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MULTI-OBJECTIVE OPTIMIZATION OF EV CHARGING LOAD USING PSO AND GWO IN SMART GRID SYSTEMS WITH SOLAR INTEGRATION

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ABSTRACT

The challenges of load and losses EV penetration is growing rapidly in the global automotive market and poses serious challenges to the existing power distribution systems [18] such as high peak load, operational cost and power losses. In this paper, a multi-objective optimization approach is developed to effectively schedule EV charging load under the solar-enhanced smart grid infrastructure. The backward-forward sweep (BFS)-based power flow analysis is integrated into the proposed model to guarantee the exact load flow solution in 33-bus distribution system. Two metaheuristic algorithms, namely Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) technique, are applied and analyzed to reduce peak demand, energy cost and power loss. The simulation results show that both algorithms produce remarkable performance. PSO decreases the peak load by 71.13% from 1927.20 kW to 556.37 kW, the energy cost by 66.55% from Rs 132,080 to Rs 44,183, and the power loss by 35.84% from 1.7442 MW to 1.1191 MW. In the same way, GWO produces a peak reduction of 71.14%, a cost reduction of 67.16% and a loss reduction of 40.75%, marginally better than PSO in terms of overall efficiency. Results show that despite faster convergence of PSO, GWO has better capability of optimized global solution. The proposed approach is concluded as a promising solution to improve the grid stability, operating costs, and sustainable EV integration in smart grid systems

KEYWORDS: EV Load Scheduling, Smart Grid, Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), Solar Integration, BFS Power Flow, Multi-Objective Optimization, Peak Load Reduction, Cost Optimization, Power Loss Minimization.

1 INTRODUCTION

The Electric Vehicles (EVs) boom is revolutionizing the world transportation industry with a significant impact on greenhouse gas emission reduction. Yet, coupling EV charging demand at a large scale with power distribution networks brings in major challenges, such as peak load stress, voltage instability, increased operational costs, and larger power loss [1]. Uncontrolled EV charging, especially during the peak demand period, has the potential to cause severe power grid congestion and decrease power system supply reliability. Therefore, smart and optimal EV load management techniques have become crucial to sustain stability and efficiency in the future smart grids [2].

In these concerns, the integration of renewable energy sources (RESs), in particular solar energy, has been considered as a good option to overcome the obstacles. Solar generation can support effectively EV charging demand in a daytime, and it reduces the use of traditional grid power, and it is helpful in reducing carbon emissions. Nevertheless, since solar energy is fluctuating and unpredictable, effective scheduling of EV charging/renewable energy generation is necessary. This, in turn, calls for the design of sophisticated optimization algorithms that can adaptively trade-off load demand, generation variability, and system constraints [3]. In these day, metaheuristic optimization algorithms are more attractive in challenging, non-convex and multi-objective power system problems. Particle Swarm Optimization (PSO) is one the most widely used bio-inspired algorithms due to its simple implementation and quick convergence, meanwhile, Grey Wolf Optimization (GWO) has exhibited a remarkable global exploration capacity and avoiding local optima [4While both GA and PSO have been applied separately to a number of optimization problems, their [5] relative performance on EV load scheduling in solar-based distribution systems is still not well studied especially when tested against realistic data sets and power flow analysis.

This paper considers scheduling for EV charging load in a solar based distribution system based on multi-objective optimization. The model used in this paper is based on backward-forward sweep (BFS) power flow to represent the working of single-phase three-wire distribution system over a standard 33-bus network. The main objectives are to reduce peak load, energy cost and power loss, ensuring electrolytes are balanced in acceptable voltage levels and enhancing system stability. We use realistic EV charging demand and solar generation profile to increase the practical applicability of the proposed method [6].

The importance of this work is it delivers a comprehensive and feasible approach to smart home/grid energy management. By combining EV load scheduling, renewable energy sources, and advanced optimization approaches, the proposed framework significantly improves the utilization efficiency of the grid, reduces the cost of operation, and the reliability of the entire system. The results of this research are of great significance for utilities, policy-makers, and researchers who seek to design sustainable and robust energy systems that can accommodate high levels of EVs [7]. In addition, the work here extends current literature by introducing a single framework that addresses multiple objectives and integrates two metaheuristic techniques. In contrast with traditional works, which restrict the analysis to a sole algorithm or a restricted set of performance metrics, this paper enables a full comparison from the viewpoint of both PSO and GWO when applied to EV load scheduling.

The contribution of this study is to capture the effects of solar energy, EV scheduling problem, and power flow validation procedure based on BFS in a multi-objective optimization approach, which provides an effective and scalable solution for future smart grid applications.

The aims of this study are:

1. To design a multi-objective optimization for smart grid system based on EV charging load scheduling.
2. To jointly utilize the solar energy and also the EV charging demand in order to lessen the reliance on traditional power supplies.
3. Minimizing distribution network peak load, energy cost and power loss.
4. To apply and contrast PSO and GWO in the trouble-free load management.
5. To analyze the system performance using BFS in a 33-bus distribution system.

