Grey Wolf Optimizer Based Coordinated Electric Vehicle Charging for Peak Load Reduction, Cost Minimization, and Voltage Profile Improvement

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***Abstract*—As EVs become more pervasive, distribution-level charging infrastructure poses new challenges, especially if EVs are charging uncoordinatedly on a large scale in the evening peak hours [6], [16], [21]. Such actions can lead to higher peak demand, poor voltage profiles and higher operating expenses [9], [22]. In this paper, a Grey Wolf Optimizer (GWO) is used to develop an optimized coordinated EV charging framework over 24 hours [1], [24]. The proposed method maximizes a composite objective function which includes electricity cost, peak demand, voltage deviation and SoC related penalty terms [11], [13], [14]. There are 40 EV charging sessions, and a MATLAB-based simulation is carried out for these sessions. While the uncoordinated baseline charges the EVs at the maximum power on arrival, the proposed GWO strategy charges the EVs optimally in a charging window within the EV arrival-departure window [4], [8]. The results indicate that using the proposed method, the peak value at the station is reduced from 250.00 kW to 218.80 kW, which is a 12.48% reduction in peak value. The energy cost decreases from 18433.99 to 17016.32, achieving a 7.69% reduction. The optimized objective function is 1.42% lower than the baseline. The voltage proxy also enhances when high load. This means improvement in load side operating conditions [16], [22]. Objective reductions also show that the GWO is better than GA and PSO for the considered full-dataset case [1]–[3].**

***Index Terms*—Electric vehicles, smart charging, Grey Wolf Optimizer, coordinated charging, peak shaving, voltage profile, metaheuristic optimization, distribution system.**

I. Introduction

The rise of EVs has brought with it the need for charging stations and operational challenges to EVs on distribution systems [10], [16]. EV charging demand is highly time-sensitive and frequently peaks during the return period of when a person is at home or at work [6], [21]. However, if a lot of EVs start charging as soon as they arrive, the profile of the charging activity can lead to uncoordinated charging causing new peak loads, feeder stress, and voltage degradation [4], [6], [22].

The objective of the Coordinated EV charging is to adjust the time and rate of the charging power while meeting the user needs including departure time and desired State of Charge (SoC) [6], [11], [16]. In the literature a few charging strategies based on optimization have been investigated, such as mathematical programming, heuristic rules, genetic algorithms (GA) and particle swarm optimization (PSO) [2], [3], [17], [18]. EV charging scheduling, however, is a nonlinear, constrained and high dimensional scheduling problem, particularly when the arrival/departure constraints, charger limits, energy demands, electricity price variation, and voltage effects are all taken into account at the same time [8], [9], [13], [14].

In this paper, a coordinated charging strategy for the EV charging station scheduling is proposed based on Grey Wolf Optimizer (GWO). GWO is a nature based metaheuristic that mimics the grey wolves hierarchy and hunting approach [1], [19]. The algorithm utilizes the three most promising solutions called alpha, beta and delta wolves, to move the search process. It is highly structured with few control parameters, and has a good compromise between exploration and exploitation, making it appealing for nonlinear engineering optimization problems [1]–[3], [20].

The main contributions of this paper are as follows:

- A coordinated EV charging framework, based on GWO, is Created for a 24-hour planning period [1], [24]. multi term objective function is constructed to minimize They are cost, peak load, voltage deviation, and SoC violations [11], [13], [14].
- The offered GWO strategy is compared with an 40 EV sessions uncoordinated charging baseline [4], [6].
- The results show reduction in peak demand, total consumption and operational expenses. The charging cost and objective function value were reduced and the voltage proxy was enhanced for optimum results during peak periods [9], [22].
- Compare the value of the optimizer results to a value: GWO vs GA and PSO [1]–[3].

II. Related Work

EV charging optimization is commonly formulated as a scheduling problem in which charging powers are decision variables constrained by arrival time, departure time, maximum charger power, and energy demand [6], [11], [13]. Uncoordinated charging typically results in load concentration during peak hours [16], [21]. Smart charging techniques attempt to shift flexible charging demand to lower-cost or lower-load periods while preserving user satisfaction [4], [8], [14].

