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A HYBRID GENETIC-GRADIENT DESCENT ALGORITHM FOR OPTIMAL ELECTRIC VEHICLE CHARGING STATION PLACEMENT

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Abstract: The strategic deployment of charging infrastructure is important to accelerate the adoption of electric vehicle (EV) and reduce transportation emissions. However, optimal charging station placement presents a complex optimization challenge, constrained by multiple factors such as construction costs and user accessibility. Traditional optimization methods often struggle to find globally optimal solutions within this multi-dimensional constraint space. To address these challenges, we propose a novel hybrid optimization framework that integrates genetic algorithms (GA) with gradient descent (GD) methods for charging station location planning. Our approach uses GA to generate promising initial solutions, followed by gradient-based optimization for solution refinement. The methodology incorporates three variants of gradient descent, including adaptive, conditional, and proximal gradient. We evaluate our framework through comprehensive simulations across various scenarios, using a carefully designed virtual environment that models realistic user demand patterns and geographical constraints. The simulation results demonstrate the effectiveness and robustness of our proposed hybrid optimization framework for optimal charging station placement.
Keywords: Electric vehicle charging infrastructure; Optimization; Genetic algorithms; Gradient descent; Infrastructure planning

1 INTRODUCTION

The United States (U.S.) is currently implementing an ambitious program to deploy public charging infrastructure to promote the widespread adoption of electric vehicles (EVs) needed to achieve climate goals [1]. However, the effectiveness of this transition heavily depends on the strategic placement of charging stations. Suboptimal or irrational station locations can significantly increase operational costs for both users and operators, potentially impeding the growth of the EV industry [2]. Therefore, an effective approach for charging station placement optimization is critical for facilitating transportation electrification and reducing emissions [3].

Current approaches to charging station optimization mainly focus on traditional analytical methods and heuristic algorithms. Analytical methods use multiple data sources, including traffic flow patterns, user demand analysis, and power supply constraints, to construct mathematical models that evaluate potential station locations [4]. However, these methods often struggle with real-world complexity, producing solutions that may deviate significantly from practical requirements [5].

Recently, heuristic algorithms, such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), have been widely adopted in charging station optimization. These methods mimic natural processes, such as evolution, annealing, or ant colony behavior, to iteratively search for optimal station locations [6]. However, while heuristic algorithms can effectively explore complex solution spaces, they cannot guarantee convergence to global optima [7].

To address these limitations, we propose a hybrid optimization methodology that combines the strengths of (GA) and gradient descent (GD) optimization. Our approach utilizes GA's global search capabilities to generate promising initial solutions, followed by gradient descent-based refinement for local optimization. Through comprehensive simulation experiments, we evaluate three variants of this hybrid approach, incorporating adaptive gradient, conditional gradient, and proximal gradient methods.

2 PROBLEM FORMULATION

In this project, the charging station optimization problem aims to determine optimal charging station placements by considering user charging demands, station construction cost, and service coverage effectiveness.

Let $\{\Omega = (x, y) \mid 0 \le x \le L, 0 \le y \le W\}$ denotes the candidate region for station placement, where L and M are the area dimensions. Within this area, let $\{\mathrm{D} = (u_i, v_i) \in \Omega, \forall i = 1, \ldots, m\}$ denote the set of m charging demand points, and $\{\mathrm{X} = (x_j, y_j) \in \Omega, \forall j = 1, \ldots, n\}$ denote the set of n charging stations to be placed, where (u_i, v_i) and (x_i, y_i) represents the coordinates of demand point i. and station j, respectively. For any demand point i and station j, their Euclidean distance is calculated as:

$$d_{ij} = \sqrt{(u_i - x_j)^2 + (v_i - y_j)^2} \tag{1}$$

The coverage effectiveness of all charging stations can be quantified through:

$$r_{\text{coverage}} = 1 - \frac{1}{m}\sum_{i=1}^{m} \text{ú}\left(\min_{j=1,\ldots,n} \sqrt{(u_i - x_j)^2 + (v_i - y_j)^2} \le R \right) \tag{2}$$

where R is the service radius of each charging station.

The construction cost primarily reflects land acquisition expenses, which typically increase with proximity to populated areas such as malls and residential districts. This relationship is mathematically expressed as:

$$c(x_j, y_j) = \sum_{k\in \mathrm{C}} \omega_k \exp(-\lambda d_{jk}) \tag{3}$$

where C is the set of population centers, d_{jk} is the distance to the population center, ω_k is the weight coefficient of the center, and λ is the distance decay parameter.

