Simulation of the Valley Filling EV Charging Algorithm

Lakshit Sethia
210102123
s.lakshit@iitg.ac.in

Maharsh Raval
210108026
r.maharsh@iitg.ac.in

***Abstract*—Electric vehicles (EVs) have the potential to increase energy efficiency in transportation, reduce greenhouse gas emissions, and relieve reliance on fossil fuels. While various EVs are either already present in the Indian market or about to enter, their integration with the power grid presents significant challenges. To address these challenges, this paper implements and analyzes both the Optimal Decentralized Control (ODC) algorithm and its asynchronous variant (AODC) proposed in *Optimal Decentralized Protocol for Electric Vehicle Charging* [1], specifically adapted for Indian grid conditions. The AODC algorithm enhances robustness by allowing EVs to skip profile updates, making it resilient to communication delays and failures. We present a comprehensive simulation framework that verifies the algorithms' valley-filling properties and examines their sensitivity to various parameters such as charging rates, number of EVs, and base load profiles characteristic of Indian power consumption patterns. Our implementation addresses both homogeneous and heterogeneous EV scenarios, providing a thorough analysis of the algorithms' convergence properties and effectiveness in the Indian context. The Python implementation of this decentralized algorithm along with the data of India can be found *here*.**

I. Notation

Some of the symbols in this paper are listed as follows.

t	Time slot, $t \in \mathcal{T} = \{1, \ldots, T\}$.
n	EV, $n \in \mathcal{N} = \{1, \ldots, N\}$.
D	Base load profile.
r_n	Charging profile of EV n.
$\bar{r}_n$	Upper bound on r_n, i.e., $r_n \preceq \bar{r}_n$.
R_n	Charging rate sum of EV n.
$\mathcal{F}_n$	Set of feasible r_n.
r	Charging profile of all EVs.
$\mathcal{F}$	Set of feasible r.
$\mathcal{O}$	Set of optimal r.
R_r	Aggregate charging profile corresponding to r.
p	Control signal.

II. Introduction

India's electric vehicle sector is experiencing remarkable growth, with EVs currently constituting 7.4% of total vehicles on Indian roads. This marks a significant transformation in the country's transportation landscape, and industry projections indicate that India is positioned to become the world's largest EV market by 2030. The next 8-10 years are expected to witness substantial investment growth in this sector, driven by both government initiatives and private sector participation. [2]

The government has established clear objectives to elevate EV sales to 30% in private cars, 70% in commercial vehicles, 40% in buses, and 80% in two-wheelers and three-wheelers by 2030. This ambitious target equates to 80 million EVs on Indian roads by 2030. Additionally, India strives to achieve complete domestic EV production through its 'Make in India' initiative, further strengthening its position in the global EV market. [3]

The simulation-based study in [4] suggests that if EV charging is not coordinated, even a 10% penetration of EVs may cause unacceptable voltage deviations. On the other hand, many studies demonstrate that "smart" charging strategies can mitigate some of the integration challenges, defer infrastructure investment needed otherwise, and even help stabilize the grid.

In this project, we will formally define the problem and simulate a decentralized iterative algorithm for scheduling EV charging, where, at each iteration, EVs adjust their charging profiles based on a control signal broadcast by the utility company, which, in turn, modifies the signal to guide these updates. This iterative process will converge to optimal charging profiles for both homogeneous and non-homogeneous scenarios, accommodating varied EV plug-in times, deadlines, charging demands, and maximum charging rates. Building on this, we will simulate the Asynchronous Optimal Decentralized Control (AODC) and Real-Time Optimal Decentralized Control (RTODC) algorithms under virtual environment conditions. Subsequently, we will simulate this decentralized scheduling algorithm for Indian grid conditions and evaluate its performance under various parameter changes, analyzing its robustness and adaptability to real-world conditions in the Indian power grid.

III. Formulation of the Problem Statement

In this section, we will be mathematically describing the problem. The problem of decentralized EV charging control is formulated as an optimization challenge, where the objective is to manage charging loads to flatten the combined grid load effectively.

Consider a scenario where a utility company negotiates with N EVs to schedule their charging profiles over T time slots of length ΔT in the future. The utility is assumed to know (precisely predict) the inelastic base load (aggregate non-EV load) profile and aims to flatten the total load (base load plus aggregate EV load) profile by shaping the aggregate EV load.

Each EV can charge after it plugs in and needs to charge a pre-specified amount of electricity by its deadline. The charging rate is kept constant at each time slot.

Let $D(t)$ denote the base load at time slot t, $r_n(t)$ denote the charging rate of EV n at time slot t, and $r_n = (r_{n,1}, \ldots, r_{n,T})$ denote the charging profile of EV n, for $t \in \mathcal{T} = \{1, \ldots, T\}$ and $n \in \mathcal{N} = \{1, \ldots, N\}$. Let $r = (r_1, \ldots, r_N)$ denote the charging profile of all EVs. The intent of flattening the total load profile is captured by minimizing

$$L(r) = L(r_1, \ldots, r_N) := \sum_{t \in \mathcal{T}} \left(D(t) + \sum_{n \in \mathcal{N}} r_n(t) \right)^2$$

where $U : \mathbb{R} \to \mathbb{R}$ is strictly convex.

