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Optimal Planning of EV Charging Stations Using Bilevel Optimization Model

Abstract: - The Electric vehicles (EVs) exponential rise in urban markets poses a number of challenges, such as the need for suitable infrastructure for charging, the best locations for charging stations, and effective scheduling of charging activities. Increasing EV load substantially affects distribution networks, environmental sustainability, and economic factors. The charging and discharging patterns of EVs are compatible with demand response (DR) programs as EV loads are flexible, controllable, and can also act as distributed energy storage. An optimization-based control strategy enables dynamic adjustment and management of EV charging and discharging profiles during DR events. This paper introduces a novel bilevel optimization framework designed to effectively balance infrastructure planning, grid reliability, DR participation, economic benefits, and user experience. The Elephant Herd Optimization (EHO) algorithm is proposed to determine the optimal size, and charging profile during DR events. The numerical results obtained from the simulation show that the optimal location and sizing, along with the application of DR programs, result in a reduction of losses and total costs. The proposed EHO algorithm achieves 30.5% peak demand reduction, $149 daily DR revenue, and 54% reduction in EV user wait times, demonstrating significant improvements over uncontrolled charging scenarios. This work promotes environmental sustainability by optimizing EV charging infrastructure and DR through advanced planning and coordination, thereby reducing grid stress, enhancing energy efficiency, and supporting the large-scale integration of low-carbon electric mobility.

Keywords: Demand response, Electric Vehicle, Elephant herd optimization, Grid stress, Scheduling.

I. INTRODUCTION

A. Motivation

To maximize the benefits of implementing demand response (DR) programs to the power utility and consumers it is necessary to plan and optimally locate the charging stations for electric vehicles (EV). Benefits of DR integration include lower grid upgrade costs, higher renewable penetration, enhanced user savings, and grid resilience [1]. Optimal location and sizing help to reduce the grid stress and flatten the peak load, and lower system costs. As EVs are flexible and controllable loads, the charging and discharging processes are highly compatible with DR. Charging stations which are equipped with DR can delay or reschedule the charging sessions based on the requirements of power utility grid.

With the DR feature, EV acts as a flexible and dynamic energy asset. EVs with vehicle-to-grid (V_2G) capability can function like a distributed energy resource [2]. The optimal planning of EV charging stations is inherently a multiobjective problem that is best addressed using a bilevel optimization approach. The selection of charging station locations significantly affects various stakeholders, including charging station owners, distribution network operators, and EV users. Additionally, uncertainties in EV user behavior lead to fluctuations in charging demand, which can directly impact the stability and operation of the distribution network. Demand Side Management (DSM) and V_2G schemes play a pivotal role in modifying the load curve and increasing grid flexibility. EV charging, as a highly adaptable and controllable load, can be strategically scheduled and managed to deliver both economic and operational advantages to the power system. By integrating DSM and V_2G, EV charging not only makes peak reduction, valley filling, and network stabilization easier, but it also opens up new revenue streams and cost-saving options for both utilities and EV owners.

B. Literature Review

Various approaches and optimization models for the optimal sizing of EV charging stations have been reported in the literature. DR programs involve adjusting EV charging loads based on grid conditions, electricity prices, or renewable energy availability. The significance of DR in energy management is critically examined in this paper [3], with an emphasis on the growing use of EVs and the integration of renewable energy sources. It examines the behavioral, legal, and technological obstacles and evaluates how well DR techniques manage the unpredictability of EV charging habits and renewable energy generation. In paper [4] challenges of large-scale EV adoption are discussed, with a focus on the significance of the optimal

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sites for charging stations. In addition to discussing the effects of EV load on distribution networks, environmental factors, and economic implications, it explores a variety of current research approaches, objective functions, restrictions, and optimization tools [4]. Research carried out in [5] examines control strategies and capacity configurations for charging stations that are linked with photovoltaic and energy storage systems. It tackles grid stability, power management, energy management, charging scheduling, and EV control strategies, including the application of intelligent optimization algorithms for capacity allocation. Paper [6] explores various charging strategies for EVs under dynamic pricing schemes, aiming to minimize charging costs, power losses, and peak loads. In order to maximize energy flow and grid stability, it assesses various control tactics and talks about coordinated charging strategies, which include the use of energy storage devices and renewable energy sources.

Paper [7] discusses the difficulties in designing EV charging infrastructure, such as optimal locations and capacities for charging stations. It explores several optimization techniques and algorithms that have been applied in recent research, offering insights into the most recent advancements and discoveries in the area. An optimal planning model for EV charging stations that considers both customer benefits and power grid efficiency is presented in this paper [8]. It determines the most optimal places, capacities, and service regions for charging stations using Voronoi diagrams and an enhanced particle swarm optimization method. For the purpose of building EV fast-charging stations, this research [9] examines metaheuristic methods such as Particle swarm optimization (PSO), Salp swarm algorithm (SSA), and Arithmetic optimization algorithm (AOA). In order to maximize economic and performance metrics, it evaluates configurations involving solar panels, battery energy storage devices, and grid connections. The work presented in paper [10] analyzes objective functions, metaheuristic techniques, and integration of renewable energy resources in optimizing distribution systems with EV charging stations. It covers factors like cost concerns, power losses, voltage stability, and greenhouse gas emissions. Paper [11] proposes evolutionary algorithms to identify the most appropriate locations for EV charging stations with the goals of maximizing covered demand and minimizing travel costs. It considers several optimization techniques and real-world applications in urban settings. A new Chicken swarm optimization (CSO) heuristic technique for the integrated design and operation of EV charging stations is presented in this work. It discusses multi-objective modeling, considering economic factors and secure power grid operation under various charging scenarios [12]. In [13] PSO algorithm is proposed for optimal placement and sizing of EV charging stations considering consumer behavior, road dynamics and environmental effects. It integrates data gathered from multiple sources to enhance infrastructure effectiveness. An optimization approach for the design and management of fast EV charging stations connected to energy storage and solar PV systems is presented in the paper. It aims to optimize earnings while taking infrastructure configuration and daily power scheduling into account [14]. This paper uses a trip chain approach to dynamically anticipate charging demand in order to solve EV charging station planning. It formulates a multiobjective optimization problem solved by combining an entropy-based method with a hybrid PSO algorithm [15].