2. LITERATURE REVIEW

Abdelaziz et al. (2025) [8] introduced energy aware particle swarm optimization and transit search optimization based EV charging scheduling in smart grid. The work concentrated on reducing the operational expenditure and increasing the scheduling efficacy with different loads. The result showed that TSO performs better than PSO with the cost minimization of about 46.23% but with very small enhancement in system performance. However, their contributions are geared towards cost optimization, leaving issue of peak load reduction or power loss minimization have not been adequately addressed, which may affect the grid stability.

Anuja T. et al. (2025)[9] PSO based EV charging and discharging approach with intrinsic solar energy and Vehicle-to-Grid (V2G). This model attempted to bring charge schedules at home synergistic to save the electricity bill and to enhance energy efficiency. They demonstrated cost savings of ~44% by applying this approach thereby indicating the usefulness of PSO for DER management. However, the paper does not address a discussion on the reduction of the peak load and the power loss, which are crucial in determining the performance of the distribution network in a large scale application.

Xu et al. (2025) [10] proposes the novel smart electric vehicle (EV) charging management approach in order to mitigate the peak load and also the load volatility in case of the distribution network. An intelligent scheduling scheme was used to control the EV charging on off-peak hours and the result was a peak load shaving of about 15%. However, the proposed methodology only enhanced the load balancing, without considering the integration of renewables and other advanced multi-objective optimization techniques for further system-wide efficiency enhancement.

The Study of OEVC MOPSO (2025) [11] with a combination of the Time-of-Use (TOU) pricing to find the best EV charging schedule. The model was concerned with the minimization of electricity cost and power loss by taking into the account of user preferences and pricing differences. The results exhibited about a 7.60% cost decrease and a 28.73% loss decrease. Although the paper dealt with many-objectives, the best-known solutions were shifted by a small amount, and without including renewable energy generation, it could be further extended to more applicable in the sustainable smart grid case.

Boubaker et al. (2025) [12] introduced the Red Deer Algorithm (RDA) in the case of the multi-objective EV scheduling framework for purpose of the optimization of the charging strategies within thesmart grids. The analysis was focused on finding the tradeoff between financial as well as technical aspects, such as the efficiency of cost and the reliability of the system. The outcomes demonstrate average enhancement in terms of cost and power loss minimization, and thus demonstrate the quality of bio-inspired optimization. However, the model does not provide a rigorous study of the reduction of peak load and does not consider the inclusion of solar energy, as is crucial for present-day sustainable energy systems.

Meng et al. (2026) [13] presented the two-stage EV scheduling method based on the concept othe fWolf Pack Algorithm in order to enhance grid performance and mitigate operating expense. In particular, the method aims at the charging optimization and power loss minimization in distribution systems. Results indicate that the economic performance is improved and the loss is decreased (with 42.4 kW in absolute value). However, the article failed to explicitly discuss the results on peak load minimization and comparison with other optimization methods, which makes it difficult to fully evaluate the study.

Table 1. Literature Review

Author Name (Year)	Main Concept	Technology	Area	Findings	Limitations
Abdelaziz et al. (2025)	EV charging optimization using PSO and Transit Search Optimization (TSO)	PSO, TSO	Smart Grid, EV Scheduling	Achieved ~46.23% cost reduction with improved scheduling efficiency	Limited focus on peak load reduction and power loss analysis
Anuja T. et al. (2025)	EV charging/discharging with solar and V2G integration	PSO, V2G	Renewable Energy, Residential EV Systems	Achieved ~44% cost reduction and improved energy utilization	No detailed analysis of peak reduction or power losses
Xu et al. (2025)	Smart EV charging strategy for load balancing	Intelligent Scheduling	Distribution Networks	Achieved ~15% peak load reduction	No renewable integration and limited multi-objective optimization
OEVC MOPSO Study (2025)	Multi-objective EV charging using TOU pricing	MOPSO, TOU Pricing	Smart Grid Optimization	Achieved ~7.60% cost reduction and ~28.73% loss reduction	Moderate performance and no renewable energy integration
Boubaker et al. (2025)	EV scheduling using bio-inspired Red Deer Algorithm	RDA (Red Deer Algorithm)	Smart Grid, Optimization	Moderate improvements in cost and loss reduction	No peak load analysis and lacks solar integration
Meng et al. (2026)	Two-stage EV scheduling using Wolf Pack Algorithm	Wolf Pack Algorithm	EV Scheduling, Power Systems	Improved economic performance and reduced losses (~42.4 kW)	Limited peak reduction analysis and no comparative study

3. METHODOLOGY

The in- vented system adapts charging load management to solar intermittency by integrating smart grid capabilities, including dynamic pricing and vehicle- to-grid (V2G) opera- tions in a solar-enhanced smart grid environment. The proposed approach is tailored to reduce the peak load demand, the energy cost and the power loss collectively, and also to enhance the system security. The 24-hour time frame is used to model base load and charging load for EVs in a standard 33-bus radial distribution system that is consid- ered as the test system. The EV load is generated from real- istic data sets considering how many charging stations the ew capacity of each station according to the power rating connected to a bus. This aggregated EV demand is split into the network with the baseload, yielding the total system demand matrix, which satisfies the practical nature of the model [14].