Therefore, the multi-objective optimization problem can be formulated as:

$$\min_{\mathrm{X}} \ F(\mathrm{X}) = w_1 f_1(\mathrm{X}) + w_2 f_2(\mathrm{X}) + w_3 f_3(\mathrm{X}) \tag{4}$$

Subject to

$$\sqrt{(x_j - x_k)^2 + (y_j - y_k)^2} \ge D_{min}, \quad \forall j,k = 1,\ldots,n, j \ne k \tag{5}$$

$$\sum_{j=1}^{n} c(x_j, y_j) \le B \tag{6}$$

where w_1, w_2, w_3 and are weighting coefficients, respectively, D_{min} is the minimum required distance between stations and B is the total construction budget. The three objective components are defined as: which can be calculated by:

$$f_1(\mathrm{X}) = \frac{1}{m}\sum_{i=1}^{m} \min_{j=1,\ldots,n} d_{ij} = \frac{1}{m}\sum_{i=1}^{m} \min_{j=1,\ldots,n} \sqrt{(u_i - x_j)^2 + (v_i - y_j)^2} \tag{7}$$

$$f_2(\mathrm{X}) = \sum_{j=1}^{n} c(x_j, y_j) = \sum_{j=1}^{n}\sum_{k\in \mathrm{C}} \omega_k \exp(-\lambda d_{jk}) \tag{8}$$

$$f_3(\mathrm{X}) = r_{\text{coverage}} = 1 - \frac{1}{m}\sum_{i=1}^{m} \text{ú}\left(\min_{j=1,\ldots,n} \sqrt{(u_i - x_j)^2 + (v_i - y_j)^2} \le R \right) \tag{9}$$

where f_1 is the average distance penalty, f_2 is the construction cost penalty, and f_3 is the coverage ratio penalty.

3 METHODOLOGY

To address the charging station placement optimization problem, we developed a hybrid approach combining GA with GD. Traditional GD algorithms, while efficient for convex problems, often struggle with non-convex objective functions due to local minima traps and sensitivity to initialization. To overcome these limitations, our approach utilizes GA for robust initial solution generation. The charging station solution from GA is subsequently input to adaptive GA for fine-tuned optimization, which enables efficient local optimization. The combination helps avoid local minima while ensuring convergence to high-quality solutions

3.1 Gradient Descent with Adaptive Learning Rate

The GD optimization is based on the fundamental principle that for a differentiable multivariate function $F(x)$, the direction of the steepest descent is given by the negative gradient $-\nabla F(a)$ at point a [8]. In the charging station optimization, the GD method aims to find a set of charging station X to minimize costs. The iterative update process follows:

$$\mathrm{X}_{n+1} = \mathrm{X}_n - \gamma_n \nabla F(\mathrm{X}_n) \tag{10}$$

where γ_n is the adaptive learning rate.

To enhance convergence stability and optimization efficiency, we implement an adaptive mechanism that dynamically adjusts learning rate at each iteration:

$$\gamma_n = \frac{\left(\mathrm{X}_n - \mathrm{X}_{n-1}\right)^T \left[\nabla F\left(\mathrm{X}_n\right) - \nabla F\left(\mathrm{X}_{n-1}\right)\right]}{\nabla F\left(\mathrm{X}_n\right) - \nabla F\left(\mathrm{X}_{n-1}\right)^2} \tag{11}$$

3.2 Genetic Algorithm

The GA serves as a robust initialization method and global search mechanism [9]. In the GA, each individual represents a potential charging station configuration and the population diversity ensures broad exploration of the solution space.

The optimization process within GA involves three key operations. First, the selection mechanism implements a fitness-proportionate approach where individuals with higher fitness values have a greater probability of being selected as parents, ensuring the preservation of high-quality solutions while maintaining population diversity. The crossover operation then creates offspring by randomly selecting crossover points from the parent solutions with equal probability, allowing an effective combination of beneficial solution components from different parents. Finally, mutation introduces controlled randomness through bit flipping with a small probability. These operations work together to balance the exploitation of promising solutions with the exploration of the search space, ultimately driving the population toward local optimum charging station configurations.

4 CONCLUSION AND DISCUSSION

4.1 Simulation Setup

In this project, the simulation scenarios were constructed with two key components, i.e., fixed population centers representing urban clusters and demand points generated using Gaussian distributions centered around population centers. The distance decay parameter λ was set to 0.1, weighting coefficients w_1, w_2, w_3 were set to 0.4, 0.4, and 0.3, respectively. Moreover, we designed four test cases with incrementally increasing complexity to assess algorithmic scalability and robustness (Table 1). Each case represents a different scale of the charging station placement problem.

Table 1 Parameter Configuration for Test Cases

Parameters	Case (a)	Case (b)	Case (c)	Case (d)
Region sizes	100	200	400	800
Demand points	10	20	40	80
Population enters	5	10	15	20
Charging stations	5	10	15	20

The GA algorithms were configured with the following parameters: population size is 50, mutation rate is 0.2 and maximum iterations is 500. For gradient-based methods, we test the performance of three variants of the gradient descent approach, including adaptive gradient (Section 3.1), conditional gradient [10] and proximal gradient [11]. The step size in conditional gradient was set to $2/(k+2)$, where k is the iteration number, with a constant value of 1 set in the proximal gradient.

4.2 Simulation Results

To evaluate the performance of the three gradient-based optimization approaches (adaptive, conditional, and proximal gradient descent), we conducted comprehensive experiments on a 100×100 region containing 10 population centers and 100 demand points. Our analysis focused on three key aspects: convergence characteristics, spatial distribution quality, and multi-objective performance metrics.