The following seven papers specifically discuss various aspects of the bilevel aggregator framework in terms of mathematical formulations, upper and lower level objectives, solver methods, and case studies evaluation with different metrics. The work carried out in [16] presents a two-layer coordination structure in which the upper level aggregator and distribution system operator coordinate EV charging to minimize load variance and smooth grid profiles. In a two-step EV power allocation method water filling algorithm is employed by the aggregators to achieve peak shaving and valley filling objectives. Interaction between an EV aggregator participating in day-ahead and balancing markets and the aggregated EV users is modelled via stochastic programming in [17]. A model of bilevel optimization for microgrids with EV integrated with DR under real-time pricing is proposed in [18]. JAYA interior point algorithm is used to coordinate the EV demand response and renewable generation uncertainty in MG scheduling. A two-layer framework using large language models to simulate and optimize EV user behavior under dynamic pricing is used in [19]. A multi-threaded LLM decision generator is proposed in this paper to examine psychological aspects, charging preferences, and EV user behavior. This paper focuses on real-time control and bilevel scheduling at a charging station with battery energy storage systems. Through coordinated planning and real time rolling optimization, reduction of peak load, cost, and grid stress is demonstrated [20]. An iterative technique is implemented to solve a hierarchical mixed-integer non-linear program to optimize EV station location, capacity, and pricing, balancing aggregator profits and user travel costs [21]. The work presented in paper presents a two-layer online feedback control algorithm to quantify flexible EV loads for DR participation, optimize dispatch, and manage aggregator revenue and user service tradeoffs [22].

The major challenges include uncertainty in EV adoption rates, user reluctance to DR participation, communication latency in DR signals, and high V_2G battery degradation. Key enablers to achieve cost efficient and grid friendly EV infrastructure are smart algorithms, dynamic pricing, and stakeholder collaboration. This research presents a comprehensive bilevel optimization model for EV charging infrastructure planning, integrating an aggregator-mediated demand response system that explicitly considers both user wait times and grid stability. The results obtained from our proposed work confirm that the strategic coordination of EV charging through price-based incentives can transform EVs from grid challenges into valuable flexibility resources, accelerating the transition to sustainable transportation and energy systems.

C. Contribution

This study focuses on developing a planning model to optimally size EV charging stations to maximize DR benefits and minimize grid stress. An optimal sizing and siting problem is a nonlinear optimization problem with multiple variables and sets of constraints. The EV charging station problem is a complex, nonlinear, multi-variable optimization problem. An Elephant herd optimization (EHO) algorithm is implemented for a multiobjective EV charging management problem considering various operating constraints.

The main contributions of this work are i) a structured approach that integrates power systems modeling, optimization techniques, and demand-side flexibility, ii) proposes a novel decomposition method that utilizes price signals in order to maintain grid-level and user-level optimization, iii) developing a multi-stage stochastic model that accounts for uncertainties in EV adoption and DR participation, iv) integrated wait time minimization in planning, and v) bilevel coordination between planning and operation. It demonstrates effective balancing of competing objectives (economic benefits vs. grid stability vs. user satisfaction).

The remainder of this paper is organized as follows. Section II formulates the research problem for the optimal planning of EV charging stations. In section III, the implementation of the EHO algorithm for optimal scheduling is described. Optimization results for different case scenarios are discussed in section IV, and section V concludes the paper.

II. Formulation of EV Charging Station Planning Problem

A. Model Description

The main stakeholders in the process of optimal siting and sizing of charging station operation include the power utility, aggregator, and EV owners. The bilevel optimization model for EV charging station planning with real-time DR and user convenience is formulated. Bilevel optimization is a hierarchical approach involving two levels of decision making. The best solution for the upper level depends on the response from the lower level since the upper level optimization problem uses the lower level problem as a constraint. In this context, the aggregator at the upper level optimizes DR incentives and infrastructure management, while EV users at the lower level minimize costs and wait times within the aggregator's framework. The main achievement of this formulation is the bilevel coordination between planning and operations. The objectives include optimizing station placement and sizing, managing real-time DR, minimizing user wait time, and optimizing costs. The practical implications of the proposed work include grid benefits, user benefits, controlled wait times, and cost-effective planning.