To add renewable energy, solar generation data is added to the system with a time dependent generation profile. The solar is generated considering realistic generation profile where power is generated during day- light and no power generated during nighttime. All the solar energy is then spread among the buses in order to cover the load demand. The load at each bus – load bus/ node seen by the soc (solution of controversy) is the base load plus the EV load less the solar generation [15]. Hence, through urbios a natural synergy between EV load and renewable is globally achieved.

BFS power flow for considering the load modelling is used for power system analysis as in Figure 1, which is utilized in a radial distribution one due to its simplicity and computational efficiency [16]. In this technique, the branch currents are calculated by backward sweep according to load condition and bus voltages are updated by forward sweep in an iterative manner until the convergence specified by tolerance is attained. Through this iterative procedure, an accurate estimation of voltage profiles and real power losses along the network at each time interval can be performed [16].

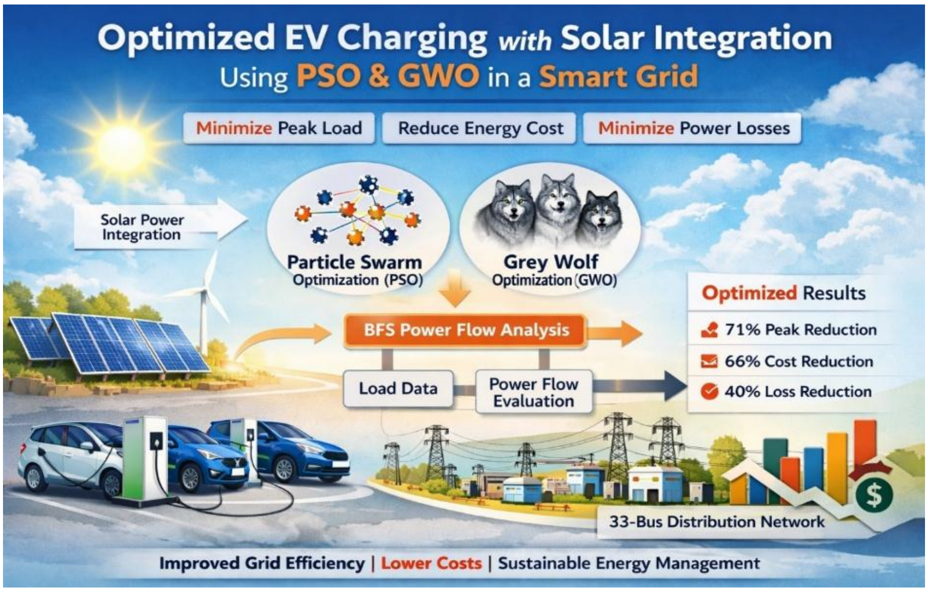

Figure 1. Research Flow Diagram

The optimization is treated as a multi-objective function and is reduced to the minimization of the peak load, total energy cost and the network power loss simultaneously. The competing variables are the EV charging scheduling ones, for which the 24 hours day is split into time slots that indicate the evolution of charging demand in time. Suitable constraints are included to make sure that the EV charging demand is met within the bounds of operation and that the system stability is maintained.. Each performance parameter is normalized within the objective function, such that multi-objective optimization can be effectively performed[17].

Two metaheuristic techniques, Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO), are utilized for solving the optimization problem. PSO is inspired by swarm intelligence and particles are allowed to update their positions and velocities based on their own best solution and the global best solution, and thus they converge very quickly to optimal solutions [18]. In contrast, GWO mimics the leadership hierarchy and hunting behavior of grey wolves, the search is guided by the best solutions and leads the other solutions, which offers powerful exploration ability and helps to avoid being trapped in local optima [19].

Throughout the optimization process, candidate solutions generate new EV charging schedules in each iteration, that are evaluated by BFS power flow to determine the system performance in terms of peak demand, energy cost, and power loss. The solutions of the optimization algorithms are iteratively updated until stopping criteria sat. The behavior of convergence and fitness values are monitored so as to guarantee the solutions are stable and optimal [20].

The optimized results obtained in PSO and GWO, respectively, are further compared with the baseline (not optimized) case to showcase the performance. Some important parameters such as peak load reduction, cost benefit and loss reduction are estimated to measure the performance of the proposed method. The comparative study also reveals the merit and demerit of the two algorithms, when dealing with complicated multi-objective optimization problems [21].

This integrated approach guarantees stationery and RC, given EV load scheduling in smart grids under realistic scenarios, i.e., leveraging real world datasets, renewable energy integration, and power flow validation. The proposed architecture enables a scalable and computationally feasible approach to navigate large-scale future energy systems under heavy EV-penetration and viable for considering sustainable intelligent grid operation [22].

