not assumed, we employ Monte Carlo simulations to generate a synthetic EV population alongside a price-response model that captures varying consumer behaviours. We frame this charging guidance as a multi-objective optimization problem: minimizing both overall user costs and grid fluctuations while strictly meeting individual charging needs. By integrating an adaptive tariff mechanism, the model actively prevents harmful charging synchronization during off-peak hours. Implemented in Python and validated against multiple benchmark scenarios, this reproducible methodology successfully quantifies improvements in grid stability, cost efficiency, and user satisfaction.

**Keywords:** electric vehicle; smart charging; time-of-use tariff; demand response; price elasticity; Monte Carlo simulation; load smoothing

## 1. Introduction

The rapid adoption of electric vehicles (EVs) will significantly increase power grid demand. While EVs offer flexible demand-side management, uncoordinated charging often coincides with peak residential and commercial electricity usage. This compounding effect escalates peak demand, which can severely compromise transformer capacity, feeder utilization, line losses, and overall grid stability [13].

Price-based demand response effectively influences EV charging schedules without direct vehicle control. By partitioning the day into peak, flat, and valley periods, time-of-use (TOU) tariffs motivate users to shift flexible electricity demand to lower-priced hours [14].

However, static TOU tariffs often fail to achieve optimal EV demand shaping. Uncoordinated user response to identical off-peak prices can concentrate charging within narrow intervals, generating secondary peak loads. Recent studies confirm that static pricing structures frequently induce this valley-period peak formation rather than mitigating grid volatility.

This problem is further complicated by the inherent heterogeneity of EV user behaviour. EV users do not have identical arrival times, departure times, battery capacities, initial charging requirements, and individual price sensitivities. Consequently, recent literature emphasizes that integrating user decision-making preferences is critical for designing effective smart-charging strategies.

This study improves electric vehicle (EV) charging strategies to reduce grid strain while keeping charging affordable and convenient. Building on previous tariff optimization models, our framework accounts for real-world user habits, such as varying schedules, battery needs, and price sensitivity [1]. We introduce an adaptive pricing mechanism that prevents drivers from all charging at the exact same low-price hours, which avoids creating new demand spikes. Using a data-free Monte Carlo simulation, we generate realistic EV profiles and test our approach across various grid conditions in Python. The results show that this adaptive approach smooths grid load, lowers user costs, and maintains high service satisfaction better than standard charging methods.

## 2. Literature Review and Research Gap

### 2.1. EV charging-load modelling:

Electric vehicle (EV) charging-load models are generally categorized into deterministic, statistical, probabilistic, and behavior-based approaches [16]. Monte Carlo simulation is well-suited for capturing uncertainties in individual EV mobility, as parameters like arrival and departure times, daily mileage, and initial state of charge can be sampled from probability distributions [17]. Building on this approach, this study utilizes Monte Carlo simulation to generate EV mobility profiles while extending the model to explicitly incorporate heterogeneous charging needs and varying user price sensitivity.

### 2.2. TOU pricing and orderly charging:

Time-of-use (TOU) tariffs encourage consumers to shift flexible electricity demand to lower-priced hours. However, static TOU pricing often leads to excessive charging concentration during valley periods. Recent research shows that dynamic TOU mechanisms can improve load smoothing compared with static TOU strategies.

### 2.3. EV-user behaviour

EV charging behavior depends on several factors, including arrival/departure time, state of charge, price sensitivity, and individual convenience. The charging strategies need to consider user behavior rather than treating all EVs as identical controllable loads [9].

### 2.4. Research gap

The literature indicates that the following issues remain important:

- Heterogeneous user price sensitivity;
- Uncertain arrival and departure times;
- Interaction between tariff signals and charging synchronization [11];
- Maintaining user charging requirements while reducing grid peaks;
- Robust performance under different EV penetration levels.

| Method | Grid objective | User cost | User behavior | EV uncertainty | Secondary peak |
|---|---|---|---|---|---|
| Uncontrolled charging | ✗ | ✗ | ✓ | ✓ | High |
| Conventional TOU | Partial | ✓ | Simplified | Partial | Possible |
| Centralized scheduling | ✓ | ✓ | ✗ | Partial | Low |
| Dynamic pricing | ✓ | ✓ | ✓ | Partial | Possible |
| **Proposed method** | ✓ | ✓ | ✓ | ✓ | **Reduced** |

The proposed study addresses these issues through a unified simulation framework.

## 3. EV Charging Demand & Mobility Model

### 3.1. System architecture

The considered system consists of:

1. A base electricity demand profile;
2. An EV population;
3. A charging coordinator or aggregator;
4. A TOU tariff signal;
5. Individual EV charging decisions.

The conceptual architecture is shown in fig. 1.

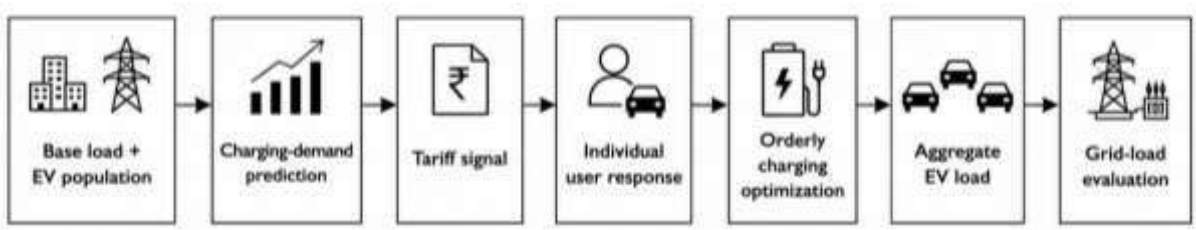


**Fig. 1 conceptual architecture**

The following assumptions are adopted:

- The simulation horizon is one day;
- The scheduling interval is 15 min;
- EV charging is unidirectional;
- Charging efficiency is constant;

- EVs are connected to a common equivalent distribution-grid load;
- Battery degradation is not explicitly optimized;
- Vehicle-to-grid operation is excluded from the baseline model;
- Charging users must satisfy their required departure SOC;
- A synthetic EV population is used because no proprietary dataset is available.