Each EV $n \in \mathcal{N}$ can only charge after it plugs in at plug_n, and before its deadline dead_n, i.e., $r_n(t) = 0$ if $t \notin [\text{plug}_n, \text{dead}_n]$. During $t \in [\text{plug}_n, \text{dead}_n]$, we assume that the EV can be charged at any rate from 0 to the maximum charging rate $r_n^{\max}$ that is determined by the charger. Define charging profile upper bound $\overline{r}_n$ as

$$\overline{r}_n(t) := \begin{cases} r_n^{\max} & \text{if } \text{plug}_n \leq t \leq \text{dead}_n, \\ 0 & \text{otherwise} \end{cases} \quad \text{for } t \in \mathcal{T}$$

for $n \in \mathcal{N}$. Then

$$0 \leq r_n(t) \leq \overline{r}_n(t), \quad t \in \mathcal{T}, \quad n \in \mathcal{N}.$$

Let B_n, $s_n(0)$, $s_n(T)$, and η_n denote the battery capacity, initial State of Charging (SOC), final SOC, and charging efficiency of EV n, respectively. The constraint that EV n needs to reach $s_n(T)$ state of charge by its deadline is captured by

$$\eta_n \sum_{t \in \mathcal{T}} r_n(t) \Delta T = B_n(s_n(T) - s_n(0)), \quad n \in \mathcal{N}.$$

Define the charging rate sum

$$R_n := \frac{B_n(s_n(T) - s_n(0))}{\eta_n \Delta T}$$

for $n \in \mathcal{N}$.

$$R_n := \sum_{t \in \mathcal{T}} r_n(t), \quad n \in \mathcal{N}.$$

IV. Different Case Studies

Before delving into the decentralized algorithm proposed for EV charging, it's essential to understand the Homogeneous and Heterogeneous EV charging cases:

1) **Homogeneous Case**: In this case, all EVs have identical charging requirements. Each vehicle is assumed to have the same plug-in time, charging deadline, maximum charging rate, and total charge needed. This setup is advantageous because it simplifies the algorithm's task of optimizing the charging profile, as all EVs follow the same scheduling structure.
2) **Heterogeneous Case**: In this case, EVs vary in their charging demands, plug-in times, and deadlines, presenting a more complex optimization problem. This variability reflects real-world conditions where each EV user's charging needs are different, leading to a dynamic and flexible schedule.

V. Decentralized Scheduling Algorithm

This method algorithm is a flexible electric vehicle charging system where cars can independently choose when to charge, guided by utility price signals. Unlike traditional centralized systems that can get overwhelmed, this method allows more electric vehicles to join the grid smoothly. Cars negotiate their charging times and rates at the start of a scheduling period, adapting to their individual availability while collectively helping balance energy demand. This decentralized method prevents gridlock and makes adding more electric vehicles to the system much easier.

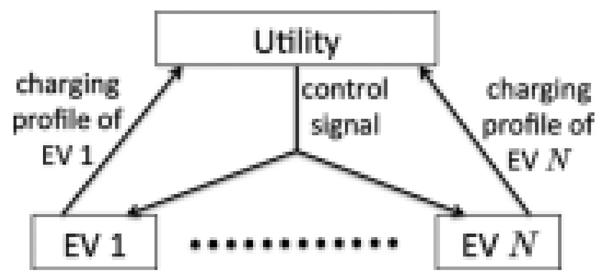

Fig. 1. Schematic view of the information flow between utility and the EVs. Given the control signal, EVs update their charging profiles independently.

A. *Algorthm 1: Optimal Decentralized Charging Algorithm*

The Optimal Decentralized Charging algorithm presents an innovative approach to electric vehicle (EV) charging coordination, where the utility company initiates the process by broadcasting a control signal to all connected EVs. In response, each EV independently optimizes its charging profile by solving an individual optimization problem that minimizes charging costs while aligning with the broadcasted signal. The utility company then aggregates these EV charging decisions, strategically adjusting the control signal for subsequent iterations to progressively minimize peak load and reduce charging costs. This iterative process continues until convergence is achieved, characterized by minimal marginal changes in charging profiles and a near-optimal grid load state that simultaneously satisfies individual EV charging requirements, effectively creating a decentralized, adaptive charging management system that balances grid efficiency with individual user needs.

B. *Algorthm 2: Asynchronous Optimal Decentralized Charging Algorithm*

We have observed the effectiveness of the Optimal Decentralized Control (ODC) algorithm. However, certain limitations

Algorithm 1: Optimal Decentralized Charging

Input: Scheduling horizon $\mathcal{T}$. The utility knows the base load profile D and the number N of EVs. Each EV $n \in \mathcal{N}$ knows its charging rate sum R_n and charging profile upper bound $\bar{r}_n$, therefore the set $\mathcal{F}_n$ of its feasible charging profiles.

Output: Charging profile $r = (r_1, \ldots, r_N)$.

Pick a parameter γ satisfying $0 < \gamma < 1/(N\beta)$.

i) Initialize the charging profile r^0 as $r_n^0(t) := 0$, $t \in \mathcal{T}, n \in \mathcal{N}$.
Set $k \leftarrow 0$, repeat steps ii)–iv).

ii) The utility calculates the control signal p^k as

$$p^k(t) := \gamma U'\left(D(t) + \sum_{n\in\mathcal{N}} r_n^k(t)\right), \ t \in \mathcal{T} \tag{7}$$

and broadcasts the control signal p^k to all EVs.

iii) Each EV $n \in \mathcal{N}$ calculates a new charging profile r_n^{k+1} by solving

$$\min \ \langle p^k, r_n \rangle + \frac{1}{2}\left\|r_n - r_n^k\right\|^2 \quad \text{s.t. } r_n \in \mathcal{F}_n \tag{8}$$

and reports r_n^{k+1} to the utility.

iv) Set $k \leftarrow k+1$, go to step ii).