B. Modeling of DR Programs

DR refers to action taken by the consumer to modify the short-term demand due to incentive payment over time in response to changes in the price of electricity. Consumers change their demand based on the dynamic power tariffs or incentives provided by the power utility. The load change due to DR can be expressed as per (1).

$$\Delta d_t = Nd_t - Id_o \tag{1}$$

Both the responsive and non-responsive consumer loads are considered to model the consumer demand function. In the case of the incentive-based DR programs, consumers generate revenues in the form of incentives after participating in them and are computed at time t as per (2).

$$INC(\Delta d_t) = inc_t(Nd_t - Id_0) \tag{2}$$

In the equations stated above Ndt is the modified demand, Id_0 is the initial demand, Δdt is the change in demand, inc_t and pen_t are the incentive and penalty rates respectively. When consumers do not honor their commitment to the load reduction with the utility regarding demand change, they have to pay the penalty based on the penalty factor at time t and is computed as per (3).

$$PEN(\Delta d_t) = pen_t(Nd_t - Id_0) \tag{3}$$

The overall change in consumer demand due to the effect of the elasticity factor is given by (4) [23]. The DR model expression gives the change in consumers demand patterns with respect to changes in energy prices considering incentives as well as penalties.

$$Nd(i) = Id_0(i)\left[1 + E(i) * \left\{\frac{c_0(i) - c(i) + Inc(i) + Pen(i)}{c_0(i)}\right\}\right] \quad (4)$$

Based on the prices and elasticity factors new demand due to both price and incentive-based programs are found. In the equations stated above, *Nd(i)* is the modified or new load demand, Id_0 is the initial demand, Δd_t is the change in demand, c_0 is the initial price, *c* is the new price and *Inc* is the incentive offered, *Pen* is the penalty value, and *E(i)* is the elasticity value. The cost for the implementation of the DR program is considered in the objective functions for the optimal loading of the charging station as per (5).

$$DR\,\text{Cost} = \sum_{k=1}^{N_{DR}} \left(\Delta d_t \times Inc(i) \times Z_k\right) \quad (5)$$

Where Z_k is the binary decision variable related to status of k^{th} responsive load. Based on the response of the consumers to participate in DR, implementation cost is impacted.

C. Objective Functions

For formulating the problem of EV charger placement in a power system network, the following objectives are considered, subject to a set of constraints. Because this is a bilevel optimization problem, there are two levels of objectives: upper and lower. The upper-level (aggregator-level) objectives include: i) Demand response maximization, ii) Grid stress minimization, and iii) Minimization of user wait time. These objectives guide the strategic placement of EV chargers to optimize both system wide and user centric performance metric

C.I. Maximize DR Benefits

The DR benefit is given by the expression (6).

$$F_1 = Max\sum_{t=1}^{T}\sum_{i=1}^{N}\left[\{DP(t) - BP(t)\} * P(i,t)\right] \quad (6)$$

DP is the time-varying DR incentive price, and *BP* is the standard or base electricity price. *P(i,t)* is the charging power of EV *i* at time *t*. This objective maximizes revenue from price arbitrage between DR incentives and base prices.

C.II. Minimize Grid Stress

The second objective is to minimize the grid stress as given by expression (7).

$$F_2 = Min\sum_{t=1}^{T}\left(\sum_{i=1}^{n}\left(P_{i,t} - P_{avg}\right)^2\right) \quad (7)$$

P is the total system load and P_{avg} is the average system load. This helps to minimize load variance to flatten demand profile and reduce grid congestion.

C.III. Minimize User Wait Time

$$F_3 = Min\sum_{i=1}^{N}\left[t^i{}_{start} - t^i{}_{arrival}\right] \quad (8)$$

The function is used to minimize the EV users wait time, In the equation t_{start} and $t_{arrival}$ is the initiation time of charging and arrival time of EV at the charging station. The significance of this objective is that it reduces waiting time between EV arrival and charging initiation.

C.IV. Composite Objective Function

All aspects related to the upper-level objectives of maximizing grid benefits, minimizing grid stress, and minimizing user wait time are given by F_4, which is a multiobjective function.

$$F_4 = Max\left\{\alpha_1 * F_1 - \alpha_2 * F_2 - \alpha_3 * F_3\right\} \quad (9)$$

In the equations α_1, α_2, and α_3 are weight factors. Normalization factors applied for dimensional consistency. Weighting factor values considered are typically 0.6, 0.3, and 0.1.

C.V. Lower Level Objectives

All the lower level objectives are related to minimizing of the charging cost and user wait time.

i) Charging cost minimization

The significance of this objective is to minimize the energy cost for each EV owner.

$$H_1 = Min\sum_{t=1}^{T} P_{i,t} * BP(t) \tag{10}$$

ii) Minimize User Wait Time

This objective considers user convenience.

$$H_2 = Min(t^i{}_{start} - t^i{}_{arrival}) \tag{11}$$

C.VI. Composite Lower Level Objective Functions

All the aspects related to the lower level objectives related to minimizing the charging cost and user wait time given by H_3 which is a multiobjective function. Here δ and ε are weight factors.

$$H_3 = Min(\partial * H_1 + \varepsilon * H_2) \tag{12}$$

C.VII. Constraints

The upper level constraints include station capacity constraint, DR price boundaries, power flow limits, and DR participation obligations.

i) The station capacity constraints ensure that the total power drawn from each station does not exceed its rated capacity.

$$\sum_{i \in S_k} P_{i,t} \leq C_k \,\forall\, k \in \{1,2,\ldots.k\} \;\forall\, t \in \{1,2,\ldots.T\} \tag{13}$$

ii) DR price boundaries are to maintain DR prices within economically viable limits.