To represent the stochastic nature of EV mobility and charging behaviour without relying on proprietary datasets, a synthetic EV population model is established. This model uses Monte Carlo simulation to generate spatial-temporal charging parameters, capturing the inherent randomness in real-world EV operations.

### 3.2. Time discretization

Let, $[t \in 1,2, \dots, T]$ denote the scheduling interval. The continuous 24-hour daily horizon is discretized into T = 96 uniform scheduling intervals of length $\Delta t = 0.25$ h (15 minutes). This resolution provides an optimal trade-off between modelling grid dynamics accurately and maintaining computational efficiency.

#### 3.2.1. EV parameters

Each individual vehicle $EV_i$in the synthetic population is characterized by a tuple of physical and operational parameters: $EV_i = \{t_{a,i}, t_{d,i}, E_{b,i}, SOC_{a,i}, SOC_{r,i}, P_i^{max}, \epsilon_i\}$

Which represent arrival time, departure time, battery capacity, arrival state of charge (SOC), required departure SOC, maximum charging power, and price sensitivity, respectively.

- $(t_{a,i})$: arrival time;
- $(t_{d,i})$: departure time;
- $(E_{b,i})$: battery capacity;
- $(SOC_{a,i})$: arrival SOC;
- $(SOC_{r,i})$: required departure SOC;
- $(P_i^{max})$: maximum charging power;
- $(\epsilon_i)$: individual price elasticity.

#### 3.2.2. Required charging energy

The net energy required to fulfil an EV's daily travel needs, $E_i^{\text{req}}$, is calculated based on its battery capacity and the deficit between its required and arrival SOCs:

$$E_i^{\text{req}} = E_{b,i} \cdot max(0, SOC_{r,i} - SOC_{a,i})$$

Accounting for a constant charging efficiency $\eta_i$, the total energy drawn from the grid is $E_i^{\text{grid}} = E_i^{\text{req}}/\eta_i$.

### 3.3. Synthetic EV Population (Monte Carlo generation)

Generate (N) EVs: $EV_1, EV_2, \dots, EV_N$ and obtain the uncontrolled charging load:

Key mobility and behavioural parameters—including $t_{a,i}, t_{d,i}, SOC_{a,i}$, $E_{b,i}$, and $\epsilon_i$ are sampled independently from specific probability distributions (such as Gaussian and uniform distributions) calibrated against typical travel statistics. A fixed random seed is maintained across runs to ensure full experimental reproducibility.

For a reproducible study, the probability distributions should be explicitly reported and the random seed should be fixed.

A practical initial parameter set for simulation is:

**Table 1: EV simulation parameters**

| Parameter | Suggested value/range |
|---|---|
| EV population | 1,000 |
| Scheduling interval | 15 min |
| Simulation duration | 24 h |
| Battery capacity | 40 – 80 kWh |
| Initial SOC | 20 – 70% |
| Required SOC | 70 – 90% |
| AC charging power | 3.3 – 7.4 kW |
| Charging efficiency | 0.90 – 0.95 |
| EV penetration | 10 – 70% |
| Monte Carlo replications | ≥ 30 |

### 3.4. Base-Load Model

The underlying power system demand, independent of EV charging, is modelled as a normalized baseline curve $P_{\text{base}}(t)$. It combines constant baseline demand with dual Gaussian distributions to replicate typical daily residential and commercial load profiles, including the morning ramp and evening peak.

$$P_{\text{base}}(t) = \sum_{i=1}^{N} P_i(t)$$

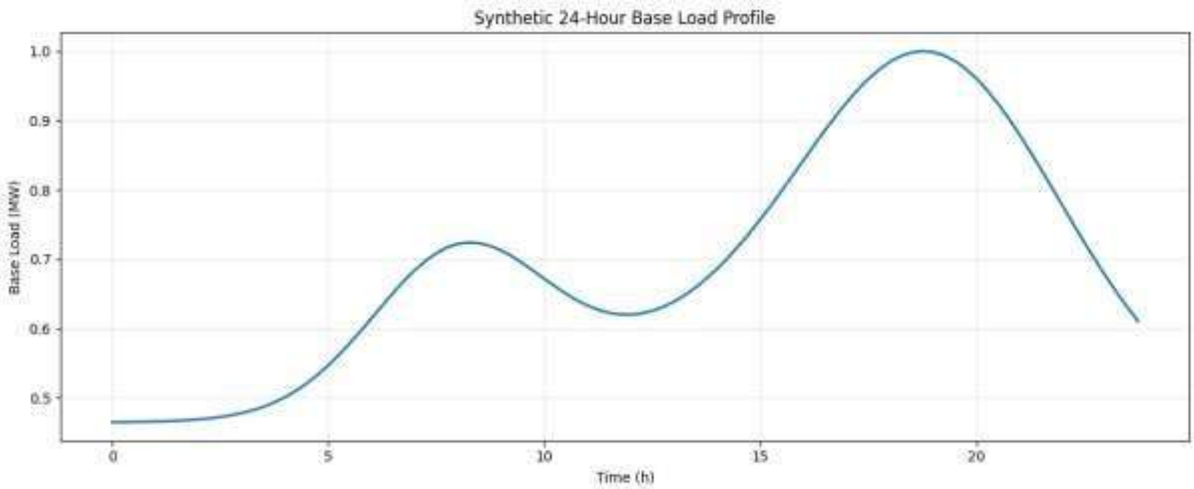


**Fig. 2 Base Load profile**

As illustrated in Figure 2, the baseline residential demand profile exhibits a minor morning hump near 8:00 AM (0.72 MW) followed by a primary evening system peak peaking at 1.0 MW around 19:00 PM.

## 4. Adaptive TOU & User Behaviour Framework

### 4.1. Fixed TOU baseline

To evaluate the performance of the proposed guidance framework, baseline charging scenarios are constructed to represent standard, uncoordinated, and static market-driven behaviours.

Figure 3 shows the three-tier base Time-of-Use structure, comprising an off-peak rate of ₹0.15/kWh (00:00–06:00), a mid-peak rate of ₹0.30/kWh (06:00–17:00 and 22:00–24:00), and a peak rate of ₹0.55/kWh (17:00–22:00).