Metaheuristic algorithms are widely used for EV charging because they can solve nonlinear, nonconvex, and constrained optimization problems without requiring derivative information [1], [20], [23]. GA and PSO are two widely used population-based optimizers [2], [3], [17], [18]. GA relies on selection, crossover, and mutation, whereas PSO uses particle velocities and personal/global best positions [2], [3]. GWO differs from these methods by updating search agents with respect to the three best solutions, thereby providing a simple mechanism for balancing global exploration and local exploitation [1], [19].

The original GWO algorithm was introduced by Mirjalili *et al.* and has shown competitive performance on benchmark and engineering design problems [1]. In this work, GWO is applied to EV charging station scheduling and compared with the uncoordinated baseline as well as previous optimizer comparison results [24], [25].

III. System Model

A. Time Horizon

The charging station is simulated over a discrete 24-hour scheduling horizon [4], [8]. Let

$$\mathcal{T} = \{1, 2, \ldots, T\} \tag{1}$$

denote the set of time slots, where $T = 24$ in the considered simulation. The time-step duration is denoted by Δt in hours.

B. EV Charging Sessions

Let $\mathcal{M} = \{1, 2, \ldots, M\}$ denote the set of EVs, where $M = 40$. Each EV i is characterized by:

- arrival time t_i^{arr},
- departure time t_i^{dep},
- maximum charging power P_i^{max},
- battery capacity E_i,
- initial SoC $SoC_{i,0}$,
- target SoC SoC_i^{star},
- charger efficiency η_i.

The charging power of EV i at time slot t is denoted by $P_{i,t}$. Charging is permitted only within the plug-in window [11], [13]:

$$P_{i,t} = 0, \quad \forall tlt; t_i^{arr} \text{ or } tgt; t_i^{dep}. \tag{2}$$

The charger power constraint is:

$$0 \le P_{i,t} \le P_i^{max}, \quad \forall i \in \mathcal{M},\ t \in \mathcal{T}. \tag{3}$$

C. Station Load

The total station load at time slot t is calculated as [6], [21]:

$$P_t^{hub} = P_t^{base} + \sum_{i=1}^{M} P_{i,t}, \tag{4}$$

where P_t^{base} is the non-EV base load.

The peak station load is:

$$P^{peak} = \max_{t \in \mathcal{T}} P_t^{hub}. \tag{5}$$

D. SoC Dynamics

The SoC of EV i evolves according to [4], [8]:

$$SoC_{i,t+1} = SoC_{i,t} + \frac{\eta_i P_{i,t} \Delta t}{E_i}. \tag{6}$$

At departure, the desired condition is:

$$SoC_{i,t_i^{dep}} \ge SoC_i^{star}. \tag{7}$$

However, because some sessions may be infeasible due to short parking duration or insufficient charger capacity, the optimization includes a penalty-based SoC treatment rather than enforcing all SoC constraints as hard constraints [4], [8].

E. Voltage Proxy

A voltage proxy is used to estimate the distribution-side voltage impact of the total hub load [9], [22]. In general, the proxy can be represented as:

$$V_t = V_0 - k_v P_t^{hub}, \tag{8}$$

where V_0 is the nominal voltage and k_v is a load-sensitivity coefficient. This simplified voltage model captures the expected decrease in voltage magnitude as loading increases [16], [22].

IV. Problem Formulation

The objective of coordinated charging is to determine the charging schedule vector [11], [13], [14]:

$$\mathbf{X} = [P_{1,1}, P_{1,2}, \ldots, P_{M,T}]^T \tag{9}$$

that minimizes the total objective function:

$$\min_{\mathbf{X}} J(\mathbf{X}). \tag{10}$$

The composite objective function is formulated as [4], [8], [9]:

$$J = w_c J_{cost} + w_p J_{peak} + w_v J_{volt} + w_s J_{soc} + w_b J_{bound}, \tag{11}$$

where w_c, w_p, w_v, w_s, and w_b are weighting factors.