$$DP(t) = DP_{\min} \;\&\; DP(t) = DP_{\max} \tag{14}$$

iii) Power flow limits constraint is for ensuring total demand not to exceed the grid connection capacity.

$$\sum_{i=1}^{N} P_{i,t} \leq P^{\max}{}_{grid} \;\forall t \tag{15}$$

iv) DR participation requirements ensure that the contractual DR obligations are met

$$\sum_{t \in T}\sum_{i=1}^{N} P_{i,t} \geq L^{\min}{}_{DR} \;\& \sum_{t \in T}\sum_{i=1}^{N} P_{i,t} \geq L^{\max}{}_{DR} \tag{16}$$

The constraints are also related to the energy requirement constraint, charging period window, and power demand rate limits.

i) Energy requirement constraint ensures that each EV receives sufficient charge by the departure time.

$$\sum_{t=1}^{T} P_{i,t} * \Delta t \geq E_i^{req} \;\forall i \tag{17}$$

ii) The charging period window constraint shows that EV can charge during its available connection period.

$$P_{i,t} = 0 \;\forall \in \left(t^i{}_{arrival}, t^i{}_{departure}\right) \tag{18}$$

iii) Power demand rate limits indicate the charging power within vehicle capabilities

$$0 \leq P_{i,t} \leq P^i{}_{\max} \;\forall i,t \tag{19}$$

iv) Location capacity limit signifies the coverage. The charging station within certain radius for EV users convenience.

$$\sum_{i \in loc_k} P_{i,t} \leq P_{\max,loc} \;\forall k,t \tag{20}$$

The decision variables for upper level and lower level optimization problem are indicated in Table 1 and 2 respectively. The bilevel optimization model effectively balances the interests of all stakeholders while maintaining operational and physical viability due to this comprehensive constraint and objective formulation.

Table 1: Aggregator level decision variables

Variable	Dimension	Description	Bounds
Price signal for DR	24 x 1	DR incentive price based on time	[0.8×BP, 2.0×BP]
Charging station limit	10 x 1	Power drawn per station (max)	[50,150] kW
Weight factors	50 x 1	Priority values for EV charging	[0.1,1.0]

Table 2: User level decision variables

Variable	Dimension	Description	Bounds
Charging power	50 x 24	Power of particular EV at particular time	[0, 7] kW
Starting time	50 x 1	Starting time slot for charging	[arrival, departure]

D. Solution Methodology

The bilevel problem is solved by using a master-slave architecture. Aggregator determines optimal DR incentives and station load limits. At the lower level, EVs respond with charging schedules. The EHO algorithm is adapted for a bilevel problem. The steps followed include population initialization, clan updating (local search), separation operator (Global exploration), and repeating the process until convergence. The optimal EV charging station problem is solved in the MATLAB environment using the EHO algorithm. The performance is validated through computer-based simulations.

III. EHO Algorithm Implementation for Optimal Scheduling

The EHO is Bio inspired swarm intelligence algorithm proposed by Wang et al [24]. It is based on the herding behavior of elephants. Good searching ability, better convergence speed, better exploration capability, the ability to obtain solution with a few numbers of function evaluations, and the potential of finding optimal solutions are some better features of EHO as compared to other algorithms [25-26]. The herd consists of clans with female elephants, calves, and male elephants. The leader of the clan is the Matriarch, and all others are under his influence. The best solution is based on the position of matriarch and worst solution is based on the position of the male elephants. The basic step to model herding behavior includes initialization. Updating the position of elephants in the clan, updating the position of the fittest elephant, separating the worst male elephant, and convergence. Clan-based search balances exploration/exploitation, the separation operator avoids local optima, and inherits gradient-free nature for non-convex problems.

It is effective for solving complex optimization problems with multiple constraints and objectives. This biologically-inspired approach provides adaptive, interpretable, and computationally efficient optimization for the complex EV-grid coordination problem, with explicit mechanisms to balance competing objectives through specialized clan behaviors.

To start the EHO algorithm, an initial population of elephants, each representing a solution, is considered. For a local search clan updating is done, and each clan's matriarch guides the updates. For global exploration, a separation operator is used which replaces the worst solutions. Steps followed include i) Initialize elephant position (Charging configuration) ii) Evaluate the fitness function based on the objective function iii) Update the position of the clan leader i.e Matriarch (updating operator), guides search toward best solutions iv) Update the position of the elephants within the clan v) Replace the worst elephant (separating operator) vi) Repeat the process until convergence is obtained.

The updated position E of the elephant j in clan ki position is given by (21). In equation r, α, and β are random number and scale factors respectively. The distribution is decided by the random number, scale factor α influences the elephant position, and β impacts the best elephant position in the standard EHO algorithm as per (22) and (23).

$$E_{new,ki,j} = E_{ki,j} + \alpha(E_{best,ki} - E_{ki,j}) \times r \tag{21}$$

$$E_{new,ki,j} = \beta \times E_{center,ki} \tag{22}$$

$$E_{center,\,ki} = \frac{1}{n_{ki}} \sum_{i=1}^{nki} E_{ki,\,j} \tag{23}$$

IV. Results and Discussions

A. Case Study Description

The optimization model considers the following input data: i) Base electricity prices, ii) EV demand forecasts, iii) Site locations (geographical data), iv) Cost data, including installation and operational costs, and v) Constraints related to power limits, travel radius, station capacity, and the energy needs of EVs. Synthetic data is generated for 10 different locations, encompassing demand profiles, DR potential, and grid parameters. A real-time DR pricing scheme is also incorporated. The synthetic data used for the model simulation is summarized in Table 3.