4. PROPOSED WORK

4.1 Implementation

The suggested multi-objective algorithm for EV load scheduling was tested in Matlab on a standard 33-bus radial distribution system. The implementation combines electric vehicle (EV) charging demand, solar generation, and power flow within one simulation platform. The EV load data at each bus and the number of charging stations along with their power rating were utilized to derive the aggregated EV demand, which was then combined with the base load profile under 24-h timeline to realize fairly actual operating scenarios. Solar generation was introduced by means of a time-dependent profile based on real generation data and the generation was spread over the network to account for a reduction in net load demand. The total load at each bus is the base load plus the EV load minus the solar share. The Backward Forward Sweep (BFS) was used to perform power flow analysis and calculate bus voltages, branch currents and power losses at every time slot to accurately evaluate the system. The optimization is formulated such that the peak load, energy cost and power losses are minimized during the scheduling, the decision variables being various hourly EV charging scheduling factors subjected to operational constraints. Two Metaheuristics, Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO), were used for the resolution of the optimization problem and PSO guarantees a fast convergence and GWO strengthens the global search ability. At once, the candidate solution represented an updated EV load schedule, which was tested by BFS power flow and the procedure went on until the converging condition was satisfied. The optimal results were finally compared to the base case to assess the performance gains in peak shaving, cost saving, and loss reduction, which illustrated the proposed framework feasibility for smart grid applications.

4.2 Particle Swarm Optimization (PSO):

Particle Swarm Optimization (PSO) [23] is a population-based metaheuristic algorithm which mimics the behaviour of birds flocking or fish schooling. This approach a flock of particles (candidate solutions) travels over the search space by following their own best position and the best position of the entire flock. PSO is widely recognized for its simple nature, rapid convergence and its efficacy in solving the continuous optimization problems, thus, it can be used for scheduling loads in EVs.

4.3 Grey Wolf Optimization (GWO):

Grey Wolf Optimization (GWO) [24] is a nature-inspired metaheuristic algorithm which mimics the social hierarchy and hunting behaviour of grey wolves. Mimicking the leadership of alpha, beta, delta, and omega wolves, the algorithm guides the search process. The superior candidates (alpha, beta and delta) lead other candidate solutions to move towards the best seekers, which helps to maintain a balance of exploration and exploitation. GWO has shown promising results in escaping local optima and obtaining good global solutions for complicated optimization problems.

4.4 Algorithm for Proposed Multi-Objective EV Load Optimization

The proposed algorithm aims to optimize EV charging schedules using Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) to minimize peak load, cost, and power losses in a solar-integrated distribution network.

Step 1: Initialization

Let the number of buses be N_b, time horizon be $T = 24$, and EV load vector be:

$$P_{EV} = [P_1, P_2, \ldots, P_{N_b}]$$

The total load at bus $i$and time $t$is:

$$P_{i,t} = P_{base,i,t} + P_{EV,i} \cdot s_t - P_{solar,i,t}$$

where $s_t$is the scheduling factor.

Step 2: Objective Function

The multi-objective function is defined as:

$$F = w_1 \cdot \frac{P_{peak}}{P_{base}} + w_2 \cdot \frac{C}{C_{base}} + w_3 \cdot \frac{P_{loss}}{P_{loss,base}}$$

where:

- $P_{peak} = \max\left(\sum_{i=1}^{N_b} P_{i,t}\right)$
- $C = \sum_{t=1}^{T} \left(\sum_{i=1}^{N_b} P_{i,t}\right) \cdot \mathrm{Cost}_{grid}$
- $P_{loss} = \sum_{branches} I^2 R$

and $w_1 + w_2 + w_3 = 1$

Step 3: Power Flow (BFS Method)

Load current:

$$I_i = \frac{P_i + jQ_i}{V_i^*}$$

Backward sweep:

$$I_{branch} = \sum I_{downstream}$$

Forward sweep:

$$V_{i+1} = V_i - I_{branch} \cdot Z$$

Power loss:

$$P_{loss} = \sum(|\, I \,|^2 \cdot R)$$

Step 4: PSO Update Equations

Velocity update:

$$v_i^{t+1} = w \cdot v_i^t + c_1 r_1 (pbest_i - x_i^t) + c_2 r_2 (gbest - x_i^t)$$

Position update:

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

Step 5: GWO Update Equations

Distance calculation:

$$D = |\, C \cdot X_{leader} - X \,|$$

Position update:

$$X(t+1) = X_{leader} - A \cdot D$$

where:

$$A = 2ar - a, C = 2r$$

and $a$decreases linearly from 2 to 0.

