Advanced Optimization Strategies for Efficient Electric Vehicle Charging Management

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Abstract: With the increasing number of electric vehicles (EVs), intelligent management of EV charging is essential to maintain the balance of the electrical grid. This article presents an advanced method for optimizing EV charging using meta-heuristic tools such as genetic algorithms (GA), Ant Colony Optimization (ACO), and a GA-ACO hybrid approach. The results indicate that integrating these techniques effectively reduces the power demand on the grid while meeting the charging requirements of EVs. The GA-ACO hybrid method, in particular, demonstrates superior performance by smoothing power demand and minimizing significant fluctuations compared to individual approaches. This study highlights the importance of combining optimization techniques to enhance the stability and reliability of EV charging management.

Keywords: Electric Vehicles (EVs), Meta-Heuristic Optimization, Genetic Algorithms (GA), Ant Colony Optimization (ACO) ,GA-ACO.

1. INTRODUCTION

In the near future, transportation electrification will bring new challenges. Initially driven by environmental concerns, the growing demand for electricity has become a critical issue. A significant increase in the number of electric vehicles (EVs) is predicted, leading to consumption peaks, particularly in the afternoon. The simultaneous arrival of vehicles and the sudden demand for battery recharging will make it difficult for system operators to manage congestion .

On the other hand, managing EV charging poses complex issues due to unpredictable dynamics and demand volatility. The uncertainty in arrival times, charging requirements, and departure times makes it difficult to estimate EV demand in advance. Analyzing historical data can help identify patterns and better understand charging needs, though the inherent unpredictability continues to challenge effective management.

Furthermore, various Vehicle-to-Grid (V2G) technologies complicate integration by enabling bidirectional interaction with the energy system . Coordinated charging can effectively improve energy utilization rates, whereas irregular charging patterns strain the energy system. Similarly, coordinated discharging can efficiently reduce the energy system's charging demand, whereas uncoordinated discharging may impact grid stability and security.

Therefore, studying effective strategies for managing EV charging and discharging behaviors is crucial to enhance potential benefits, such as load flattening . EV charging scheduling should prioritize transportation needs while ensuring reasonable grid interaction. Considering these factors, appropriate scheduling strategies and efficient optimization solutions are essential for specific application scenarios.

2. MÉTHODOLOGIE

For this study, data on total power demand from the local network over a day, from 8 AM to 8 PM with 15-minute intervals, was utilized. Information regarding electric vehicles (EVs), including arrival and departure times as well as charging durations, was generated for realistic simulation purposes

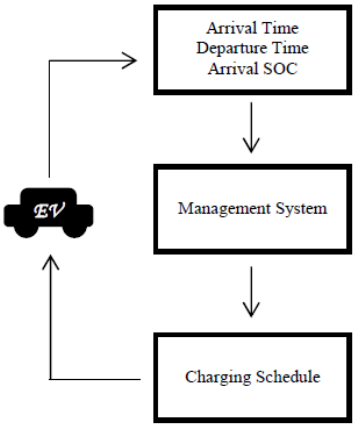

Figure 1. Management system structure

2.1 Formulation of the Optimization Problem

The method of smart charging aims to optimize energy usage in electrical grids while ensuring that electric vehicles are charged efficiently and on time.

The total energy demand at any given time *t* is the sum of the grid's energy demand ($D_{grid}\ (t)$) and the energy demand from electric vehicles ($D_{EV}(t)$)This relationship can be expressed in (1) :

$$D_{Total}\ (t)\ = D_{grid}\ (t)\ + D_{EV}(t) \quad (1)$$

The energy demand from electric vehicles at time t is determined by the number of vehicles charging at that time (V(t)) and the power per vehicle (P) in (2) :

$$D_{EV}(t) = V(t) \times \mathrm{P} \quad (2)$$

The primary goal of smart charging is to minimize the total energy demand on the grid, formulated as an optimization problem.