The following aspects are considered in the simulation model: (i) The time horizon is a 24-hour operation with a 1-hour resolution, (ii) The EV fleet consists of 50 vehicles with heterogeneous charging requirements (ranging from 10 to 50 kWh) and a maximum charging rate of 7 kW; users travel time limits are also considered, (iii) The charging infrastructure comprises 10 charging stations, each with a maximum capacity of 100 kW, (iv) The pricing structure features time-varying prices with DR based incentives, and the base price ranges from \$0.12 to \$0.17 per kWh, (v) The optimization algorithm used is the EHO with bilevel decomposition. In the model, the aggregator acts as a central controller. The lower level determines optimal charging schedules for individual EVs, while the upper level optimizes station management and DR participation.

Table 3: Data considered for optimization

Parameters	**Value/Range**	**Description**
Arrival time of EV	8-19 hour	Uniform distribution
Energy demand	10-50 kWh	Energy variation
Maximum charging rate	7 kW	Decides level of charger
Base price of electricity	0.12 to 0.17 \$/kwh	Time variation
Capacity of charging station	100 kW	Per location

B. Optimization Results

The key findings, sensitivity analysis, benchmarking, and practical implications are discussed in this subsection. The model is designed to maximize DR benefits by leveraging time varying electricity prices by shifting EV charging loads to low price periods. It helps to optimize the charging schedules and respond to prices. It also helps in reducing grid stress user wait time, and improving station utilization capacity.

B. I DR Price Values

The optimization outcomes for the upper level objectives obtains DR prices. The key observation from the results are peak DR incentives, off peak discounts and maximum differential price obtained. The optimal DR price obtained is shown in Figure 1. The key observations from results are i) Peak DR incentives are from period 18:00 to 20:00 hours (\$0.185 to \$0.205) which are 67% above base prices, ii) Discounts during off peak hours is from (01:00 hours to 05:00 hours (\$0.065 to \$0.085) which are 40% below base prices, iii) The maximum price difference is \$0.12/kWh.

B. II. Load Profile Comparison

After optimization, the load curve demonstrates significant improvements. Both uncontrolled and optimized load values were analyzed, revealing a noticeable reduction in peak demand, an improved load factor, and effective valley filling, resulting in a smoother load curve. These outcomes are illustrated in Figure 2. The optimized load data facilitate the balancing of grid requirements, enhance economic efficiency, and increase user satisfaction through the mathematical coordination of available resources.

This approach supports peak shaving, reduces peak demand by 24–34%, and contributes to a more stable and flattened load profile.

It helps in valley filling with a minimum load increased from 0 kW to 15 kW. It helps in load factor improvement from an initial value of 0.63 to 0.79, which results in a 25.8% increase. It also helps in congestion management by maintaining the station utilization below 95%. The total energy value is maintained without any curtailment. The optimized load profile significantly flattens the aggregate load curve by effectively shaving the peak during high-demand (hours 18 to 21) and filling the valley during low-demand (hours 01to 07).