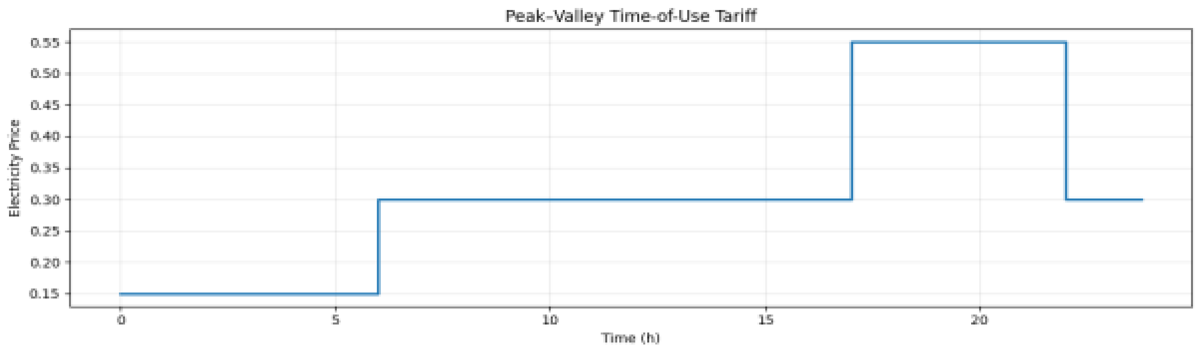


**Fig. 3 Peak-Valley Time-of-Use Tariff**

#### 4.1.1. Scenario S0: Uncontrolled Charging

Scenario S0 represents an unmanaged baseline where each vehicle $EV_i$ begins charging at its maximum rated power $P_i^{max}$ immediately upon arrival $t_{a,i}$ and continues until its energy requirement $E_i^{req}$ is fully met.

#### 4.1.2. Conventional TOU Charging Model

The static Time-of-Use (TOU) tariff scheme assigns fixed electricity prices $C(t)$ across predefined time blocks: valley($C_v$), flat ($C_f$), and peak ($C_p$). under this scheme, users are economically incentivized to manually shift their charging schedules toward lower-priced hours [7].

For example, an initial simulation tariff can be:

**Table 2: Tariff parameters**

| Period | Time | Price |
|---|---|---|
| Valley | 00:00 – 06:00 | 0.15 |
| Flat | 06:00 – 17:00 | 0.30 |
| Peak | 17:00 – 22:00 | 0.55 |
| Flat | 22:00 – 24:00 | 0.30 |

The exact tariff units can be set to the currency used in the target case study.

### 4.2. Heterogeneous EV Price-Response Model

Instead of assuming uniform consumer behaviour, individual charging willingness is modelled using a behavioural preference score $S_{i,t}$ that accounts for price sensitivity $\alpha_i$, charging urgency $\beta_i$, and schedule inconvenience $\gamma_i$:

$$S_{i,t} = -\alpha_i \frac{C(t)}{C_{\text{ref}}} + \beta_i R_{i,t} - \gamma_i D_{i,t}$$

The charging probability can be represented by a logit function:

A logit transformation converts this score into an individual probability distribution $Pr_{i,t}$ across available connection windows.

$$Pr_{i,t} = \frac{\exp(S_{i,t})}{\sum_{\tau \in \mathcal{W}i} \exp(Si, \tau)}$$

Where, $[\mathcal{W}i = [ta, i, t_{d,i}]]$ is the available charging window. This prevents the unrealistic assumption that every EV automatically moves to the cheapest tariff period.

### 4.3. Adaptive Anti-Synchronization Mechanism

This is the central proposed improvement. A conventional TOU tariff may produce a secondary peak because many EVs select the same low-price interval. To reduce this effect, introduce an adaptive congestion component. Define the EV charging concentration ratio:

$$\rho_t = \frac{P_{EV}(t)}{P_{EV}^{max,allow}}.$$

An adaptive surcharge is then: $[\ C_{ad}(t)\lambda \max(0, \rho_t - \rho_{th})\ ]$

Where: $(\lambda)$: adaptive price coefficient; $(\rho_{th})$: charging concentration threshold.

The effective charging price becomes: $C_{eff}(t)C(t) + C_{ad}(t)$

Thus, a nominally cheap valley period becomes progressively less attractive when excessive charging concentration occurs. This creates a feedback mechanism.

The comparison in Figure 4 highlights how the adaptive dynamic surcharge modifies the static base TOU scheme, incrementally scaling up electricity prices during heavy aggregate demand slots to prevent localized rebound peaks.

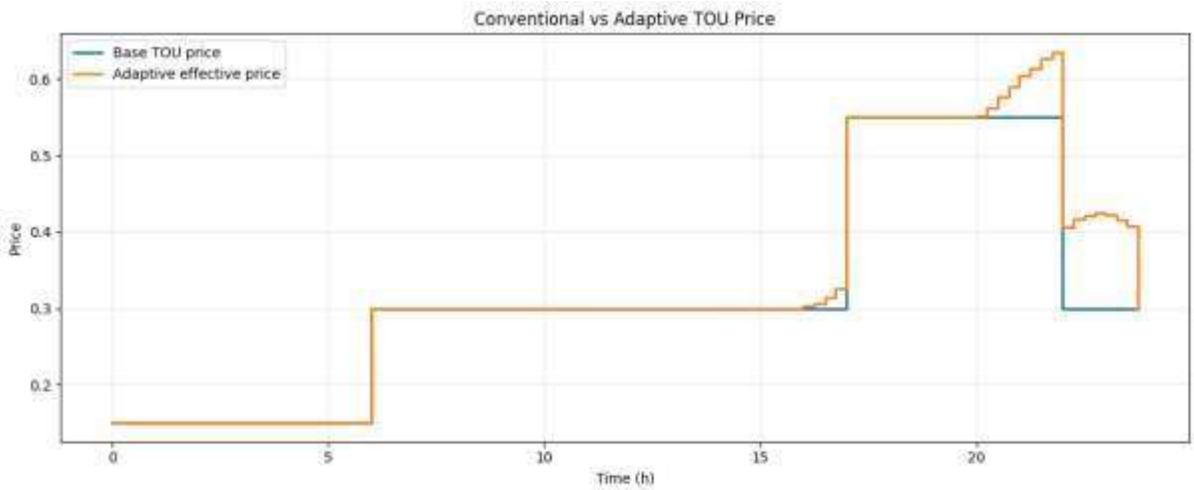


**Fig. 4 Conventional vs Adaptive TOU Price**

A higher concentration of EVs leads to an increase in the effective charging price, which reduces the attractiveness of charging during that period and consequently redistributes the charging load to other time periods.