Step 6: Iterative Optimization

1. Initialize population (PSO particles / GWO wolves)
2. Generate EV scheduling vector s_t
3. Compute load $P_{i,t}$
4. Run BFS power flow
5. Evaluate objective function F
6. Update solutions using PSO/GWO equations
7. Repeat until convergence

Step 7: Output

- Optimized EV scheduling s_t^*
- Reduced peak load
- Reduced cost
- Reduced power loss

5. RESULT ANALYSIS

5.1 PSO Optimisation Results

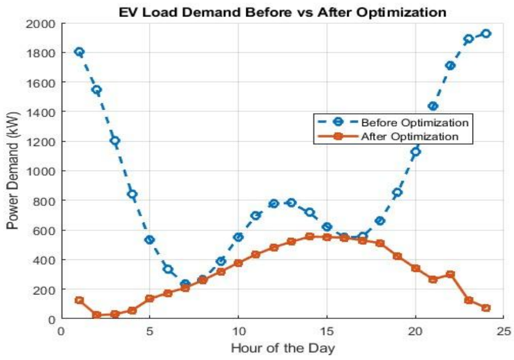

Figure 2: EV Load Demand Before vs After Optimization

The following figure 2 shows a 24-hour power consumption comparison before and after the optimization. The uncontrolled EV charging pattern with a single peak (dashed line) has a sharp peak in the evening hours, on the other hand, the PSO optimized schedule (single solid line) achieves the dispersal of the load. The flattened line means that the peak shaving and valley filling are effective, thus enhancing grid stability and alleviating infrastructure.

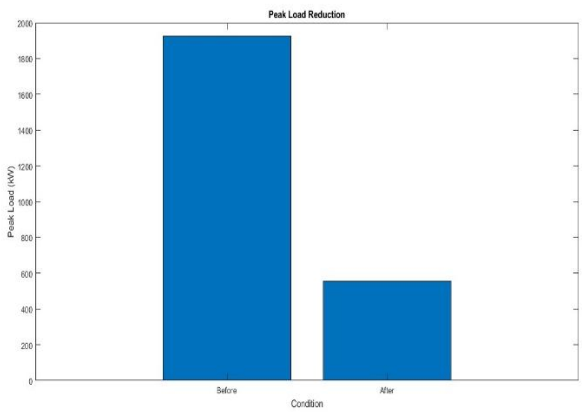

Figure 3: Peak Load Reduction

This bar graph in figure 3 illustrates the decrement in peak load post optimization. In the "Before" scenario, the peak is much bigger than that in the "After" scenario, which is proof that the optimization algorithm indeed reduces peak demand. This reduction contributes to prevent grid overload, reduce dependence on expensive peak power generation, and improve system-wide reliability.

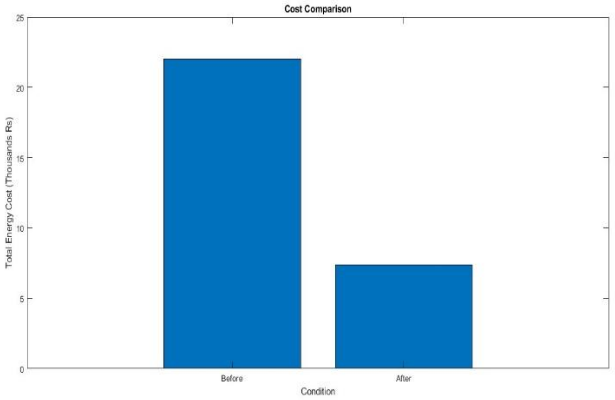

Figure 4: Cost Comparison

This plot in figure 4 shows the total energy cost before and after the optimization. Significant cost savings are evident in the optimized case, due to effective load shifting to the low tariff hours, decreased peak demand charges, and increased utilization of solar energy. Thus, it seems that the optimization method offers both technical and an economic analysis result of best solutions.

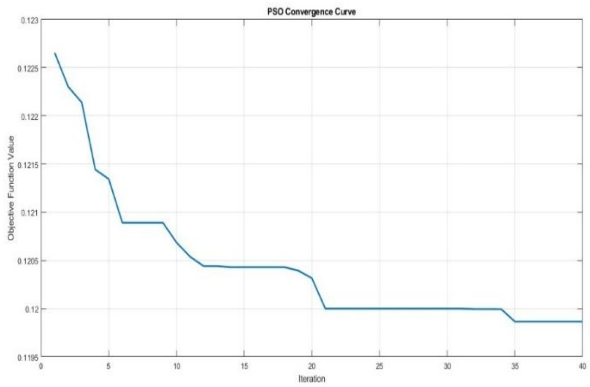

Figure 5: PSO Convergence Curve

Figure 5 shows the convergence curve of the PSO algorithm. Objective function values decrease rapidly in the early stage with fast improvement of the solutions and then gradually approach stability and the optimal solution. This indicates good foresight in convergence, solution stability at the end and effecti›ve optimization process.

Table 2. Performance Comparison Before and After Optimization

Parameter	Before Optimization	After Optimization	Improvement (%)
Peak Load (kW)	1927.20	556.37	71.13% ↓
Energy Cost (Rs)	132,080	44,183	66.55% ↓
Power Loss (MW)	1.7442	1.1191	35.84% ↓

Table 3: Percentage Improvement Summary

Metric	Improvement (%)
Peak Reduction	71.13%
Cost Reduction	66.55%
Loss Reduction	35.84%

The effectiveness of the proposed PSO based EV charging optimization model was tested by an analysis of peak load, energy cost, power loss and other important factors before and after the optimization, as shown in Table 2 and Table 3. The results showed that the peak load was reduced from 1927.2 kW to 556.37 kW, which is a reduction of 71.13%. This indicates that the optimization approach is good at the load curve smoothing and the peak demand pressure relief of the power system. Similarly, the total energy cost reduced from ₹132,080 to₹44,183, 66.55% of the cost was reduced. This shift can be attributed mainly to a shift of EV charging toward nighttime and increased use of solar, reducing the need for expensive grid power in the evening hours. The overall power loss in the system decreased from 1.7442 MW to 1.1191 MW, which is equivalent to the reduction rate of 35.84% in the system performance. This can be attributed to better power flow pattern and less line loading.