The objective function to minimize is the sum of the total energy demand over a period, represented in (3):

$$\sum_{t=1}^{n} D_{Total} \qquad (3)$$

This optimization is subject to two main constraints.

First, the total energy demand at any time *t* must not exceed the grid's maximum capacity, ensuring in (4):

$$D_{Total}\ (t)\ \leq\ D_{Max} \quad (4)$$

Second, each vehicle i must be fully charged within its designated charging window in (5)

$$\sum_{t=t_{start,i}}^{t_{end,i}} P \leq\ E_{req,i} \quad (5)$$

where $t_{start,i}$are the start and end times of charging for vehicle *i*, and $t_{end,i}$ is the energy required to fully charge the vehicle

2.2 *Modeling and Data Generation of Vehicles in a Charging Station*

In our study, we modeled and simulated the behavior of vehicles in a charging station.

The variables and parameters defined were crucial for accurately representing the system. The variable *n* represents the number of considered moments, and the state of charge (SOC) range of the vehicles is given by [10,90].

The maximum time for each moment, time_{max}, is calculated as $\frac{12\times 60}{n}$, allowing for a detailed temporal resolution of vehicle interactions within the charging station.

To simulate the number of vehicles at each moment, we used a uniform distribution in (06) :

$$vehicle_i \sim Uniform(1, vehicle\_range)$$

Where $i \in [1, n]$,this random generation ensures a realistic variation in the number of vehicles arriving at different times. For each vehicle, the entry time E_i is determined in (07) :

$$E_i\ = \lfloor time_m ax \times rand \rfloor + (j-1) \times time_{max} \quad (07)$$

where j represents the current moment and rand is a uniform random variable between 0 and 1.

This approach accounts for the randomness of vehicle arrivals while maintaining an organized structure over time

The charging time C_i for each vehicle is randomly generated within the SOC range determined in (08) :

$$C_i \sim uniform\ (\ 10{,}90) \qquad (08)$$

This range reflects the varying states of charge that vehicles might require upon arrival. Additionally, the exit time S_i for each vehicle is calculated to ensure it is always greater than the entry time plus the charging time in (09):

$$\mathrm{Si}=\lfloor 12\times 60\times \mathrm{rand} \rfloor \qquad (09)$$

under the constraint in (10)

$$S_i > E_i + C_i \quad (10\ )$$

This constraint guarantees that each vehicle stays long enough to complete its charging session before exiting the station. The resulting vehicle information matrix vehicle $_{\mathrm{info}}$is structured to include the entry time E_i charging time C_i ,and exit time S_i for each vehicle , represented in (11) :

$$\text{vehicle}_{\text{info}} = \begin{pmatrix} \boldsymbol{E_1} & \boldsymbol{C_1} & \boldsymbol{S_1} \\ \vdots & \vdots & \vdots \\ \boldsymbol{E_k} & \boldsymbol{C_k} & \boldsymbol{S_k} \end{pmatrix} (11)$$

where $k = \sum_{i=1}^{n} vehicle_i$This comprehensive matrix enables detailed analysis and optimization of the charging station's operation.

By utilizing the equations mentioned above, our model provides a robust framework for simulating the dynamics of vehicle behavior in charging stations, thereby offering valuable insights for improving the efficiency and management of electric vehicle infrastructure.

2.3 *Optimization Algorithms for Efficient Management of Charging Stations*

2.3.1. *Genetic Algorithm (GA) Optimization*

The Genetic Algorithm (GA) draws inspiration from Charles Darwin's concept of natural evolution, employing the principles of natural selection. It selects the fittest offspring for the next generation population .

In our study, the genetic algorithm is utilized to optimize the charging of electric vehicles (EVs) by minimizing their impact on power demand. The goal is to optimize EV charging times to reduce fluctuations in total energy demand, thereby smoothing the load curve and mitigating demand peaks on the electrical grid

- Initialization and Solution Generation: We begin by generating a population of potential solutions, where each solution represents a charging schedule for the EVs.