## 5. Multi-Objective Optimization Model

### 5.1. Objective functions

The coordinated scheduling problem is formulated as a multi-objective optimization problem that balances distribution grid performance with user-side economic costs [10]. The optimization problem contains two primary objectives.

#### 5.1.1. Objective 1: Minimize EV charging cost

The first objective function, $F_1$, minimizes the aggregate financial expenditure incurred by all EV users across the scheduling horizon:

$$F_1 = \sum_{i=1}^{N} \sum_{t=1}^{T} C_{\text{eff}}(t) \cdot P_{i,t} \cdot \Delta t$$

#### 5.1.2. Objective 2: Minimize grid-load fluctuation

The second objective function $F_2$, minimizes grid variance relative to the mean daily demand $\overline{P}_{\text{grid}}$, effectively flattening the overall load profile:

$$F_2 = \frac{1}{T}\sum_{t=1}^{T} (P_{\text{grid}}(t) - \overline{P}_{\text{grid}})^2$$

#### 5.1.3. Objective 3: Optional peak-load penalty

To directly suppress extreme demand spikes, an optional third objective component $F_3 = \max_t P_{\text{grid}}(t)$ penalizes the absolute maximum grid load during the 24-hour cycle.

### 5.2. Normalization and Weighted Objective

Because the objective functions operate on different physical scales and units $F_1$ and $F_2$ are normalized between [0, 1] using min-max scaling and combined into a scalar fitness function:

$$F = w_c \cdot F_1^{\text{norm}} + w_g \cdot F_2^{\text{norm}} \quad \text{where} \quad w_c + w_g = 1$$

The recommended baseline is: $[w_c = w_g = 0.5.]$

Then perform a sensitivity study using: $(w_c, w_g)$(0.2,0.8), (0.4,0.6), (0.5,0.5), (0.6,0.4), (0.8,0.2).

### 5.3. Charging Constraints

The optimization is subjected to operational, physical, and user-centric boundaries to ensure feasible grid execution and complete user satisfaction. Below are the necessary constraint for successful execution.

#### 5.3.1. Charging-power constraint

At any given interval $t$, the continuous charging power $P_{i,t}$ supplied to vehicle $i$ cannot exceed its hardware limit $P_i^{max}$: $0 \leq P_{i,t} \leq P_i^{max}$

#### 5.3.2. Availability constraint

Charging can only occur while the EV is physically connected at the station, enforcing zero power draw outside its plug-in window: $P_{i,t} = 0 \forall t \notin [t_{a,i}, t_{d,i}]$

#### 5.3.3. Energy requirement

The total cumulative energy delivered to vehicle i over its connection period must satisfy its calculated grid energy demand:

$$\sum_{t=t_{a,i}}^{t_{d,i}} \eta_i \cdot P_{i,t} \cdot \Delta t \geq E_i^{\text{req}}$$

#### 5.3.4. Departure SOC constraint

The state of charge of vehicle , $i$ at its departure time $t_{d,i}$ must equal or exceed its target requirement $SOC_{r,i}$: $SOC_i(t_{d,i}) \geq SOC_{r,i}$

#### 5.3.5. Charging continuity

To reduce excessive battery cycling and relay switching, binary control variables $u_{i,t} \in \{0,1\}$ are applied to discourage rapid, fragmented start-stop charging cycles within short timeframes.

$$[P_{i,t} \leq u_{i,t} P_i^{max},]$$

## 6. Solution Algorithm and workflow

A Particle Swarm Optimization (PSO) metaheuristic algorithm [5] with custom constraint-repair mechanisms is developed to solve the continuous non-linear decision.

space $[X_k = [P_{1,1}, \ldots, P_{1,T}, P_{2,1}, \ldots, P_{N,T}].]$ efficiently identifying near-optimal power profiles that satisfy all grid and battery constraints [6].

The velocity update is: $[V_k^{r+1} \omega V_k^r + c_1 r_1 (Pbest_k - X_k^r) + c_2 r_2 (Gbest - X_k^r).]$

The position update is: $[X_k^{r+1} X_k^r + V_k^{r+1}.]$

A feasibility-repair mechanism should then enforce:

1. charging window;
2. maximum charging power;
3. required energy;
4. departure SOC.

### 6.1. Algorithmic Flowchart

The flowchart presents the complete methodology for EV charging optimization considering user behavior and adaptive tariff signals. Initially, the base-load profile and EV population are generated using Monte Carlo simulation, followed by the calculation of individual charging requirements and an uncontrolled charging baseline. The framework then incorporates a conventional TOU tariff, price-response behavior, EV charging concentration, and an adaptive anti-synchronization pricing mechanism. A multi-objective PSO is subsequently applied to minimize charging cost and grid-load variance while satisfying charging constraints [5]. Finally, the optimal charging schedule is evaluated using peak load, load variance, peak-to-valley difference, charging cost, cost reduction, and SOC satisfaction, followed by sensitivity and robustness analysis