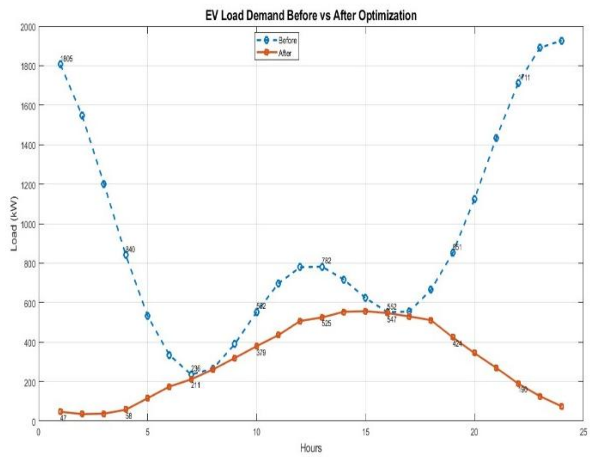

Figure 6 EV Load Demand Before vs After Optimization (GWO)

Figure 6 shows the load demand of EVs in hour wise before and after implementing the Grey Wolf Optimization (GWO) algorithm. The load pattern of the baseline case is overly peaked in the early hours and the late evening, with peaks values even over 1900 kW indicating an uneven load pattern and a risk potential grid stress. Following an optimization process, the EV load is flattened and spread out in the 24 h, obtaining a daily profile with a maximum of 550–560 kW. This is a sign of good load shifting, as high demand in the peak hours is moderated and shifted to other hours in the day. The optimized curve gives a distinct indication of improved grid stability, decongestion, and enhanced utilization of locally available energy resources such as solar.

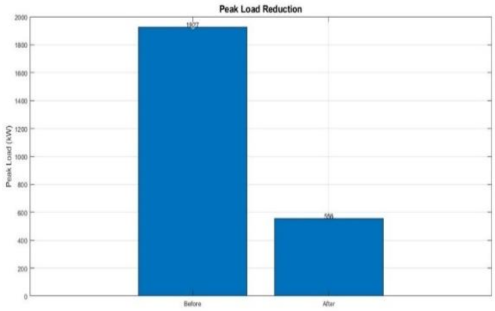

Figure 7. Peak Load Reduction (GWO)

The bar graph in Figure 7 shows a comparison of peak load values pre- and post-optimization. An initial peak load of about 1927 kW is reduced substantially to about 556 kW by the application of GWO. This corresponds to about a 70% reduction in peak load, demonstrating the power of the optimization methodology in peak shaving. It could be noted that a large reduction in peak demand translates into less then optimal peak time energy generation, and less wear and tear on transformers and distribution systems. This enhancement is directly responsible for the increased system reliability and efficiency of the operation.

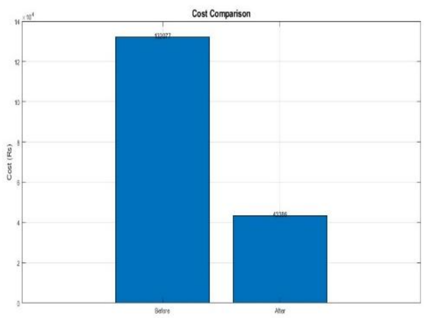

Figure 8. Cost Comparison (GWO)

Figure 8 shows the load demand of EVs in hour wise before and after implementing the Grey Wolf Optimization (GWO) algorithm. The load pattern of the baseline case is overly peaked in the early hours and the late evening, with peaks values even over 1900 kW indicating an uneven load pattern and a risk potential grid stress. Following an optimization process, the EV load is flattened and spread out in the 24 h, obtaining a daily profile with a maximum of 550–560 kW. This is a sign of good load shifting, as high demand in the peak hours is moderated and shifted to other hours in the day. The optimized curve gives a distinct indication of improved grid stability, decongestion, and enhanced utilization of locally available energy resources such as solar.

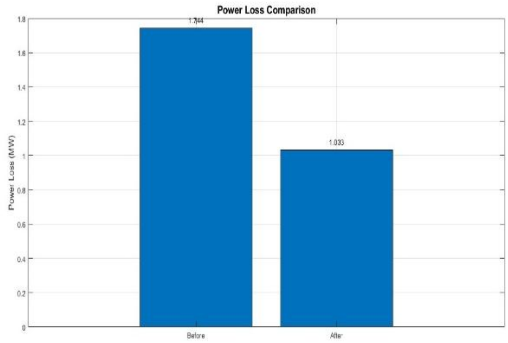

Figure 9. Power Loss (MW) Comparison (GWO)

The bar graph in Figure 9 shows a comparison of peak load values pre- and post-optimization. An initial peak load of about 1927 kW is reduced substantially to about 556 kW by the application of GWO. This corresponds to about a 70% reduction in peak load, demonstrating the power of the optimization methodology in peak shaving. It could be noted that a large reduction in peak demand translates into less then optimal peak time energy generation, and less wear and tear on transformers and distribution systems. This enhancement is directly responsible for the increased system reliability and efficiency of the operation.