Algorithm 2: Asynchronous Optimal Decentralized Charging

Input: Scheduling horizon $\mathcal{T}$. The utility knows the base load profile D and the number N of EVs. Each EV $n \in \mathcal{N}$ knows its charging rate sum R_n and charging profile upper bound $\bar{r}_n$, therefore the set $\mathcal{F}_n$ of its feasible charging profiles.

Output: Charging profile $r = (r_1, \ldots, r_N)$.

Pick a parameter γ satisfying $0 < \gamma < 1/\left(N\beta(3d+1)\right)$.

i) Initialize the charging profile r^0 as $r_n^0(t) := 0$, $t \in \mathcal{T}, n \in \mathcal{N}$.
Set $k \leftarrow 0$, repeat steps ii)–iv).

ii) If $k = 0$ or $k - 1 \in K_0$, the utility calculates the control signal p^k as

$$p^k(t) := \gamma U'\left(D(t) + \sum_{n\in\mathcal{N}} r_n^{k-b_n(k)}(t)\right), \ t \in \mathcal{T}$$

and broadcasts the control signal p^k to all EVs.

iii) For each EV $n \in \mathcal{N}$, if $k \in K_n$, it calculates a new charging profile r_n^{k+1} by solving

$$\min \ \left\langle p^{k-a_n(k)}, r_n \right\rangle + \frac{1}{2}\left\|r_n - r_n^k\right\|^2 \quad \text{s.t. } r_n \in \mathcal{F}_n$$

and reports r_n^{k+1} to the utility.

iv) Set $k \leftarrow k+1$, go to step ii).

in the ODC algorithm have become apparent. The current ODC approach requires all EVs to use the most recent control signal to update their charging profiles in every iteration. This synchronous computation may be impractical, especially as the number of EVs grows. Ensuring every EV updates in every iteration can be a challenge in a large-scale system, leading to increased communication burdens. To address this, we will simulate a more advanced approach: the Asynchronous Optimal Decentralized Control (AODC) algorithm under the same experimental conditions as that of the ODC algorithm. In AODC, EVs are not required to update their charging profiles in every iteration and can proceed with potentially outdated control signals, making the system more robust to communication delays and scalable for larger EV populations.

More formally, Each EV $n \in \mathcal{N}$ only updates its charging profile at iterations $K_n \subset \{0, 1, \ldots\}$, i.e., $r_n^{k+1} = r_n^k$ if $k \notin K_n$. Similarly, the utility only updates the control signal at iterations $K_0 \subset \{0, 1, \ldots\}$, i.e., $p^{k+1} = p^k$ if $k \notin K_0$. The algorithm assumes that each EV updates its charging profile at least once every d iterations, and the utility updates the control signal at least once every d iterations i.e., The delays $a_n(k)$ and $b_n(k)$ are independent of k and $a_n(k) \leq d$ and $b_n(k) \leq d$ for $n \in \mathcal{N}$ and $k \geq 0$.

C. *Algorthm 3: Real-Time Optimal Decentralized Charging Algorithm*

Following AODC, we will explore an even more realistic approach with the Real-Time Optimal Decentralized Control (RTODC) algorithm. Unlike the ODC, which operates offline and requires all EVs to negotiate charging schedules at the beginning of a scheduling period, RTODC considers EVs as they connect to the grid over time. In this real-time setup, an EV n becomes "active" only when it is plugged in and available to charge at time t, requiring participation only from currently active EVs. Let $\mathcal{N}_t$ denote the set of active EVs at time t. Thus, participation is limited to $n \in \mathcal{N}_t$ rather than the entire EV population $\mathcal{N}$. This modification makes RTODC more practical for real-world conditions, where EVs connect and disconnect from the grid dynamically. Through RTODC, we aim to achieve a charging system that adapts to real-time availability, further enhancing scalability and efficiency in integrating EVs into the grid.

VI. Virtual Simulation Setup

Initially, we will be simulating these Optimal Decentralized EV Charging algorithms in a virtual environment with the following assumptions:

Algorithm 3: Real-Time Optimal Decentralized Charging

Input: The number K of iterations in each time slot. The utility knows the base load profile D. At time slot $t = 1, 2, \ldots$, the utility knows the number N_t of active EVs, and picks a time window size T that covers the deadlines of all active EVs; each active EV $n \in \mathcal{N}_t$ knows its deadline d_n, charging rate sum R_n^t and charging rate upper bound $\bar{r}_n(\tau)$ for $t \leq \tau \leq d_n$.

Output: At time slot $t = 1, 2, \ldots$, output the charging rate $r_n(t)$ for active EVs $n \in \mathcal{N}_t$.

Pick a parameter γ satisfying $0 < \gamma < 1/\beta$. At time slot $t = 1, 2, \ldots$:

a) Initialize the charging profiles r_n^0 for active EVs $n \in \mathcal{N}_t$ as

$$r_n^0 := \begin{cases} 0 & \text{if } n \notin \mathcal{N}_{t-1} \\ r_n^K & \text{if } n \in \mathcal{N}_{t-1} \end{cases}$$

where r_n^K is the charging profile of EV $n \in \mathcal{N}_{t-1}$ in iteration K of the previous time slot $t-1$. Set $k \leftarrow 0$.

b) The utility calculates the control signal p^k as

$$p^k(\tau) := \frac{\gamma}{N_t} U' \left(D(\tau) + \sum_{n \in \mathcal{N}_t} r_n^k(\tau) \right), \; t \leq \tau \leq t + T$$

and broadcast the control signal to active EVs $n \in \mathcal{N}_t$.
If $k = K$, set $r_n(t) \leftarrow r_n^K(t)$ for $n \in \mathcal{N}_t$, go to step e).