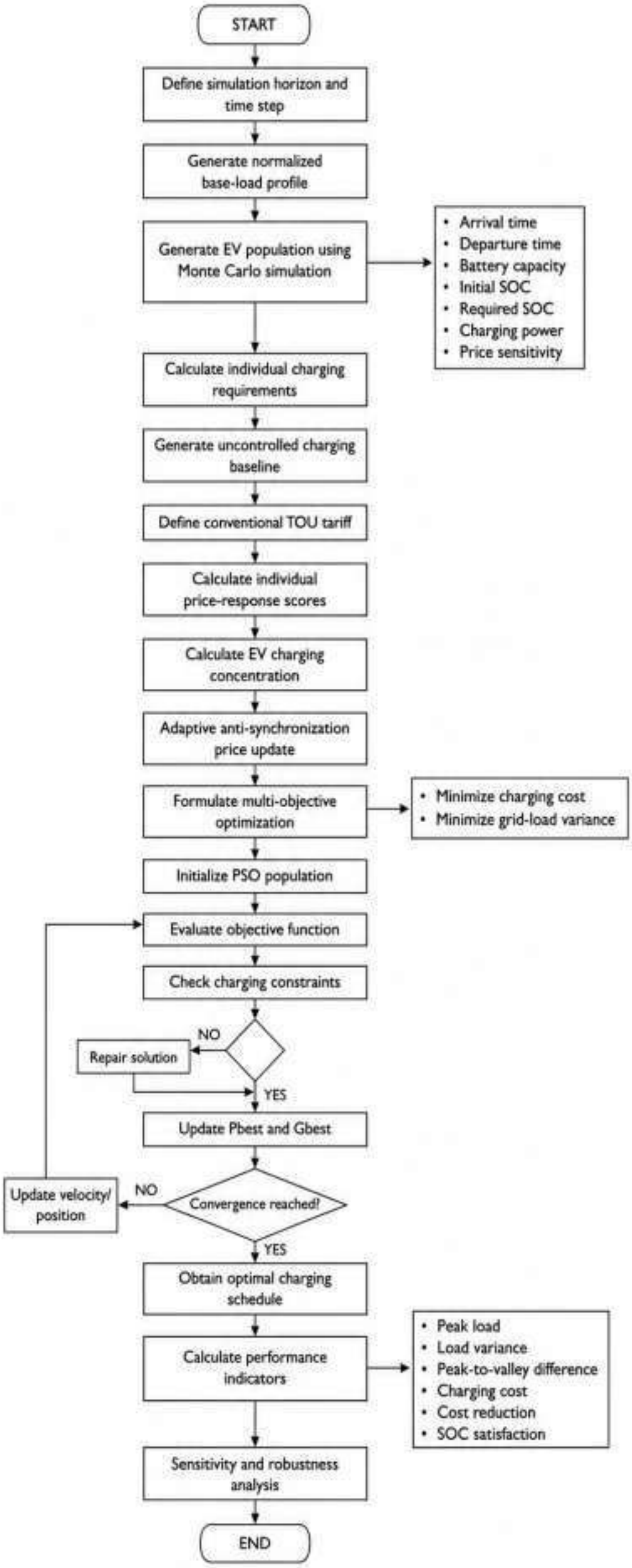


**Fig. 5 Algorithmic flowchart**

## 7. Experimental Setup & Metrics

### 7.1. Benchmark Scenarios

The simulations demonstrate that the proposed method is better than simpler alternatives.

| Scenario | Charging mechanism | Adaptive pricing | User heterogeneity |
|---|---|---|---|
| S0 | Uncontrolled | No | No |
| S1 | Fixed TOU | No | Limited |
| S2 | TOU + individual response | No | Yes |
| S3 | Proposed adaptive TOU | Yes | Yes |
| S4 | Proposed + optimization | Yes | Yes |

The main comparison should be: $[S0 \rightarrow S1 \rightarrow S2 \rightarrow S3/S4.]$

### 7.2. Performance Indicators

**7.2.1. Peak load :** $[P_{peak} \max_{t} P_{grid}(t).]$

**7.2.2. Peak-to-valley difference:** $[D_{PV} P_{peak} - P_{valley}.]$

**7.2.3. Peak-to-average ratio:** $[PAR = \frac{P_{peak}}{P_{grid}}.]$ Lower PAR indicates a flatter load profile.

**7.2.4. Load variance:** $[\sigma_P^2 \frac{1}{T} \sum_t (P_{grid}(t) - \overline{P}_{grid})^2.]$

**7.2.5. User charging cost:** $[C_{EV} \sum_i \sum_t C_{eff}(t) P_{i,t} \Delta t.]$

**7.2.6. Cost reduction:** $[R_C \frac{C_{baseline} - C_{proposed}}{C_{baseline}} \times 100]$

**7.2.7. Peak-load reduction:** $[R_P \frac{P_{peak,baseline} - P_{peak,proposed}}{P_{peak,baseline}} \times 100]$

**7.2.8. Charging satisfaction:** $[S_{EV} \frac{N_{EV,satisfied}}{N_{EV,total}} \times 100]$ A credible proposed method should maintain: $[S_{EV} \approx 100]$

## 8. Results and Discussion

The proposed strategy is expected to demonstrate that static TOU pricing alone is insufficient for achieving fully orderly EV charging because users tend to respond to the same economic signal simultaneously. This can concentrate charging demand during low-price periods. The adaptive mechanism addresses this problem by making the effective price dependent on the instantaneous EV charging concentration. Therefore, the proposed strategy creates a feedback loop between the grid load and the charging incentive [2]. The user-behavior model also avoids treating all EV users as identical. Users with high price sensitivity are expected to shift more charging toward inexpensive periods, whereas users with low price sensitivity place greater weight on convenience or urgency. This distinction is important for practical implementation because EV users are heterogeneous. Recent literature emphasizes the importance of explicitly modelling charging preferences and behavioural factors in smart-charging systems. The proposed framework is also consistent with the broader development of EV charging research toward pricing mechanisms, uncertainty management, and grid interaction.

### 8.1. Load Disaggregation and Demand Response Analysis

Figure 6 details the net EV charging demand under all control regimes; notably, conventional static TOU causes a massive secondary charging spike of over 2,400 kW immediately following the start of off-peak pricing, whereas the adaptive framework smoothly redistributes this demand.