- Fitness Evaluation**:** Each solution is evaluated using a fitness function designed to measure the impact of EV demand on the electrical grid. The fitness function is defined as in (12) :

$$Fitness\ (x)\ = \frac{1}{\sum_{t=1}^{N}(P_{total}(i)-P_{moy})^2+\sum_{j=1}^{M} Penalty\ (P_j)} \quad (12)$$

Here:

$-\ P_{total}$:represents the total power demand at time instant t

$-\ P_{moy}$ is the average power demand.

- **N** is the number of time periods considered.

$Penalty\ (P_j)$ represents penalties applied to avoid demand peaks, where **M** is the number of periods for which a penalty is applied.

- Evolutionary Process**:** Over generations, the population evolves through mutation and crossover processes. New solutions are generated by combining and modifying existing ones. Each new solution undergoes the same fitness evaluation process.

- Selection and Iteration**:** The best solutions from each generation are selected to form the next generation. This iterative process continues for a predefined number of generations.

- Optimal Solution**:** After convergence, the best solution obtained is considered the optimal charging plan for the EVs. This iterative and adaptive approach allows the genetic algorithm to find solutions that minimize the impact on the electrical grid, thereby avoiding demand peaks and optimizing overall grid stability.

2.3.2 *Ant Colony Optimization algorithm Optimization*

Swarm intelligence is a relatively new approach to optimizing problems that typically mimics the social behavior of birds and animals. Ant colony optimization (ACO), which models ant behavior in locating and moving food, is the most prominent type of Swarm intelligence Initially, ACO algorithms were used for discrete optimization problems with fixed parameters in stationary environments. However, real-world problems are often dynamic and variable over time, requiring solutions that adapt to environmental changes.

In addition to solving static optimization problems, ACO and its variants can also tackle dynamic optimization problems. In our research, we apply ACO to smart electric vehicle (EV) charging management. Smart EV charging poses additional challenges due to the dynamic variability in recharge demand and electrical grid capacities. Our enhanced ACO algorithm continuously adapts to current network conditions and recharge demands by adjusting pheromone levels.

Initialization and Solution Construction**:** The algorithm begins by initializing an initial population of potential solutions, which represent various charging schedules for EVs. Each solution is generated randomly, yet constrained to prevent excessive initial loads. Concurrently, a pheromone matrix is established to model the attractiveness of these solutions.

Optimization Process**:** During each iteration (generation), virtual "ants" construct new solutions following rules based on pheromone trails and probabilistic decisions. These solutions are evaluated based on their effectiveness in minimizing the total energy demand on the network, considering both EV charging needs and initial network demand. The fitness function assigns a score to each solution, incorporating these criteria while applying penalties to encourage a balanced distribution of the load.

Pheromone Update: Pheromone trails are adjusted based on the relative performance of newly constructed solutions. Better-performing solutions reinforce the associated pheromone trails, thereby increasing their attractiveness for future generations of virtual ants. This continuous updating allows the algorithm to progressively converge towards optimal solutions.

Selection of the Best Solution**:** In each iteration, the best solution is selected based on its fitness score. If it surpasses the current best solution maintained in the population, it is retained as a candidate for subsequent generations. This iterative process continues until the algorithm converges towards an optimal solution, representing a charging schedule for EVs that minimizes peak demand on the network while optimizing the use of available resources

2.3.3 *Ant Colony Optimization algorithm Optimization*

The GA-ACO hybrid approach combines the diverse exploration capabilities of Genetic Algorithms (GA) with the refinement of solutions guided by pheromone trails in Ant Colony Optimization (ACO). This synergy enables the efficient generation of optimized charging plans for electric vehicles, balancing the growing demand with the stability of the electrical grid

- Genetic Algorithms (GA**)** operate by generating an initial population of random solutions, each representing a charging schedule for electric vehicles (EVs). Each solution is evaluated using a fitness function that considers the total power demand, encompassing both grid demand and EV requirements, while penalizing demand peaks. New solutions are created through crossover and mutation of existing solutions, thereby exploring new possibilities across generations.