The electricity cost term is:

$$J_{cost} = \sum_{t=1}^{T} \lambda_t P_t^{hub} \Delta t, \tag{12}$$

where λ_t is the electricity tariff at time slot t.

The peak load penalty is:

$$J_{peak} = \left(\max_{t \in \mathcal{T}} P_t^{hub} \right)^2. \tag{13}$$

The voltage deviation penalty is:

$$J_{volt} = \sum_{t=1}^{T} \left(V_{ref} - V_t \right)^2, \tag{14}$$

where V_{ref} is the desired reference voltage.

The SoC shortfall penalty is:

$$J_{soc} = \sum_{i=1}^{M} \left[\max \left(0, SoC_i^{star} - SoC_{i,t_i^{dep}} \right) \right]^2. \tag{15}$$

The boundary penalty J_{bound} penalizes violations of charger power and availability constraints [1], [9].

V. Grey Wolf Optimizer for EV Charging

A. Overview of GWO

GWO is a swarm-intelligence optimization algorithm inspired by grey wolf hunting behavior [1], [19]. Candidate solutions are represented as wolves. The best three candidate solutions are named alpha (α), beta (β), and delta (δ), while the remaining solutions are omega wolves. The position of each wolf corresponds to a complete EV charging schedule [24], [25].

B. Position Update Equations

For a candidate wolf position $\mathbf{X}$, the encircling behavior is mathematically described as [1]:

$$\mathbf{D} = |\mathbf{C} \cdot \mathbf{X}_p - \mathbf{X}|, \tag{16}$$

$$\mathbf{X}(k+1) = \mathbf{X}_p - \mathbf{A} \cdot \mathbf{D}, \tag{17}$$

where $\mathbf{X}_p$ is the prey position, k is the iteration number, and $\mathbf{A}$ and $\mathbf{C}$ are coefficient vectors:

$$\mathbf{A} = 2a\mathbf{r}_1 - a, \tag{18}$$

$$\mathbf{C} = 2\mathbf{r}_2. \tag{19}$$

Here, $\mathbf{r}_1$ and $\mathbf{r}_2$ are random vectors in $[0, 1]$, and a decreases linearly from 2 to 0 over iterations [1].

Because the exact global optimum is unknown, GWO estimates the prey position using the three best solutions [1], [20]:

$$\mathbf{D}_\alpha = |\mathbf{C}_1\mathbf{X}_\alpha - \mathbf{X}|, \tag{20}$$

$$\mathbf{D}_\beta = |\mathbf{C}_2\mathbf{X}_\beta - \mathbf{X}|, \tag{21}$$

$$\mathbf{D}_\delta = |\mathbf{C}_3\mathbf{X}_\delta - \mathbf{X}|. \tag{22}$$

The updated candidate positions are:

$$\mathbf{X}_1 = \mathbf{X}_\alpha - \mathbf{A}_1\mathbf{D}_\alpha, \tag{23}$$

$$\mathbf{X}_2 = \mathbf{X}_\beta - \mathbf{A}_2\mathbf{D}_\beta, \tag{24}$$

$$\mathbf{X}_3 = \mathbf{X}_\delta - \mathbf{A}_3\mathbf{D}_\delta. \tag{25}$$

The final position update is:

$$\mathbf{X}(k+1) = \frac{\mathbf{X}_1 + \mathbf{X}_2 + \mathbf{X}_3}{3}. \tag{26}$$

C. Constraint Handling

After each GWO position update, the solution vector is repaired or penalized according to [1], [9]:

- charging power lower and upper bounds,
- EV arrival and departure windows,
- charging station operating limits,
- SoC shortfall at departure,
- voltage deviation.

This penalty-based treatment enables the optimizer to search a high-dimensional feasible region while discouraging schedules that violate user or grid requirements [1], [8].

VI. Simulation Setup

The proposed method is implemented in MATLAB. A total of 40 EV sessions are generated. The uncoordinated baseline charges each EV at its maximum available charging power from arrival to departure [6], [21]. The GWO optimizer then searches for an improved charging schedule [1], [24].