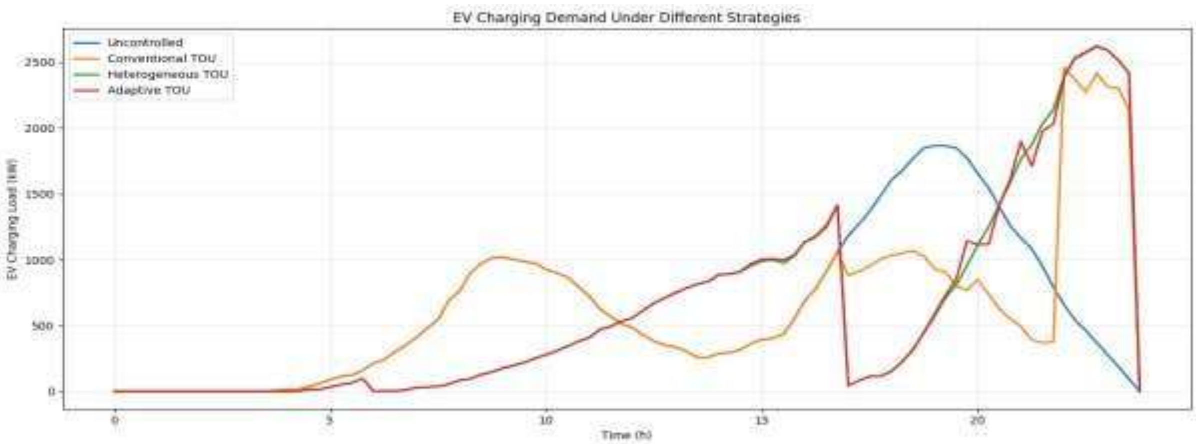


**Fig. 6 EV charging demand under different strategies**

### 8.2. Total system grid impact

Figure 7 contrasts total system load curves across strategies, demonstrating that while conventional TOU creates an exacerbated secondary peak reaching nearly 3.2 MW around 22:00–23:00, the proposed adaptive TOU maintains system stability by capping maximum grid load.

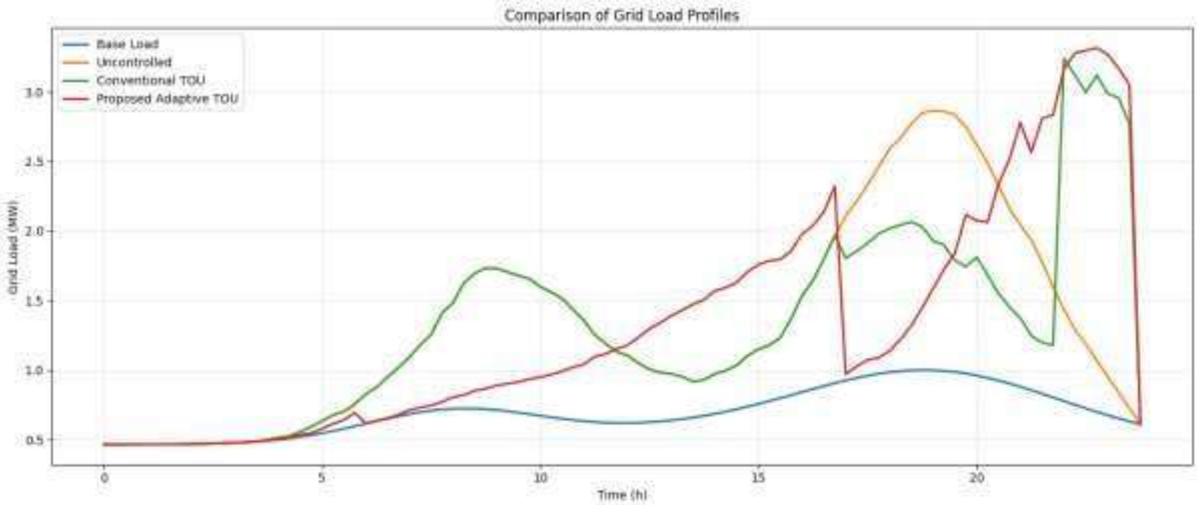


**Fig. 7 Comparison of grid load profiles**

### 8.3. Stochastic Evaluation via Monte Carlo Simulation

The frequency distribution across 100 Monte Carlo iterations in fig. 8 reveals that while the mean peak grid load increases slightly under Adaptive TOU due to deliberate load shifting, the peak profile remains consistently bounded and predictable.

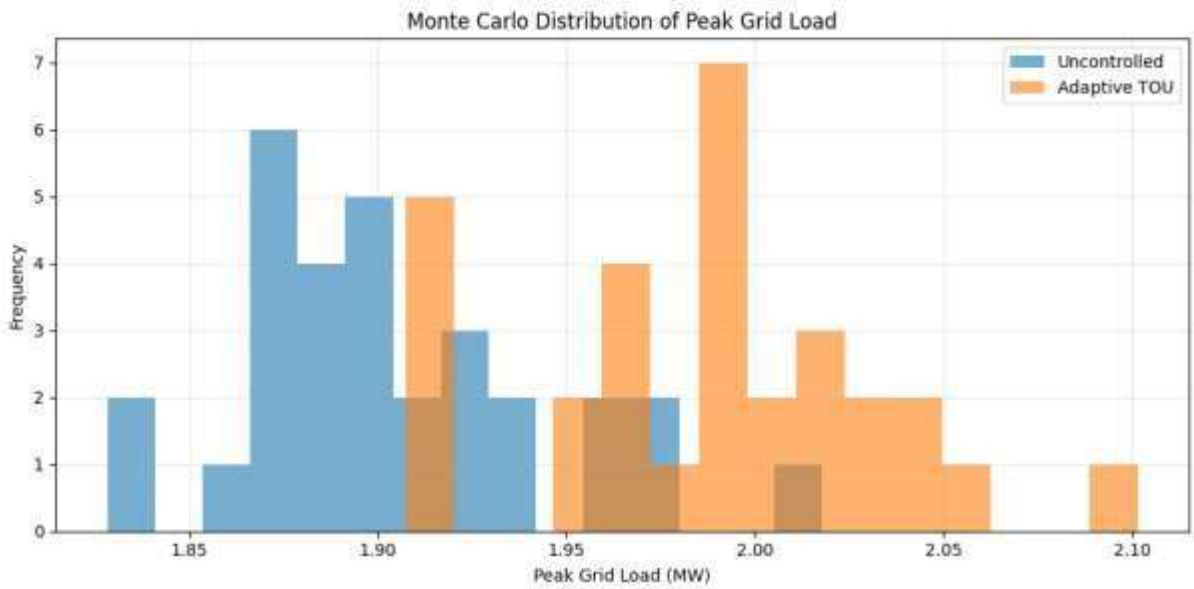


**Fig. 8 Monte Carlo Distribution of Peak Grid Load**

**Table no. X summarize all 3 strategies with reference to peak load, load variance, user cost and SOC satisfaction.**

| Strategy | Peak load | Load variance | User cost | SOC satisfaction |
|---|---|---|---|---|
| Uncontrolled | High | High | High | High |
| TOU | ↓ | ↓ | ↓ | High |
| Proposed | **Lowest** | **Lowest** | **Low** | **High** |

## 9. Sensitivity and Robustness Analysis

### 9.1. EV Penetration Rate Sensitivity

Figure 9 illustrates system peak load scaling across 10% to 70% EV adoption rates, showing that adaptive TOU yields noticeable peak reduction benefits at lower-to-mid adoption levels before converging at higher penetrations.