- Ant Colony Optimization (ACO)**,** on the other hand, uses pheromone trails to guide the search towards promising solutions. Ants construct solutions by following these pheromone trails, influencing future solutions towards attractive areas of the search space. The best solutions reinforce pheromone trails, increasing the likelihood that similar solutions will be explored in the future, while allowing for continued exploration through pheromone evaporation.

Combining these approaches creates an iterative process where the best solutions from previous generations influence the generation of new solutions, gradually improving the optimal charging plan for EVs and minimizing impact on the electrical grid

3. CASE STUDY

In our study, we present the power demand in kW over a typical day from 8 AM to 8 PM, at 15-minute intervals. Our analysis includes curves illustrating the impact of three distinct optimization strategies based on Genetic Algorithms (GA), Ant Colony Optimization (ACO), and a GA-ACO hybrid approach on the power demand across three different scenarios.

Model parameters	
Maximum number of EVs per 15 minutes	50
Charging power of each EV	6KW
Maximum EV SOC	90
Minimun EV SOC	10
GA settings	
Population Size	20 individuals
Number of generations	50
Crossover probability	0.8
Mutation probability	0.01
ACO settings	
Population Size	20 individuals
Number of generations	50

4. RESULTS AND DISCUSSION

4.1.The different scenarios :

4.1.1.Scenarios 01 : Real-time management with Genetic Algorithm (GA)

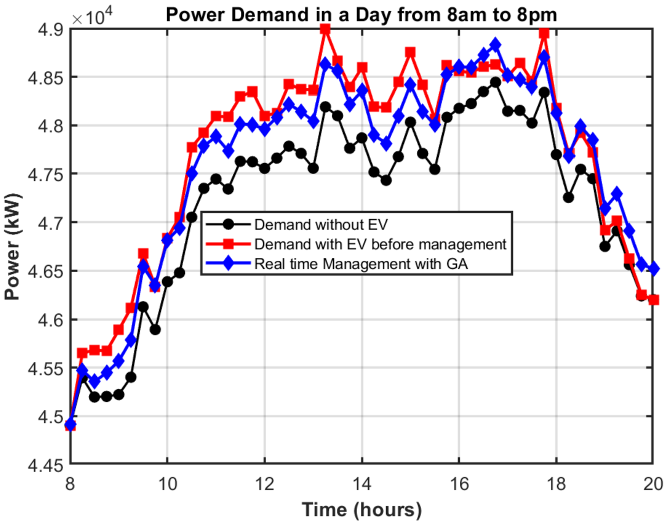

Figure 2. Real-time management with (GA)

4.1.2.Scenarios 02 : Real-time management with Ant Colony Optimization (ACO)

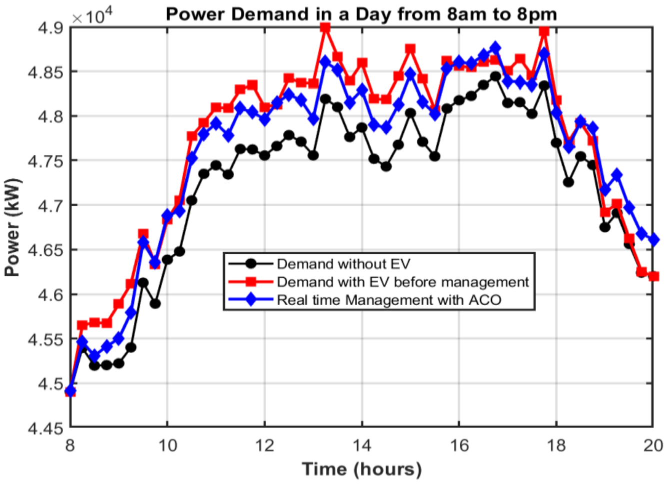

Figure 3. Real-time management with (ACO)

4.1.3.Scenarios 03 : Real-time management with a hybrid GA-ACO approach.