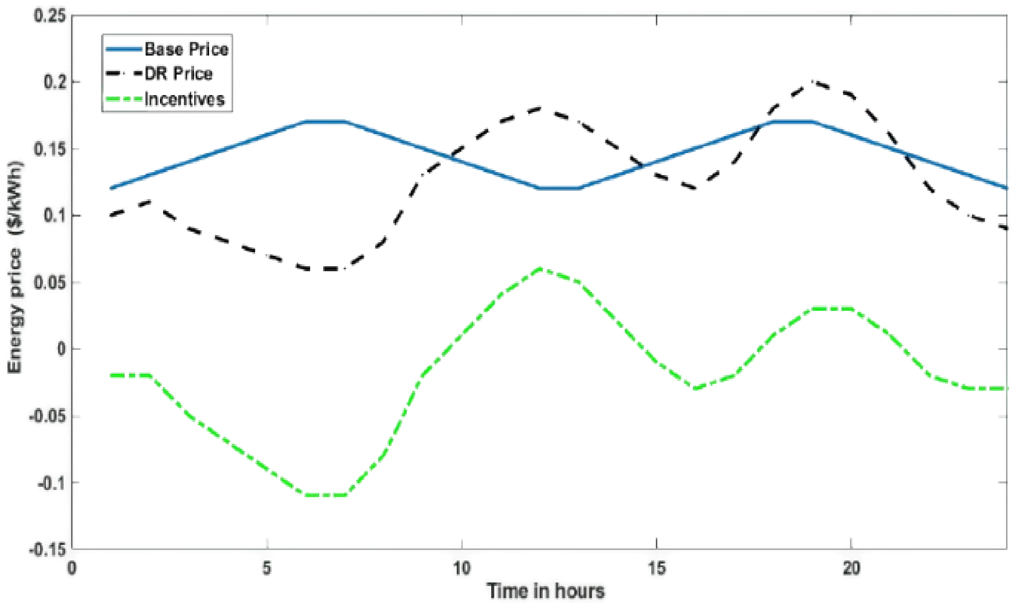

Figure 1. Energy pricing

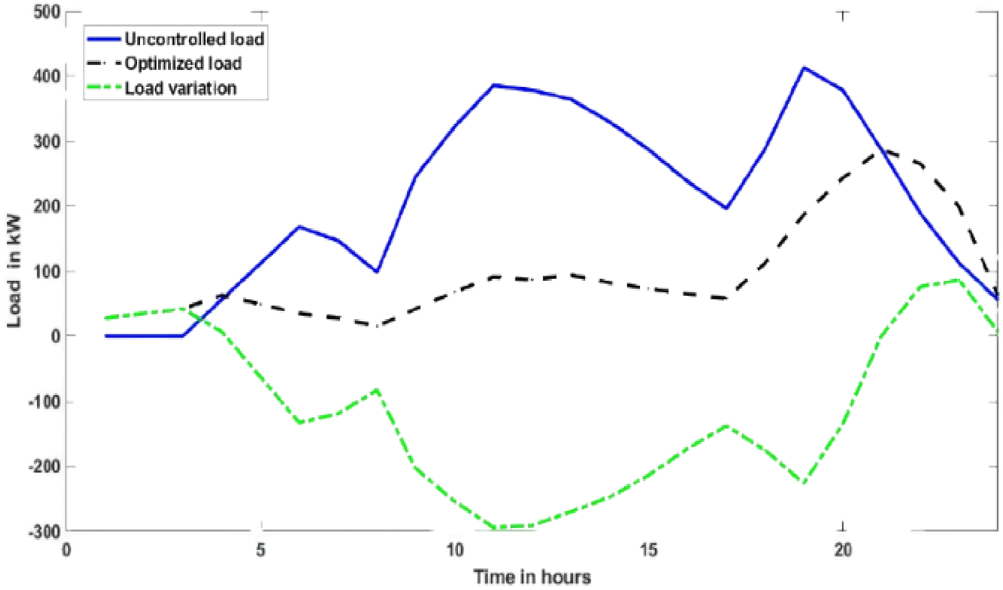

Figure 2. Load profile comparison

B. III. Load Profile Comparison

The optimization results also reveal the distribution of EV user wait times, as shown in Table 4. With optimization, the wait time distribution is as follows: i) From 0 to 1 hour, 26 EVs (52%), ii) Between 01 to 02 hours, it is 15 EVs (30%), iii) From 02 to 03 hours, 6 EVs (12%), and iv) More than 3 hours, 3 EVs (6%). EV wait time distribution for users is shown in Figure 3. These results demonstrate that the optimization process improved user satisfaction by minimizing wait times while ensuring charging completion assurance.

Table 4: Wait time statistics for EV owners in hours

Station	Normal	Optimal	Improvement
Waiting time (Mean)	2.81	1.275	-54%
Waiting time (Median)	2.51	0.76	-0.69%
Waiting time (Maximum)	6.51	4.21	-35.33%
Standard deviation	1.46	0.91	-37.6%

B. IV. Grid Impact Assessment

Grid stress was evaluated as part of the grid impact assessment, with two scenarios considered: uncontrolled stress, calculated from an uncontrolled load profile, and optimized stress, derived from an optimized load profile. Table 5 summarizes the grid stress indices for both cases. Results from the optimization model demonstrate effective minimization of grid stress by distributing the charging load more evenly and penalizing usage during peak hours to reduce the risk of overloading. Load factor (LF) improves with optimization.

Table 5: Grid stress indices

Charging station	Unoptimized	Optimized	Improvement
Variance of load (kW^2)	3510	2408	-31.39%
Max. deviation (kW)	205	79	-61.46%
LF	0.63	0.79	25.3%

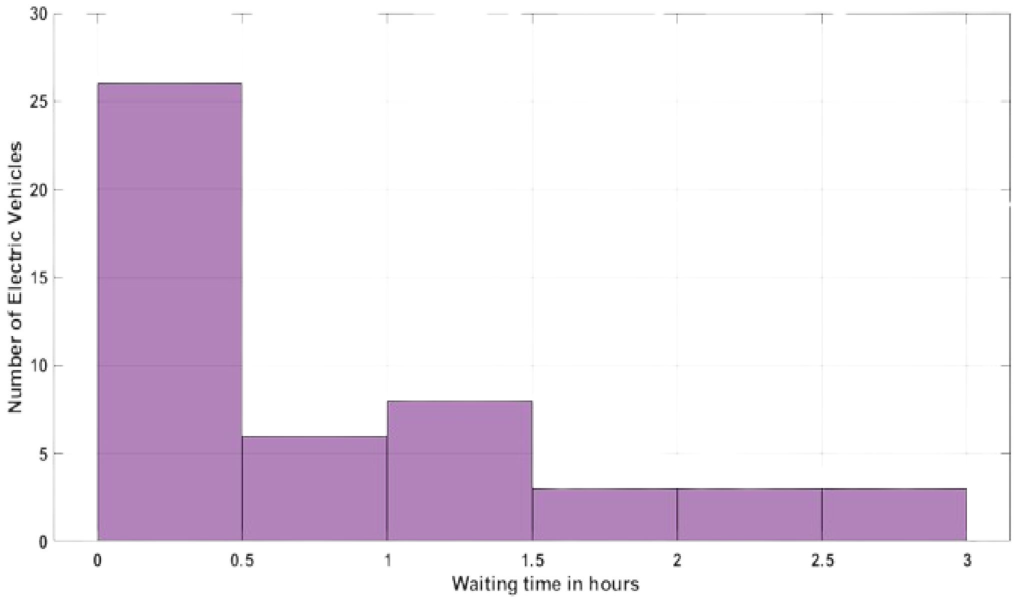

Figure 3. EV wait time distribution

B. V. Interpretation of EHO Results

The complex bi-level EV aggregator problem can be effectively optimized using the EHO implementation, which manages several constraints and objectives while striking a balance between computing efficiency and solution quality. The EHO algorithm parameters are listed in Table 6. The EHO convergence with fitness values is shown in Figure 4.