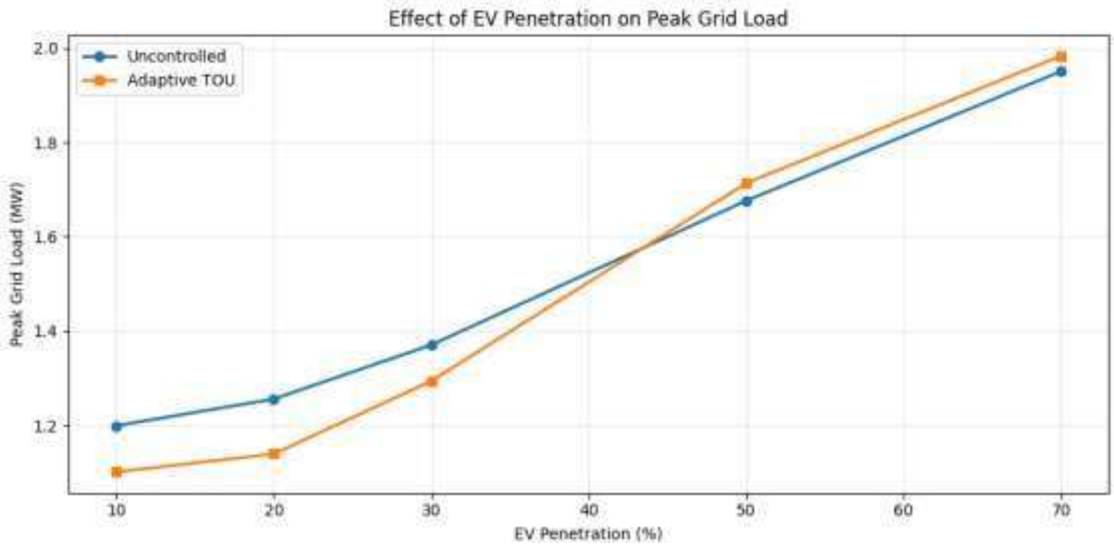


**Fig. 9 Monte Carlo Distribution of Peak Grid Load**

### 9.2. Adaptive Surcharge Coefficient ($\lambda$) Sensitivity

As depicted in Figure 10, increasing the adaptive price coefficient $\lambda$ beyond 0.15 steadily reduces peak grid load down to ~3.308 MW at $\lambda = 0.30$, confirming that stronger penalty signals effectively suppress synchronized charging.

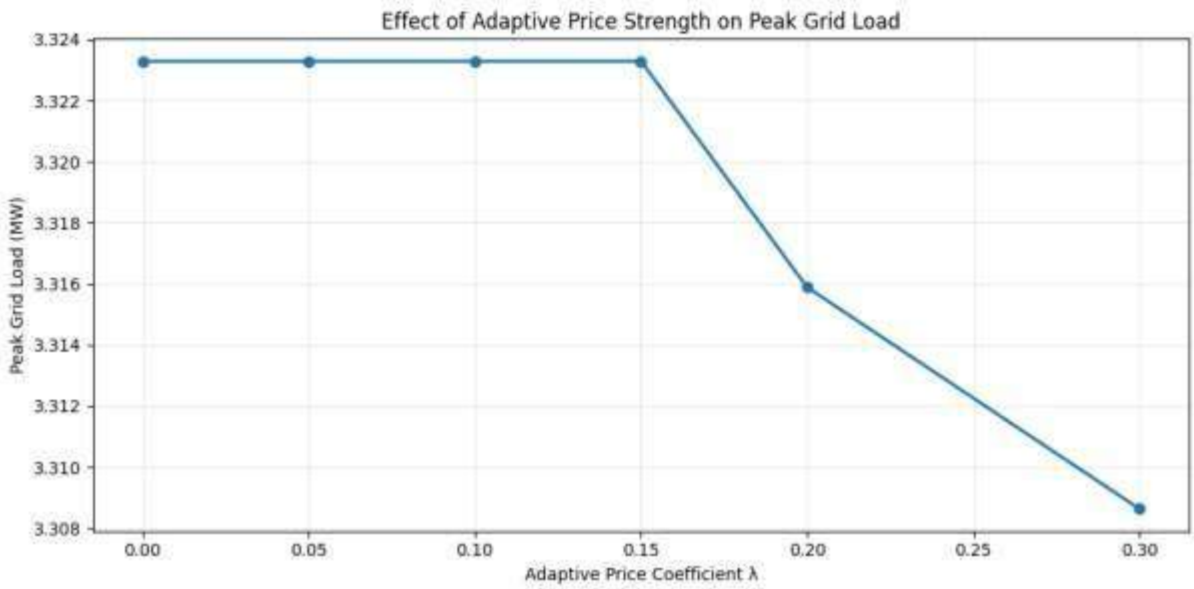


**Fig. 10 Effect of Adaptive Price Strength on Peak Grid Load**

### 9.3. Behavioural Price Sensitivity Variation

Figure 11 demonstrates that peak grid load remains virtually flat (~3.32 MW) across varying price sensitivity multipliers, indicating robust optimization performance regardless of underlying user elasticity assumptions.