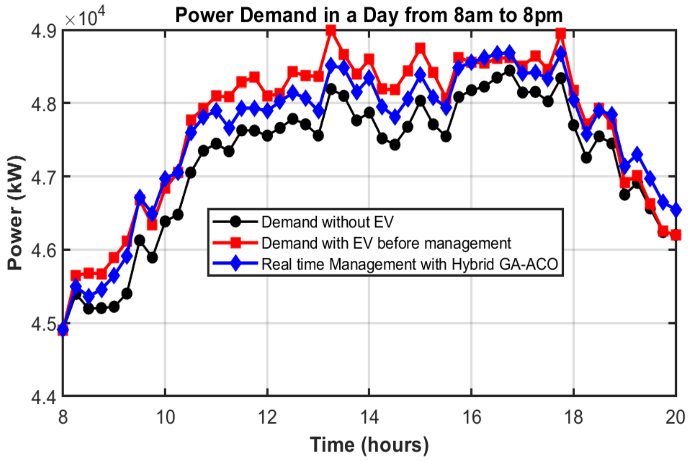

Figure 4. Real-time management with *GA-ACO*

4.2. Comparison of the variances of different power demand strategies

Variance analysis helps to identify which strategies lead to more stable and predictable power demands. Lower variance indicates that the power demand is more consistent, which is beneficial for grid management and energy planning. High variance, on the other hand, suggests significant fluctuations, which can pose challenges for maintaining grid stability and efficiency.

To compare the variances of different power demand strategies, we can use statistical methods such as Analysis of Variance (ANOVA)

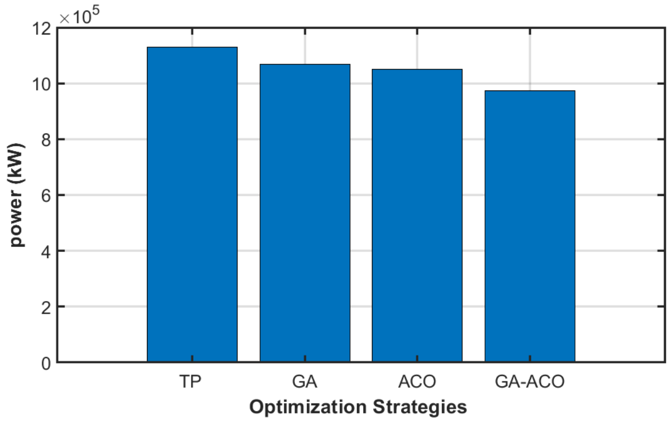

Figure 5. *Comparison of the variances*

5. ANALYSIS OF RESULTS

5.1.Compared Scenario Results:

Demand without Electric Vehicles :

The analysis of the results begins by examining the demand without electric vehicles, represented by the black line represented in figures (02 &03 &04 &06) . This reference curve shows the base power demand without the influence of electric vehicles. There is a progressive increase in demand throughout the day, with marked peaks in late morning and late afternoon. This trend reflects the typical behavior of daily energy consumption, corresponding to usual human activities.

Demand with Electric Vehicles before Management :

The addition of the demand from electric vehicles, represented by the red line in figures (02 &03 &04 &06), leads to a significant increase in the overall power demand. The demand peaks become noticeably higher, especially during peak hours. This increase is due to the charging of electric vehicles, often scheduled after work hours, thus coinciding with the natural consumption peaks. This situation highlights the challenge of integrating electric vehicles without adequate demand management. Without intervention, this overload can impose constraints on the power grid, increasing the risks of outages and necessitating costly investments in infrastructure.