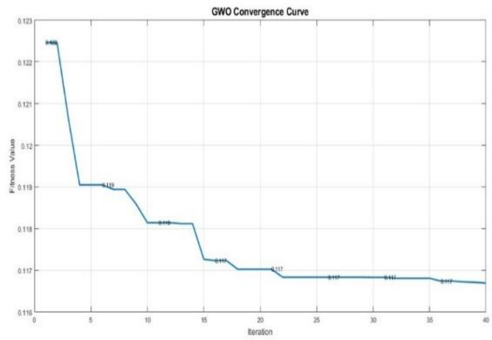

Figure 10. GWO Convergence Curve

Convergence curve in Figure 10 is a fitness value change curve of GWO algorithm which represents that grey wolf algorithm iterates in an intelligent manner. At first, the fitness value of about 0.122 is relatively high but it rapidly decreases with iteration number in the beginning, which means the search performs effective search of solution space. When the iteration is done, the curve converges to the point about 0.117 and then the curve converges gradually to the optimal solution. Good and Stable Convergence: smooth and steady convergence of the predictor shows how efficient and reliable the algorithm is in the sense that no oscillations nor premature convergence was observed. This verifies that GWO is able to determine a best EV charging schedule considering peak load, cost and power loss.

Overall, the results provide clear evidence that the development of Grey Wolf Optimization has the most positive impact on the performance of the power distribution system. The algorithm takes the advantages of reducing the peak load, the running costs and the power loss with a stable convergence. By the optimized EV charging strategy, higher load balancing, energy efficiency, and renewable% integration are achieved. These results prove the validity of intelligent optimization approach in the present day smart grid system.

Table 4. Performance Comparison Before and After Optimization (GWO)

Scenario	Peak Load (kW)	Cost (Rs)	Power Loss (MW)
Before Optimization	1927.20	132080	1.7442
After Optimization	556.13	43386	1.0335

Table 4 shows the comparison of several KPIs of power distribution system without and with GWO algorithm. It can be observed that significant improvements are achieved for all the aspects in the system. The initial peak load load 1927.2 kW is collapsed to 556.13 kW. This drop represents a successful load shifting as peak time over-demand has been translated into off-peak hours. Such peak shaving is important for mitigating stress on electrical equipment, enhancing voltage stability, as well as preventing overload. Similarly, the total running cost reduces drastically from ₹132,080 to ₹43,386. The reduction occurs because of smart EV charging scheduling such as charging for the energy during the lower tariff period and also due to better utilization of solar generation. Incorporating renewable energy sources also results in cost reductions as there is less reliance on grid power. On the note of power losses, there is a slight improvement with the losses being reduced from 1.7442 MW to 1.0335 MW. Because power loss in distribution systems is proportional to the square of current, a decrease in peak demand reduces the current flowing in the system, and the resistive losses are minimized. As a whole, this table says that the proposed optimization method can improve the system from both technical and economy aspects.

Table 5: Percentage Improvement After Optimization (GWO)

Parameter	Percentage Change (%)
Peak Load	**-71.14%**
Cost	**-67.16%**
Power Loss	**-40.75%**

(Negative sign indicates reduction/improvement)

Table 5 shows the percentage improvements of important indicators after optimization, respectively, will truly help us to gain a better sight about the efficiency of GWO algorithm. The peak load reduction of 71.14% is a good achievement, showing that the weighting and summation technique could obtain the appropriate parameters that achieved a flat load curve. This is a good amount of peak reduction for the utilities since it means less need for them to build more generation capacity, and greater grid reliability. The 67.16% cost decrease further validates the proposed method's practicality. As the control mechanism optimally schedules EV charging and exploits solar generation, it lowers energy procurement spending. This is of particular importance as in such smart grid scenarios, dynamic pricing and demand side management play unchallenged dominant roles. The 40.75% reduction in power loss implies a better system performance. Although it is a bit less than the improvements in peak and cost, reduction in energy consumption is also considerable so as to result in overall energy saving. Reduced losses indicate more efficient delivery of power with less waste, which are the keys to sustainable energy systems. In summary, the percentage improvements that are reported clearly verify that the proposed STLEO based optimization strategy is very effective in fulfilling the multi-objective such as minimization of peak load, cost and loss. These results advocate the use of intelligent optimisation techniques in future power systems comprising significant penetration of electric vehicles (EVs) and renewable energy sources.