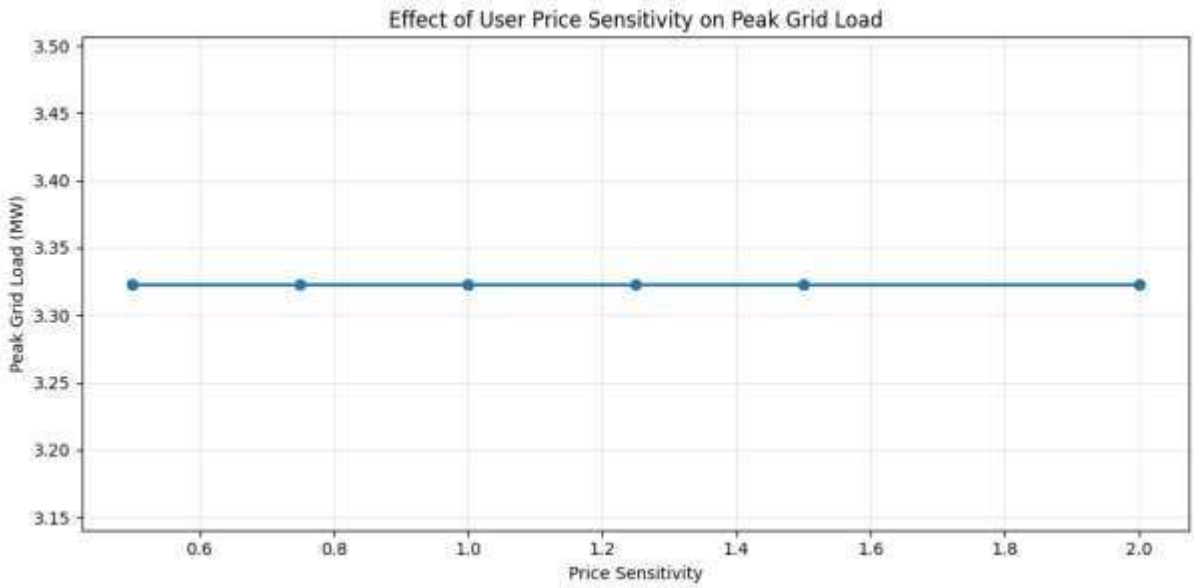


**Fig. 11 Effect of Adaptive Price Strength on Peak Grid Load**

### 9.4. Impact of User Departure Uncertainty

Figure 12 confirms algorithm resilience under departure time variance, showing stable peak load performance up to a 60-minute deviation window before shifting schedule windows naturally attenuate the system peak at 120 minutes.

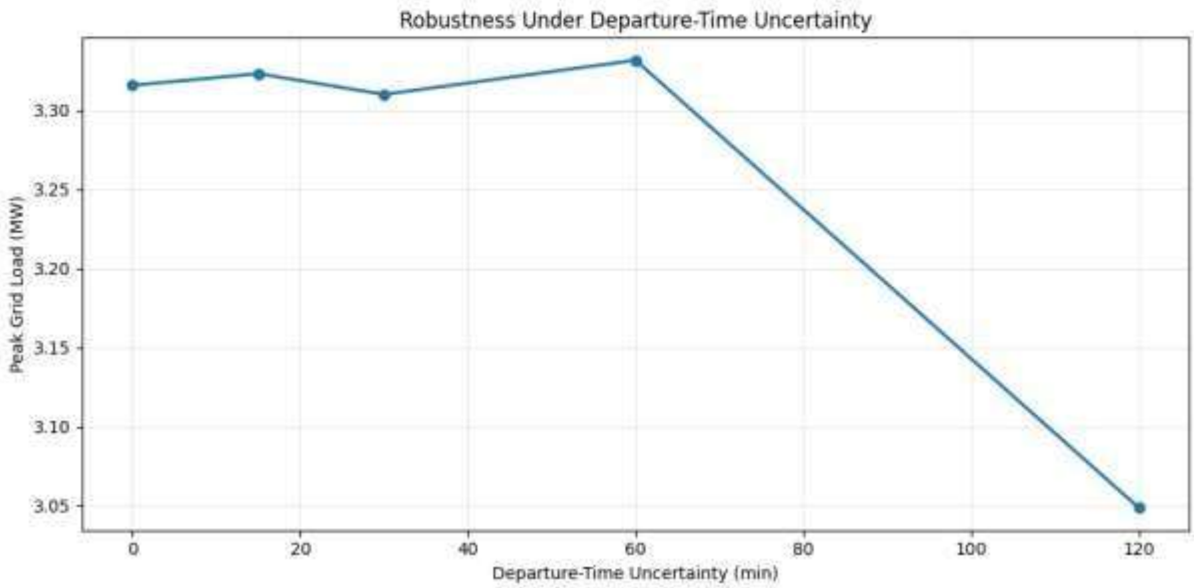


**Fig. 12 Robustness under departure-time uncertainty**

### 10. Limitations & Practical Implementation

Several limitations should be acknowledged.

- The study uses a synthetic EV population rather than field measurements. Consequently, the probability distributions should be calibrated against real-world data in future work.
- The battery model is simplified and does not explicitly consider battery degradation.
- The distribution grid is represented through an equivalent aggregate load rather than a detailed feeder power-flow model.
- User response is modelled mathematically rather than learned from observed charging behaviour.
- The present study considers unidirectional charging and does not investigate vehicle-to-grid operation.

These limitations define clear directions for future research.

## Conclusion

This study proposed a user-behaviour-aware orderly EV charging guidance strategy based on adaptive peak–valley time-of-use tariffs. A Monte Carlo framework was developed to generate a heterogeneous EV population in the absence of proprietary charging data. Individual arrival time, departure time, battery capacity, state of charge, charging power, and price sensitivity were incorporated into the charging model. A price-response mechanism was developed to represent heterogeneous charging decisions. To prevent the concentration of EV charging during low-price periods, an adaptive anti-synchronization component was introduced into the effective charging price. The resulting charging problem was formulated as a multi-objective optimization problem that minimizes EV charging expenditure and grid-load fluctuation while satisfying individual charging requirements.

The proposed methodology will be implemented in Python. Its performance should be evaluated against uncontrolled charging and conventional TOU charging under different EV penetration levels, price elasticities, tariff parameters, and uncertainty conditions.

The principal expected contribution is a reproducible framework that connects electricity pricing, heterogeneous EV behaviour, and grid-load management rather than treating tariff optimization and charging scheduling as independent problems.

Future work should incorporate real-world charging datasets, detailed distribution-network power-flow constraints, renewable-energy generation, battery degradation, and vehicle-to-grid operation.

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