c) Each EV $n \in \mathcal{N}_t$ calculates a new charging profile r_n^{k+1} by solving

$$\begin{aligned} \min_{r_n} \quad & \sum_{\tau=t}^{d_n} p^k(\tau) r_n(\tau) + \frac{1}{2} \left(r_n(\tau) - r_n^k(\tau) \right)^2 \\ \text{s.t.} \quad & 0 \leq r_n(\tau) \leq \bar{r}_n(\tau), \; t \leq \tau \leq d_n; \\ & \sum_{\tau=t}^{d_n} r_n(\tau) = R_n^t \end{aligned}$$

and reports r_n^{k+1} to the utility.

d) Set $k \leftarrow k + 1$, go to step b).

e) For each $n \in \mathcal{N}_t$, set $R_n^{t+1} \leftarrow R_n^t - r_n(t)$. If $R_n^{t+1} = 0$ or $d_n \leq t$, EV n becomes inactive for slot $t+1$. If EV $n \notin \mathcal{N}_t$ becomes available for negotiation and needs to charge electricity, it becomes active for slot $t+1$. Set $t \leftarrow t + 1$, and go to step a).

- The total scheduling horizon, T, is divided into 15-minute intervals from 8:00 PM to 9:00 AM, yielding $T = 52$ time slots.
- The base load profile as shown in Fig.-2 represents typical energy consumption in the absence of EV charging. We chose the average residential load profile in the service area of South California Edison from 20:00 on February 13, 2011 to 9:00 on February 14, 2011, as the base load profile per household as mentioned in the original paper to match the results. [1]

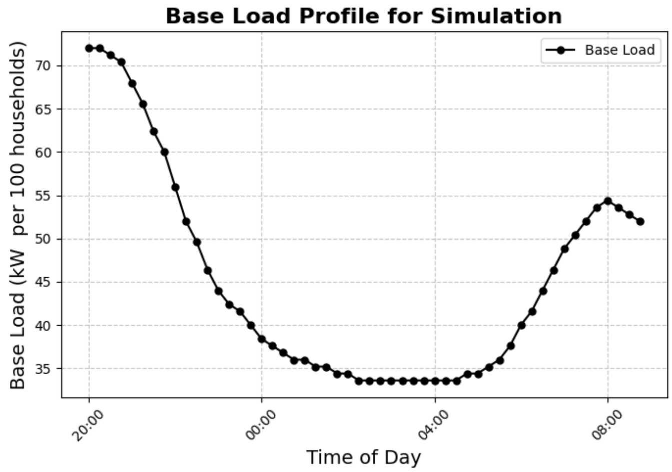

Fig. 2. Base Load Profile for Simulation.

- We are simulating the charging process of $N = 20$ electric vehicles (EVs).
- The arrival times and departure times for each EV are randomly assigned, with arrival times between the first half of the scheduling horizon and departure times between the second half, ensuring each EV has a feasible charging window of at least 5 hours (or 10-time slots).
- The energy requirement, E_{target}, for each EV is a random value between 5 and 25 kWh, simulating variability in charging needs.
- The Lipschitz constant, β, is set to 2.0, which is used in the control signal calculation to ensure stability in the optimization process.
- The minimum and maximum charging rates, $r_{\min}$ and $r_{\max}$, are set to 0 kW and 3.3 kW respectively, in alignment with typical home charging limitations.
- The gamma parameter, γ, which satisfies $0 < \gamma < \frac{1}{N\beta}$, is chosen as $\gamma = \frac{0.5}{N\beta}$ to ensure convergence of the decentralized algorithm.
- The maximum number of iterations for the optimization algorithm is set to 1000, with a tolerance of 10^{-3}, to ensure convergence.

VII. Simulation Results

Subsequent figures illustrate the simulation results for three cases:

1) **Simulation results** for the **ODC algorithm** run on the virtual environment setup.
   - **Fig. 3** shows the total load demand along with the Non-EV base load.
   - **Fig. 4** depicts the charging profile of all 20 EVs.

2) **Simulation results** for the **AODC algorithm** run on the virtual environment setup.
   - **Fig. 5** shows the total load demand along with the Non-EV base load.
   - **Fig. 6** depicts the charging profile of all 20 EVs.
3) **Simulation results** for the **RTODC algorithm** run on the virtual environment setup.
   - **Fig. 7** shows the total load demand along with the Non-EV base load.
   - **Fig. 8** depicts the charging profile of all 20 EVs.

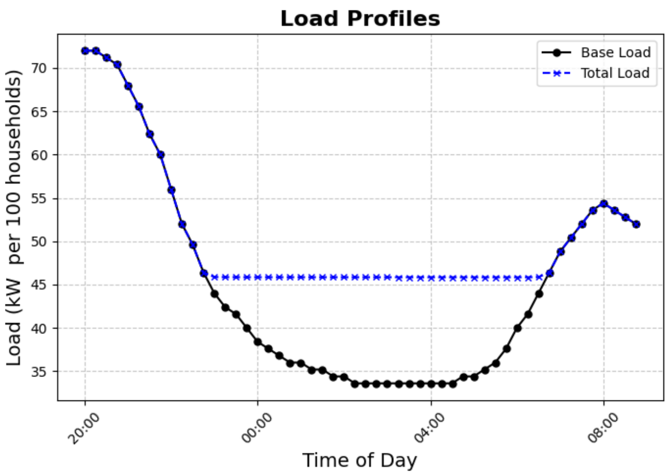

Fig. 3. Total Load for heterogeneous using the ODC algorithm.