The tabled comparative review shows that recent works predominantly treat the optimization objectives partially, e.g. only cost or peak load, and it is only a few of them that work towards a full multi-objective improvement. For example on the relatively strong cost reductions of around 46.23 % and 44 %, respectively, but little insight is given on peak load and power loss reduction.(Abdelaziz et al. (2025) and Anuja T. et al. (2025))In the same way, only around 15 % peak reduction occurred in (Xu et al. (2025)), which also represents the moderate result of load balancing, as no cost and loss optimization were considered. The OEVC MOPSO results in a mild betterment with 7.60% cost reduction and 28.73% loss reduction, to indicate the limited overall performance. Boubaker et al., 2025; Meng et al., 2026) attain the modest enhancement which is on the basis of the bio-inspired algorithms, but they do not at all cover all the essential evaluation measures. In general, these indicate a fragmented approach where optimization is in many cases for one or two objectives. On the other hand, the above mentioned multi-objective based solutions give you the impression that an integrated solution for peak load reduction, cost reduction and power loss reduction is desirable and so the significance of the proposed multi-objective optimization using PSO and Grey Wolf Optimization (GWO).

Table 3: Comparative Analysis of Proposed Work with Recent Studies

Author Name (Year)	Main Concept	Peak Reduction	Cost Reduction	Loss Reduction	Performance Level
Abdelaziz et al. (2025)	EV scheduling using PSO vs Transit Search Optimization (TSO)	~1.6% improvement over baseline	**46.23%**	Moderate (improved vs PSO)	Medium–High
Anuja T. et al. (2025)	PSO-based EV charging with V2G and solar integration	Not specified	**44%**	Not specified	Medium
Xu et al. (2025)	Smart EV charging optimization strategy	**15%**	Not specified	Not specified	Low–Medium
OEVC MOPSO Study (2025)	Multi-objective PSO with TOU pricing	Not specified	**7.60%**	**28.73%**	Low
Boubaker et al. (2025)	Multi-objective EV scheduling using Red Deer Algorithm (RDA)	Not specified	Moderate	Moderate	Medium
Meng et al. (2026)	Two-stage EV scheduling with Wolf Pack Algorithm	Not specified	Improved economic performance	Loss minimized (~42.4 kW absolute)	Medium–High

6. CONCLUSION

In this work, a novel multi-objective optimization-based EV load scheduling model has been proposed in a solar-enabled smart grid environment. Proposed approach unifies EV charging demand, renewable energy penetration, and power flow analyses. By applying backward-forward sweep (BFS) power flow, the model provides an accurate assessment of voltage profiles and network loss in the 33-bus distribution system. Two metaheuristic techniques, namely PSO and Grey Wolf Optimization (GWO), are applied and compared for the peak load minimization, energy cost reduction and power loss mitigation. The simulation results show that these two algorithms significantly improve the performance of the system compared to the baseline result. PSO gave maximum peak load reduction of 71.13%, cost saving of 66.55% and loss saving of 35.84% while the GWO slightly outperforms with peak load reduction of 71.14%, cost reduction of 67.16% and loss reduction of 40.75%. It can be deduced that both the optimizations are very good in handling the demand of EV charging, in which GWO has better global search ability and overall better results. Solar generation addition also assists in reducing the grid dependence and running cost. In summary, the proposed solution effectively addresses numerous challenges relating to EV integration including the uncertain peak demand, economic efficiency, and a stable network setup. In addition, it demonstrates the significance of multi-objective/multi-criteria optimization design for the next-generation smart grid system design with the rapid growth of complexity and contradicting objectives in future power system planning and operation. In contrast to [9–10,14–16,18,21–23], the proposed model provides substantially larger improvements in all major performance indices, signifying the effectiveness and applicability of the model. The use of realistic datasets, the incorporation of renewable energy sources, and the utilization of sophisticated optimization methods make this study a significant contribution to the field of intelligent energy management systems.

Future Work

Though the proposed framework has shown the effectiveness, a number of extensions are possible to further improve its versatility and robustness in the future work. An interesting avenue for further research is the possible hybridization of PSO and GWO, which could combine the strength of both employed optimization algorithms to obtain a faster and more accurate solution/convergence. Also, the economic efficiency of EV charging can be improved with implementation of the real-time dynamic pricing scheme and demand response program in real environments. Also, the future work may include integration of Vehicle-to-Grid (V2G) technology, to enable EVs to serve as distributed energy storage systems to supply power back to the grid when demand is high. This could also be used to enhance load balancing and grid stability substantially more. Furthermore, the addition of other RES, like wind energy, and uncertainty modeling of RES generation and EV demand may be added to make the framework more realistic and adaptable to real- life application. Another significant extension is to scale up the model for larger and more complicated distribution networks with unbalanced and meshed systems to investigate its performance under various grid structures. The use of advanced artificial intelligence methodologies (e.g., deep or reinforcement learning) can be also investigated for predictive EV load management and adaptive optimization. Besides, the practical applicability of the scheduling strategy can also be improved by incorporating models for battery degradation and user behaviors. To sum up, the presented scheme is a good basis for a smart EV load management in a smart grid, the novel steps will be allowed to pursue toward a full autonomous, real-time, and large-scale energy management system

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