Real-Time Management with Genetic Algorithm :

represented in the figure (02 &06) , reduces power demand compared to the unmanaged situation (red line). This algorithm simulates the process of natural selection to optimize the distribution of the load. It adjusts the demand by delaying or advancing the charging of electric vehicles based on the available capacity of the grid. The demand peaks are less pronounced thanks to this technique, although management is not optimal during all peak hours. Some periods of high demand may not be sufficiently mitigated, indicating that the algorithm still has room for improvement.

Real-Time Management with Ant Colony Optimization, represented in the figure(03 &06), proves more effective than the genetic algorithm. Inspired by the behavior of ants searching for food and communicating via pheromones, this method allows for a significant reduction in demand peaks by distributing the load more evenly. The green curve is generally lower than the blue curve, indicating a better distribution of power demand. This contributes to a more stable and predictable use of the power grid, avoiding overloads.

Real-Time Management with Hybrid GA-ACO Method :

The hybrid method combining the genetic algorithm and ant colony optimization, represented in the figure (04 &06), offers the best demand management observed. This hybrid approach combines the advantages of both algorithms, allowing for efficient search for optimal solutions and refined load distribution for increased efficiency. The curve shows the most significant reduction in demand peaks, especially during peak hours. This hybrid method achieves a smooth demand curve close to the demand without electric vehicles, indicating highly effective management. By integrating the strengths of both approaches, the hybrid method ensures a dynamic and adaptive response to demand variations, minimizing overload risks and optimizing the use of grid resources.

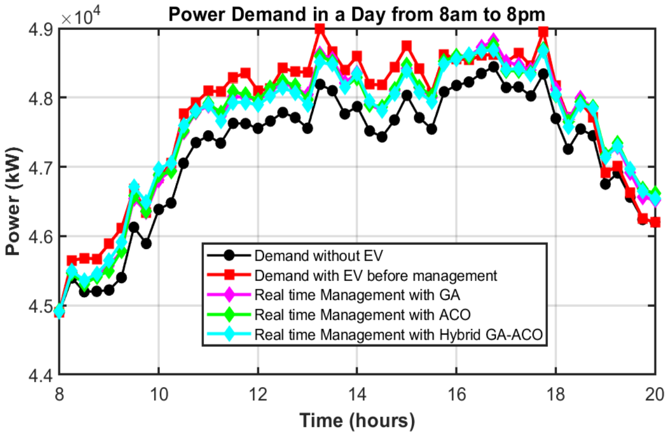

Figure 6. Real-time management with (*GA, ACO,* GA-ACO)

5.2. Discussion of Comparison of the Variances of Different Power Demand Strategies

The figure 05 presents a comparison of variances among different power demand management strategies. Here is a detailed analysis of the results:

Total Power: The variance of total power demand without management is high, as indicated by the first bar in the graph. This reflects significant fluctuations in power demand without any management intervention

GA (Management with Genetic Algorithm): The variance is high, indicating that management with GA alone can be less stable and exhibit significant fluctuations.

ACO (Management with Ant Colony Optimization): The variance is slightly lower than that of GA, showing better management and a more uniform distribution of power demand.

GA-ACO Hybrid: The lowest variance among the management methods, indicating that the hybrid method is the most effective at smoothing power demand and avoiding significant fluctuations.

6. CONCLUSIONS

The results of this study demonstrate the effectiveness of optimization strategies using GA, ACO, and their hybrid GA-ACO approach in reducing power demand peaks and smoothing the load curve. In particular, the hybrid GA-ACO method provides superior performance in minimizing fluctuations. These methods enable better integration of electric vehicles (EVs) into the power grid, thereby minimizing the risk of destabilizing the network.

The comparative analysis reveals that the hybrid GA-ACO optimization offers the most stable and effective power demand management compared to other studied methods. Although GA and ACO optimizations alone are already effective in reducing demand fluctuations, the combination of these techniques in a hybrid approach significantly enhances this performance. These results highlight the importance of sophisticated management strategies to integrate electric vehicles into the grid without causing significant power demand fluctuations

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