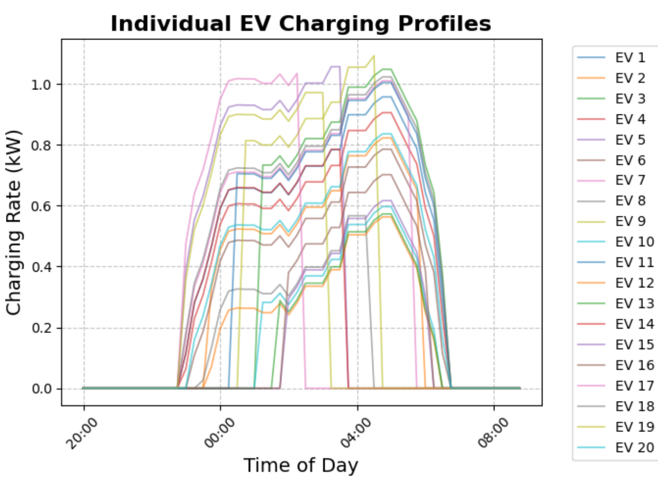

Fig. 4. Individual EV Charging Profiles for heterogeneous using the ODC algorithm.

VIII. Simulation of Real-Time Optimal Decentralized EV Charging under Indian Grid Conditions

A. Indian Grid Setup

For our simulation of the decentralized EV charging algorithm under Indian grid conditions, we utilize the October

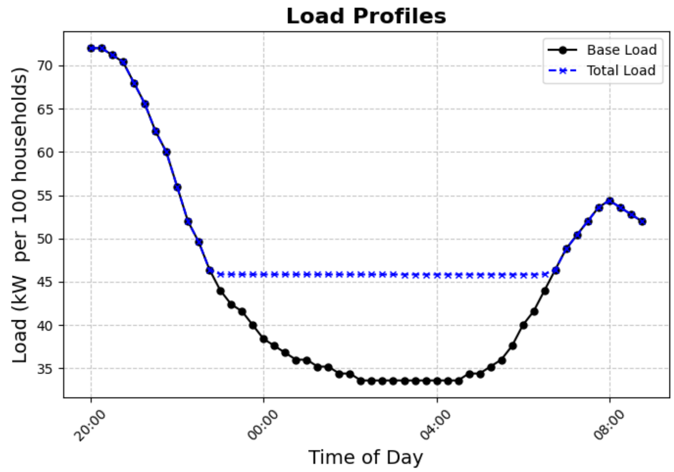

Fig. 5. Total Load for heterogeneous using the AODC algorithm.

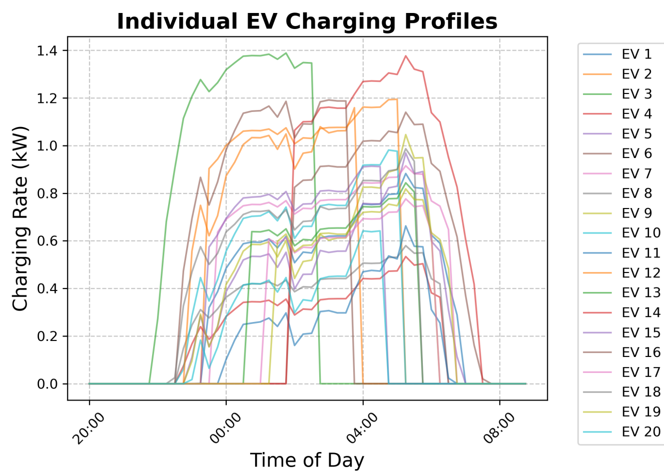

Fig. 6. Individual EV Charging Profiles for heterogeneous using the AODC algorithm.

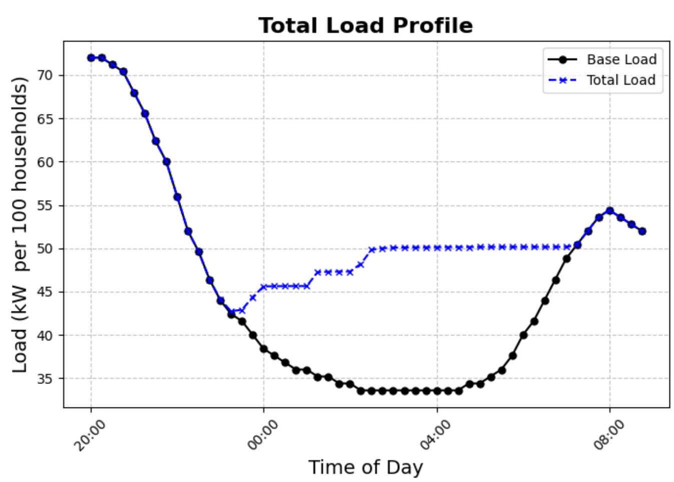

Fig. 7. Total Load for heterogeneous using the RTODC algorithm.

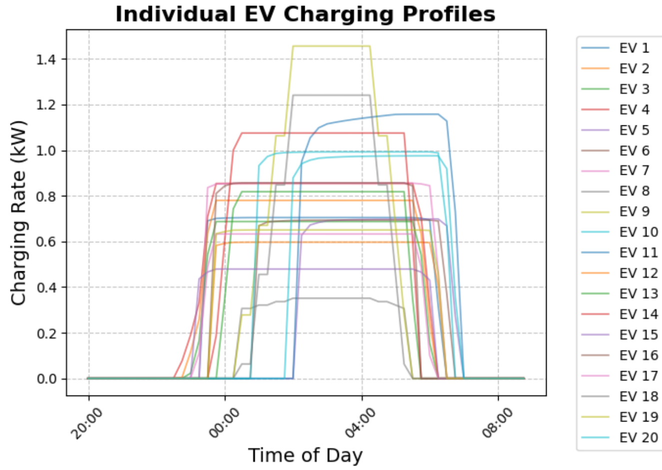

Fig. 8. Individual EV Charging Profiles for heterogeneous using the RTODC algorithm.