The simulation workflow consists of:

1) Load system configuration and time-varying profiles.
2) Generate 40 EV sessions.
3) Evaluate feasibility based on maximum deliverable energy.
4) Construct the uncoordinated charging baseline.
5) Run the GWO optimizer.
6) Evaluate objective value, peak load, cost, voltage proxy, and SoC success.
7) Generate load, convergence, and voltage plots.

VII. Results and Discussion

A. Feasibility and SoC Performance

The feasibility analysis indicates that 45.00% of the EV sessions are feasible under maximum-power charging within their available parking windows. The optimized schedule achieves 30.00% SoC success across all EV sessions and 66.67% SoC success when only feasible sessions are considered. This indicates that some EV sessions are physically unable to reach their target SoC due to limited connection time or charger availability [4], [8].

B. KPI Summary

Table I summarizes the baseline and optimized performance.

TABLE I
KPI Comparison Between Baseline and GWO-Optimized Charging

Metric	Base	GWO	Improvement
Objective, J	8.5807×10^{10}	8.4591×10^{10}	1.42%
Peak load	250.00 kW	218.80 kW	12.48%
Cost	18433.99	17016.32	7.69%

The GWO-optimized schedule reduces peak demand by 31.20 kW. This is important because peak demand is directly related to transformer loading, feeder congestion, and demand charges [6], [16], [21]. The cost reduction of 1417.67 shows that GWO successfully shifts charging away from expensive or high-impact time slots [11], [13], [14].

C. Station Load Profile

Fig. 1 shows the station load before and after GWO optimization. The uncoordinated charging case reaches a maximum load of 250 kW during the evening peak period. The optimized GWO profile reduces the maximum load to 218.80 kW while maintaining a similar charging service pattern [4], [8].

The optimized curve demonstrates peak shaving during the most stressed evening interval. Instead of allowing all EVs to charge immediately at maximum power, the GWO

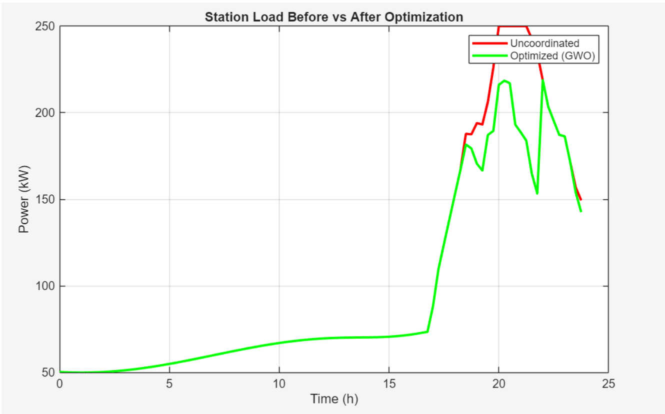

Fig. 1. Station load before and after GWO optimization.

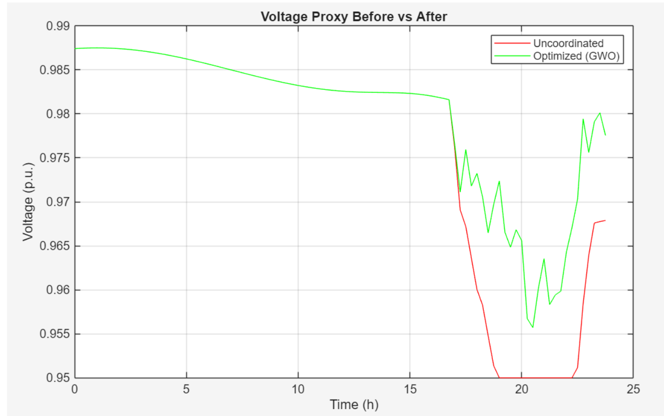

Fig. 3. Voltage proxy before and after GWO optimization.

schedule redistributes charging power within the allowable time windows [4], [11], [13].

D. GWO Convergence

Fig. 2 presents the convergence behavior of GWO over 100 iterations. The objective function decreases rapidly during the early iterations and then stabilizes after approximately 15–20 iterations. This behavior indicates that GWO quickly identifies promising regions in the search space and then performs local exploitation around the best candidate solutions [1], [20].