Initial stage: From iterations 1 to 10. It is observed that rapid fitness improvement as constraints are satisfied. The grid stress decreases by 19% because the charging loads are getting redistributed.

Mid optimization stage: From iterations 11 to 25. It is observed that the DR benefits grow linearly with price-responsive scheduling. Waiting times are getting reduced as charging starts aligning with the arrivals.

Final convergence stage: From iterations 26 to 50. In DR benefits there is marginal gain (More than 2% after iteration 30). Grid stress and wait time tradeoff becomes prominent. The Pareto-optimal balance is achieved through algorithm implementation. The fitness stabilizes after a certain number of iterations. DR benefits and wait times showed inverse relationships. EHO algorithm finds the globally competitive solution within a short time.

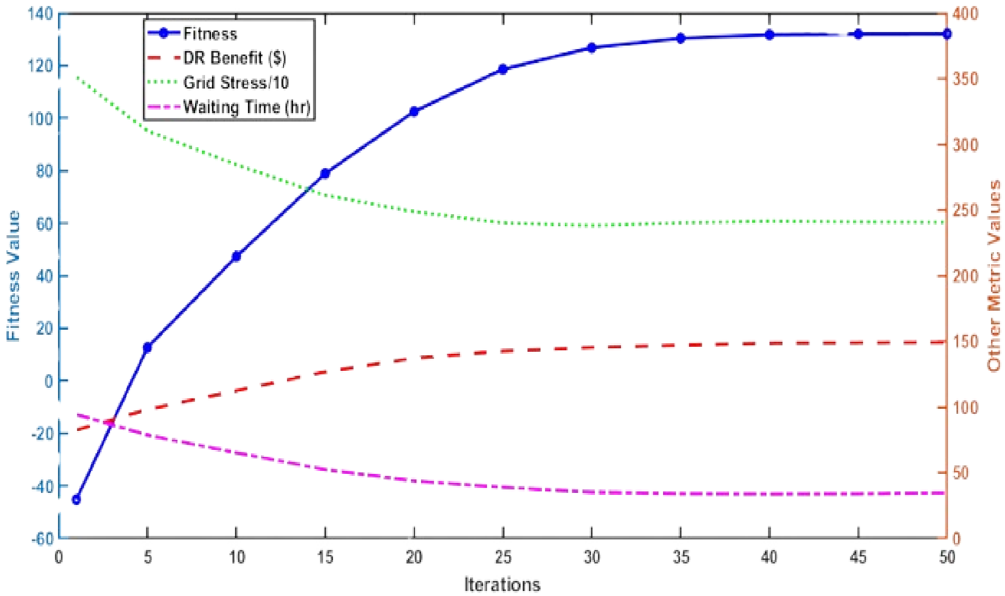

Figure 4. EHO optimization convergence

Table 6: EHO algorithm parameters

Parameters	Value	Description
Number of Elephants	50	Number of candidate solutions
Clan size	10	Elephant groups with different strategies
Maximum iterations	50	Criterion for stopping
Updating operator rate(α)	0.6	Updating step size of clan
Separation operator rate (β)	0.3	Percentage of worst solution replaced

B. VI. Charging Station Utilization

The utilization of all 10 charging stations is computed. The optimization results indicate the station utilization capacity. By optimal charging with DR implementation the average station utilization improved from 72% to 85% (13% increase). Congestion is identified at stations 5 to 7 with 92 to 97% utilization. Stations 8 to 10 remained underutilized. It is recommended to redirect new EV users to stations 8 to10. The charging station utilization parameters are shown in Table 7.

B. VII. Economic Performance of Model

The economic analysis of the model is carried out based on parameters such as DR revenue, user costs, total savings, per unit cost. The uncontrolled and optimized parameters are listed in Table 8. The revenue distribution peak hours (18 to 21): 68% of total DR revenue, off-Peak hours (01 to 07): 22% of total DR revenue, shoulder hours: 10% of total DR revenue. The price differential strategy generates substantial revenue while reducing user costs, creating a win-win scenario for both the aggregator and EV users. DR revenue is the summation of the product of the optimized load times the difference between the optimized price and the DR price. DR revenue generation helps to achieve \$120 to \$180. It helps in user cost reduction saves 18-25% as compared to uncontrolled charging. For the user, it helps in wait time optimization and maintains 85% of EVs with less than 1.5 hour wait. It helps in ensuring the energy guarantee. It ensures all EVs receive more than 94% of the requested charge.