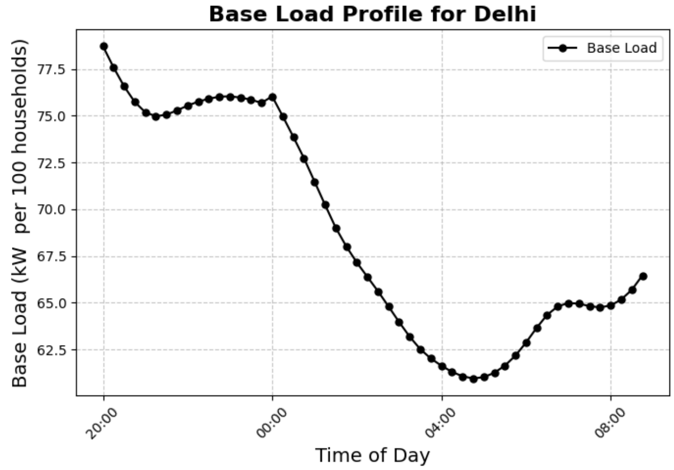

Fig. 9. Base Load Profile of Delhi for Indian context simulation.

2024 average electricity demand data of Delhi NCR [8], segmented into 15-minute intervals. The base load profile for the same is shown in Fig.-9. As of 2024, the estimated number of registered EVs in Delhi NCR is approximately 10.875 lakh, reflecting a 25% rise from 8.7 lakh EVs in 2021. [5] [6] With a population of 33,807,400 [7] and assuming an average household size of 5, this translates to 16 EVs per 100 households. The electricity demand data, measured in megawatts (MW) for the state, has been scaled down proportionally to represent 100 households, enabling localized and practical testing of the algorithm in a representative grid setup.

B. EV Specifications

To simulate the decentralized EV charging algorithm under Indian grid conditions, we have categorized the EVs into three main types: four-wheelers, two-wheelers, and three-wheelers. These categories are further divided into subcategories based on their body type or use case: Mini/Compact Cars(Type A), Sedans(Type B), and SUVs(Type C) for four-wheelers; Bikes(Type D) and Scooters(Type E) for two-wheelers; and Passenger Carriers(Type F) for three-wheelers. For the simulation, we allocate 70% of the EVs to four-wheelers, 20% to two-wheelers, and 10% to three-wheelers, reflecting their usage distribution. The total scheduling horizon, T, is divided into 15-minute intervals from 8:00 PM to 9:00 AM, yielding $T = 52$ time slots. Charging deadlines and arrival times are based on typical Indian charging habits, where most users charge between 8:00 PM and 9:00 AM. The detailed specifications of each EV are given in the table-1 below:

TABLE I
DETAILED INDIAN EV PROFILE DATA

ID	Type	Battery Capacity (kWh)	Max Power (kW)	Arrival Time	Deadline Time
1	Type A	17.3	3.3	8:30 PM	7:00 AM
2	Type A	24	14.2	9:00 PM	6:30 AM
3	Type B	35	11	10:00 PM	8:00 AM
4	Type B	32	11	9:15 PM	6:45 AM
5	Type C	50.3	22.5	8:45 PM	7:30 AM
6	Type C	39.2	30	10:30 PM	8:30 AM
7	Type A	25	7	9:00 PM	6:00 AM
8	Type A	15	7	11:00 PM	7:45 AM
9	Type D	3.24	3	8:15 PM	6:15 AM
10	Type D	4.4	9	10:45 PM	7:30 AM
11	Type E	2.9	5.8	9:00 PM	6:45 AM
12	Type E	4	8.5	8:30 PM	7:15 AM
13	Type F	8.9	2	9:45 PM	6:30 AM
14	Type F	9	2.5	10:15 PM	7:45 AM
15	Type C	72.6	150	8:00 PM	8:00 AM
16	Type A	29.2	21.5	9:30 PM	7:30 AM

C. Some Other Setup Conditions

- The Lipschitz constant, β, is set to 2.0, which is used in the control signal calculation to ensure stability in the optimization process.
- The gamma parameter, γ, which satisfies $0 < \gamma < \frac{1}{N\beta}$, is chosen as $\gamma = \frac{0.5}{N\beta}$ to ensure convergence of the decentralized algorithm.
- The maximum number of iterations for the optimization algorithm is set to 1000, with a tolerance of 10^{-3}, to ensure convergence.

D. Simulation Results

ODC Algorithm under Indian Grid Conditions:

- **Fig. 10:** Total load demand with Non-EV base load and EV load under ODC.
- **Fig. 11:** Individual EV charging profiles, showing synchronized offline scheduling.

RTODC Algorithm under Indian Grid Conditions:

- **Fig. 12:** Total load demand with Non-EV base load and EV load under RTODC.
- **Fig. 13:** Individual EV charging profiles, showing dynamic real-time scheduling.