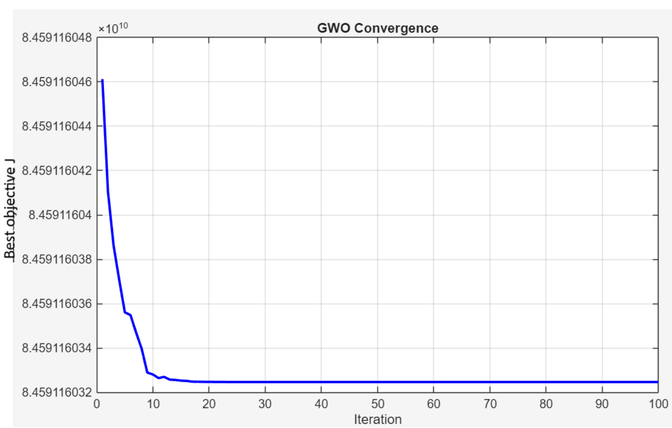

Fig. 2. Convergence curve of the GWO optimizer.

E. Voltage Proxy Improvement

Fig. 3 shows the voltage proxy before and after optimization. During high-load evening hours, the optimized GWO profile maintains a better voltage response than the uncoordinated case. Although the voltage proxy still approaches the lower operating region during peak charging periods, the optimized schedule reduces the severity of voltage depression [9], [16], [22].

F. Comparison with GA and PSO

Fig. 4 compares GA, PSO, and GWO for the full dataset. GA shows limited objective reduction and remains near the highest objective value. PSO improves steadily and reaches a lower objective than GA. GWO demonstrates the strongest improvement, particularly after the mid-iteration region, where its objective value drops sharply and reaches the lowest final value among the compared optimizers [1]–[3], [17], [18].

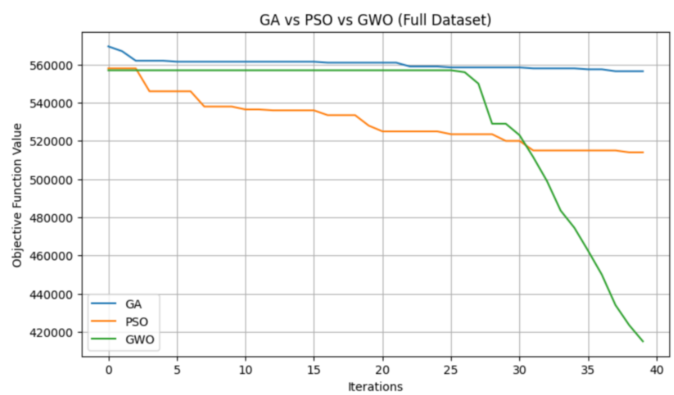

Fig. 4. Objective function comparison of GA, PSO, and GWO on the full dataset.

This comparison suggests that GWO provides better exploration and exploitation balance for the considered EV charging optimization problem. The alpha-beta-delta guidance mechanism allows the search agents to escape less effective regions and converge toward a better charging schedule [1], [20].

VIII. Conclusion

This paper presented a Grey Wolf Optimizer based coordinated EV charging strategy for reducing peak load, minimizing charging cost, and improving voltage profile behavior [1], [24]. A MATLAB simulation was conducted for 40 EV charging sessions over a 24-hour horizon. The proposed GWO method was compared with an uncoordinated charging baseline [4], [6].

The optimized schedule reduced the station peak load from 250.00 kW to 218.80 kW, corresponding to a 12.48% reduction. The charging cost decreased from 18433.99 to

17016.32, corresponding to a 7.69% reduction. The total objective function decreased by 1.42%. The voltage proxy results show improved voltage behavior during peak charging hours [9], [22]. The convergence curve confirms that GWO stabilizes within a small number of iterations, and the optimizer comparison indicates that GWO outperforms GA and PSO for the considered full-dataset case [1]–[3].

Future work will focus on improving SoC satisfaction by introducing adaptive penalty weights, feasibility-aware initialization, vehicle-to-grid operation, renewable energy integration, and real distribution feeder validation using power-flow models [9], [10], [16].

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