Table 7: Charging station utilization

Charging station	Utilization (%)	Peak Hour	Average utilization
1	86	19	Adequate
2	84	19	Adequate
3	92	20	Near capacity
4	87	20	Adequate
5	96	21	Requires expansion
6	93	21	Near capacity
7	91	20	Near capacity
8	81	19	Underused
9	79	18	Underused
10	83	19	Underused

Table 8: Economic performance indicators

Metric	Unoptimized	Optimized	Improvement
DR revenue (\$/day)	0	149.0	--
Cost for EV user (\$/day)	735.42	647.97	-11.9%
Total savings (\$/day)	--	236.7	--

B. VIII. Sensitivity Analysis

A sensitivity analysis was conducted to assess the robustness of the proposed bilevel optimization model and to comprehend how changes in important parameters impact the optimization results. This study assists in identifying crucial parameters that have a major impact on performance and provides insights into how the model behaves under various operating settings. The objective of weight parameter analysis is to assess the trade-offs between competing objectives. The weight parameter sensitivity is based on weight factors. The weight combinations are varied in different proportions. DR revenue, grid stress, and average wait time are computed by varying the weight factors. The variation limit in the model for α_1, α_2, and α_3 is considered. DR benefit weight values $\alpha_1 \in [0.3, 0.8]$, Grid stress weight: $\alpha_2 \in [0.1, 0.4]$, Wait time weight: $\alpha_3 \in [0.1, 0.4]$, with $\alpha_1 + \alpha_2 + \alpha_3 = 1$. The impact of the weight factors on the performance parameters is presented in Table 9.

Table 9: Impact of weight factors

Weight factors (α_1: α_2: α_3)	DR benefit (\$)	Grid stress (kW^2)	Waiting time (hour)	Fitness Value
0.8:0.1:0.1	161.40	2,681	1.81	124.6
0.6:0.3:0.1	148.30	2,406	1.27	132.1
0.4:0.4:0.2	134.20	2,214	0.94	128.7
0.3:0.3:0.3	120.80	2,380	0.67	118.9
0.5:0.2:0.4	141.60	2,321	1.04	129.8
0.7:0.2:0.1	156.80	2,509	1.46	130.2
0.4:0.2:0.4	137.40	2280	0.81	126.1

It is observed that the optimal weight combination of (α_1: α_2: α_3) 0.6:0.3:0.1 achieved the highest fitness (132.1). The tradeoff relationships indicate i) a strong negative correlation (-0.88) between the DR Benefit and grid stress, ii) a moderate negative correlation (-0.71) between the DR benefit and wait time, and iii) a weak positive correlation (0.34) between the grid stress and wait time. The sensitivity analysis reveals several critical insights, such as i) No single weight combination optimizes all objectives simultaneously, ii) Optimal parameters vary based on grid conditions and user requirements, so an adaptive strategy is needed, and iii) DR benefits show diminishing returns beyond a certain price value.

B. IX. Validation Metric Assessment

The important performance indicators based on the optimization results are listed in Table 10, and the validation data metrics after optimization are listed in Table 11.

Table 10: Performance indicators

Metric	Unoptimized	Optimized	Improvement
Peak demand (kW)	413	287	-30.5%
LF	0.63	0.79	+25.3%
Waiting time avg. (hr)	2.8	1.27	-54.3%
Grid stress (kW²)	3510	2408	-31.39%
Revenue due to DR ($/day)	0	149	--
EV user cost ($/day)	736	648	-11.95%
Utilization of charging station	23 to 97%	62 to 97%	More balanced

Table 11: Validation metrics obtained after optimization

Validation metric	Threshold	Achieved
Energy fulfillment	≥95%	98.1%
Charging station capacity compliance	100%	100%
Participation rate in DR	≥70%	83%
Wait time in hours (max)	≤ 4	3.8

B. X. Recommendations

Strategies: For DR price optimization, load management, and EV user engagement operational strategies are discussed in light of the optimization results. These strategies aim to enhance grid efficiency, balance supply and demand, and improve user participation based on the findings.

DR Price Optimization: i) Maintain 1.6 to 1.8 times the base price as DR prices from 18:00 to 21:00 hours, ii) Offer 41 to 50% discounts from 01:00 to 05:00 hours to users, and iii) Implement real-time price adjustments based on congestion.

Load Management: i) Shift 25 to 30% of the peak load to off-peak periods, ii) Maintain a minimum load of 20 to 30 kW overnight.

User Engagement: i) Provide wait time predictions and incentives, ii) Implement priority charging for flexible users, and iii) Offer cost transparency and savings reports to users.

Charging Infrastructure Planning: Immediate actions and medium-term planning are suggested based on optimization results.

Immediate actions needed are i) Upgrade capacity of station 5 by 20 to 30%, ii) New EVs to be redirected to charging stations 8, 9 and10.

Medium-term planning: i) Add 2 to 3 new stations in high-demand areas, ii) Implement vehicle to grid capabilities for grid support.

V. Conclusion

This paper proposes a bilevel optimization model for optimal EV charging station usage and evaluates system network performance across multiple scenarios. The model integrates economic and technical performance indicators to verify algorithmic effectiveness. By maximizing DR benefits while alleviating grid stress, the framework reduces user wait times and travel burdens while supporting cost recovery and profitability. Practical implementation demonstrates a 30.5% peak load reduction, contributing to grid upgrade cost savings and enhanced user satisfaction. DR revenue generated helps offset infrastructure costs. Results confirm the technical and economic viability of the proposed framework, with substantial improvements across all performance indicators while maintaining scalability for real-world deployment. This work enhances environmental sustainability by optimizing EV charging operations and DR programs.

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