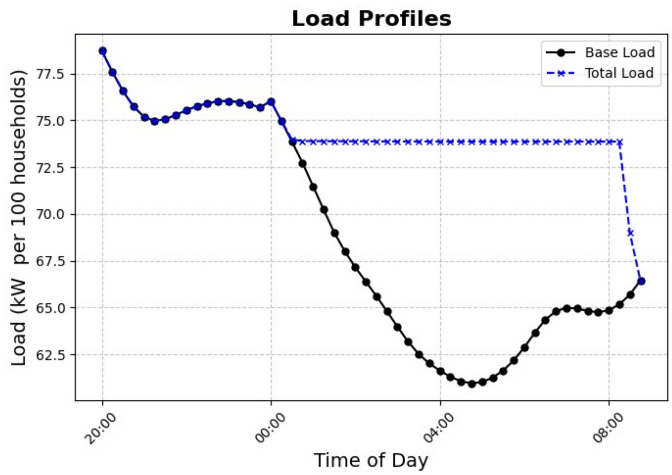

Fig. 10. Total Load for Indian Grid Condition using the ODC algorithm.

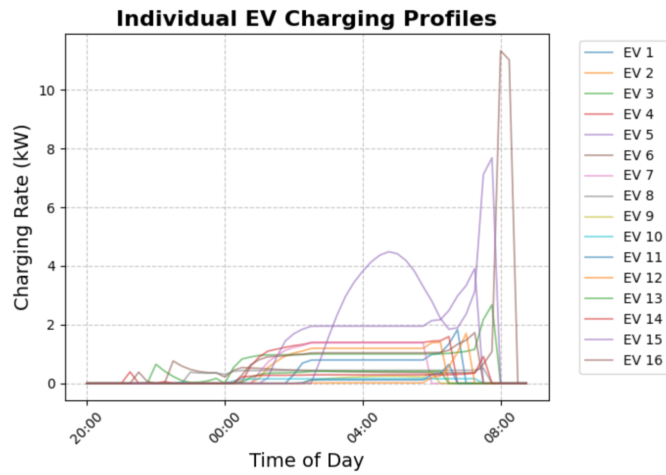

Fig. 13. Individual Indian EV Charging Profiles

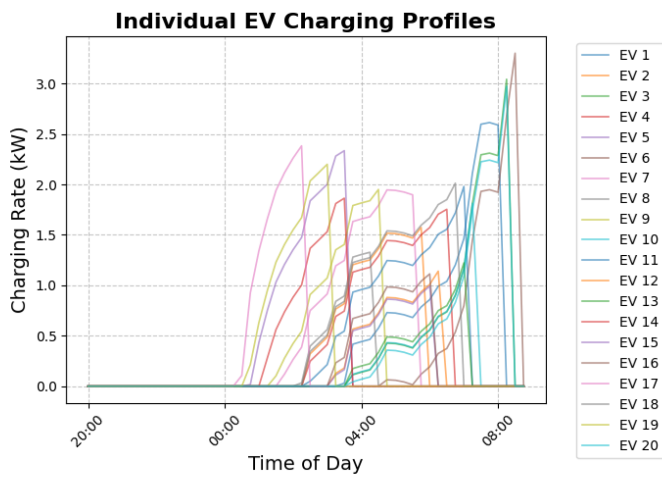

Fig. 11. Total Load for Indian Grid Condition using the ODC algorithm.

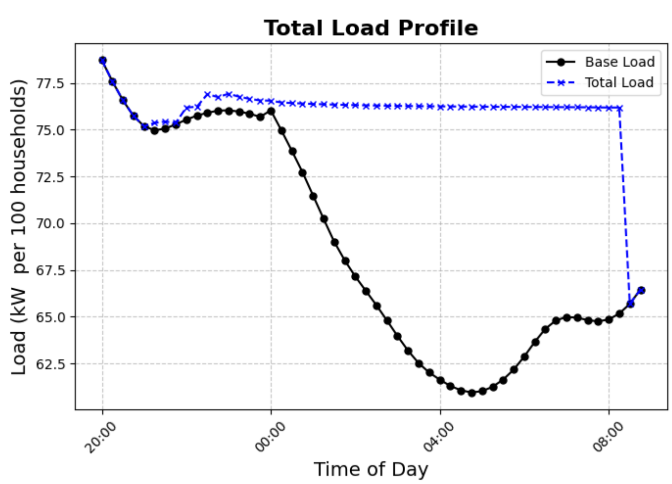

Fig. 12. Total Load for Indian Grid Condition using the RTODC algorithm.

IX. Performance Analysis & Comparison of Different Decentralized Scheduling Algorithms

This study simulated the ODC, AODC, and RTODC algorithms using the data from the original paper, successfully reproducing the results presented therein. Subsequently, the data was updated to reflect the Indian grid context, and both offline (ODC, AODC) and online (RTODC) algorithms were executed. Since ODC and AODC are offline algorithms with similar scheduling principles, they produced identical total load results under the updated Indian grid conditions. The results are presented in Fig. 10, Fig. 11, Fig. 12, and Fig. 13.

A. Key Observations:

From Fig. 3 and Fig. 5, it was observed that the **valley filling** of the energy demand curve for offline algorithms (ODC and AODC) remains nearly **constant** across the algorithms. This is because the **total charging energy required by all EVs**, which fills the dip in the curve, is determined by the total energy demand, irrespective of the scheduling algorithm used. However, the **effectiveness of offline algorithms can be compared based on their convergence rates**, or the number of iterations required to reach a stable solution. This performance index is critical in determining the algorithm's efficiency in practical implementations.

B. Performance Index for Offline Algorithms:

TABLE II
Convergence Rates for ODC and AODC

Algorithm	Homogeneous	Hetero. Rates	Hetero. Rates + Times
ODC	41 iterations	48 iterations	98 iterations
AODC	118 iterations	178 iterations	258 iterations

The table-2 highlights that ODC outperforms AODC in terms of convergence rate across all tested scenarios. This is due to ODC's synchronous updates, which ensure faster stabilization. However, AODC offers greater robustness by accommodating communication delays, making it more practical in real-world applications where perfect communication cannot be guaranteed.

C. Comparative Analysis of Algorithms:

- **ODC (Optimal Decentralized Control):** ODC demonstrates the fastest convergence among the tested algorithms. It updates the control signal synchronously and requires all EVs to participate, making it efficient but reliant on ideal communication.
- **AODC (Asynchronous ODC):** AODC is slower in convergence compared to ODC, as shown by the performance index, but it offers greater resilience by allowing asynchronous updates. This makes it robust to communication delays or failures.
- **RTODC (Real-Time ODC):** RTODC is highly suitable for dynamic, real-world scenarios. Unlike ODC and AODC, which are offline algorithms, RTODC finds optimal solutions for each time slot independently. It initiates charging immediately when EVs arrive, particularly during dips in non-EV demand, making it the most adaptable and flexible algorithm.

D. Summary of Algorithm Suitability:

- **ODC**: Best suited for offline, highly coordinated setups with reliable communication.
- **AODC**: Balances robustness and performance, accommodating communication disruptions effectively.
- **RTODC**: Ideal for dynamic environments with real-time EV arrivals, providing superior adaptability and flexibility.

E. Conclusion of the performance analysis:

In conclusion, the choice of algorithm depends on the specific application scenario. RTODC stands out in real-time, unpredictable conditions, while ODC is optimal for controlled and coordinated offline setups. AODC bridges the gap by balancing performance and resilience in real-world scenarios. The convergence rates highlight the trade-offs between speed and robustness, providing a quantitative basis for selecting the appropriate algorithm.

X. Limitations and Future Works for Decentralized EV Charging Algorithms

1. **Late Arrivals with Near-Term Deadlines:** These algorithms schedule charging based on the arrival time and deadline provided by the user. However, when an EV arrives late with a near-term deadline, it may be prioritized late due to the current non-EV base load demand. This can result in delayed charging, creating challenges in urgent situations. A potential solution for this limitation is the use of hybrid vehicles, which can operate on both electric and traditional fuels, ensuring usability even when immediate charging is unavailable.

2. **Ensuring Priority for Low-Charge EVs:** To address the risk of delayed charging for critical EVs, a **minimum charge threshold** can be implemented. This threshold would prioritize EVs with low battery levels, allowing them to participate in the charging negotiation process earlier. Such a mechanism ensures that EVs with urgent charging needs are accommodated promptly, improving the system's responsiveness in emergency scenarios.

3. **Lack of Consumer Incentives:** For the scheduling algorithms to operate efficiently, they require consumers to schedule their charging over a duration longer than the expected charging time. This allows the algorithms to dynamically update charging rates and distribute the load effectively, rather than charging at the maximum rate continuously. However, there is no clear incentive for consumers to provide a longer charging window. Without such incentives, users may set early deadlines, leading to possible spikes in demand that can destabilize the grid. Introducing consumer incentives, such as reduced tariffs for flexible scheduling or rewards for aligning with grid requirements, could mitigate this issue and promote optimal usage.

XI. Conclusion

This project initially presented the successful implementation and simulation of the Optimal Decentralized Charging (ODC), Asynchronous Optimal Decentralized Charging (AODC), and Real-Time Optimal Decentralized Charging (RTODC) algorithms on a virtual simulation setup. This was followed by the simulation of the decentralized algorithm for Indian grid conditions and context, where it was observed that the algorithms performed fairly well for the Indian scenario. Subsequently, a performance comparison of different algorithms was conducted, highlighting the conditions under which each algorithm should be preferred. In all cases, the algorithms demonstrated successful convergence.

References

[1] L. Gan, U. Topcu and S. H. Low, "Optimal decentralized protocol for electric vehicle charging," *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 940-951, 2012.

[2] M. Seetharaman, M. Sampat, P. Kashyap, P. Sagi, A. Agarwal, and V. Modi, "India Electric Vehicle Report 2023," Technical Report, Dec. 7, 2023.

[3] "Electric Vehicle Industry in India," India Brand Equity Foundation (IBEF), Aug. 2024. [Online]. Available: https://www.ibef.org/industry/electric-vehicle

[4] J. A. P. Lopes, F. J. Soares, and P. M. R. Almeida, "Integration of electric vehicles in the electric power system," Proc. IEEE, vol. 99, no. 1, pp. 168–183, Jan. 2011.

[5] Times of India, "Delhi second only to UP in number of EVs registered," Dec. 2021. [Online]. Available: https://timesofindia.indiatimes.com/city/delhi/delhi-second-only-to-up-in-number-of-evs-registered/articleshow/88173552.cms. [Accessed: Nov. 2024].

[6] Economic Times, "AAP govt unveils sops, targets 25% new EVs in Delhi by 2024," Dec. 2019. [Online]. Available: https://economictimes.indiatimes.com/news/politics-and-nation/aap-govt-unveils-sops-targets-25-new-evs-in-delhi-by-2024/articleshow/72948247.cms. [Accessed: Nov. 2024].

[7] World Population Review, "Delhi Population 2024," [Online]. Available: https://worldpopulationreview.com/cities/india/delhi. [Accessed: Nov. 2024].

[8] EAL, "Average Electricity Demand of October 2024 for Delhi," Indian Institute of Technology Kanpur. [Online]. Available: http://eal.iitk.ac.in. [Accessed: Nov. 14, 2024].