Figure 1 illustrates the changes in objective values of the three gradient descent optimizers through 1000 iterations. The results show that all three methods demonstrated rapid initial optimization in the first 50 iterations, with the objective value decreasing sharply below 6×10^0. However, their subsequent convergence patterns differed significantly. The adaptive and proximal gradient methods achieved stable convergence after approximately 50 iterations, while the conditional gradient required nearly 100 iterations to stabilize. Moreover, the adaptive gradient consistently maintained the lowest final objective value of 4.18, compared to 4.28 and 5.36 for the proximal and conditional gradients respectively, indicating its superior optimization capability.

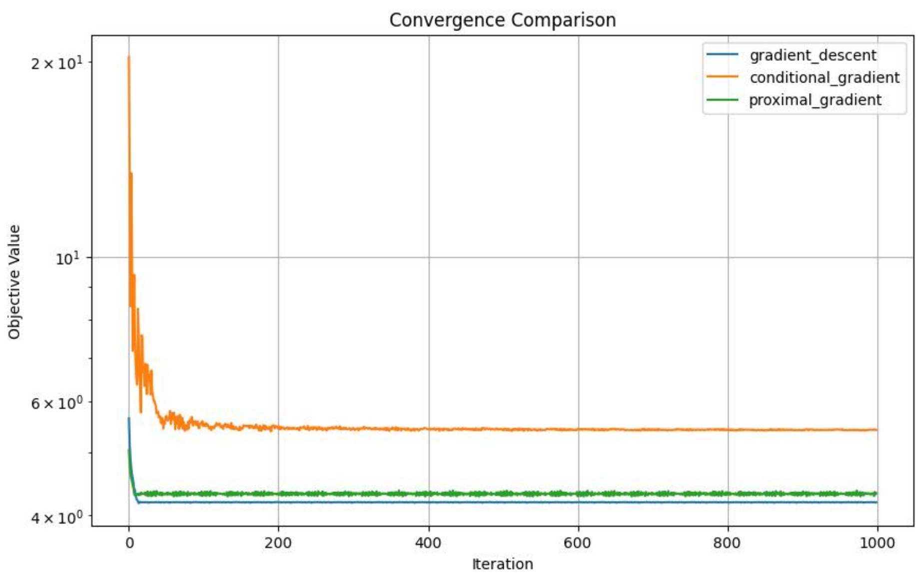
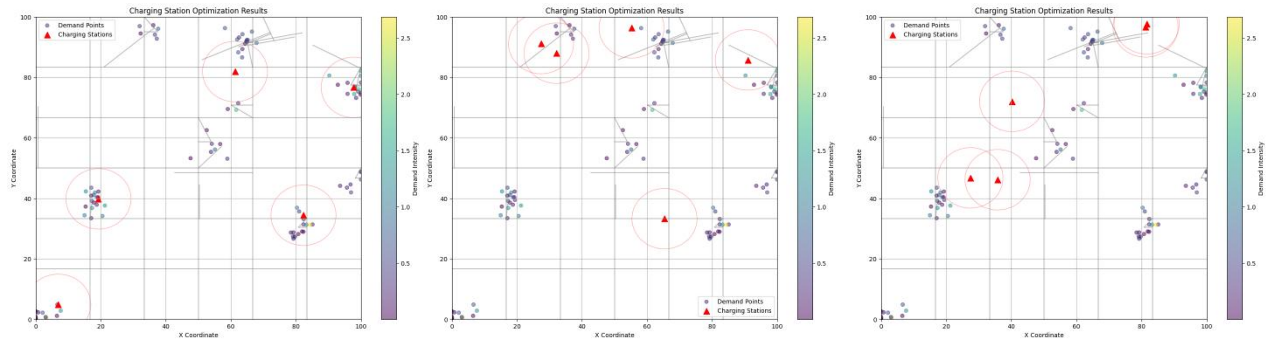


Figure 1 Variation of Objective Values with Number of Iterations for Three Algorithms

To evaluate the practical applicability of these algorithms, we analyzed the spatial distribution patterns of charging stations generated by each algorithm. As shown in Figure 2, the adaptive gradient method (Figure 2a) produced notably more uniform and well-dispersed charging station locations across different population centers compared to the other approaches. The conditional gradient (Figure 2b) tended to cluster stations more closely together, while the proximal gradient (Figure 2c) generated an intermediate distribution pattern. This spatial analysis suggests that the adaptive gradient achieves better coverage of the service area while maintaining reasonable distances between facilities.



(a) Adaptive gradient (b) Conditional gradient (c) Proximal gradient

Figure 2 Layout Comparison of Charging Base Stations Generated by the Three Algorithms

Figure 3 further compares the performance of each method across three key metrics: average distance to demand points, construction costs, and coverage rate. The results show that the adaptive gradient achieved the lowest average distance penalty of 7.80 units, representing a 25% improvement over the conditional gradient's 10.40 units. While its construction cost (3.21) was slightly higher than the proximal gradient's 3.03, it achieved the highest coverage rate of 65%, compared to 59% for both conditional and proximal gradients respectively. These results demonstrate that the adaptive gradient successfully balances the competing objectives of minimizing costs while maximizing service coverage.

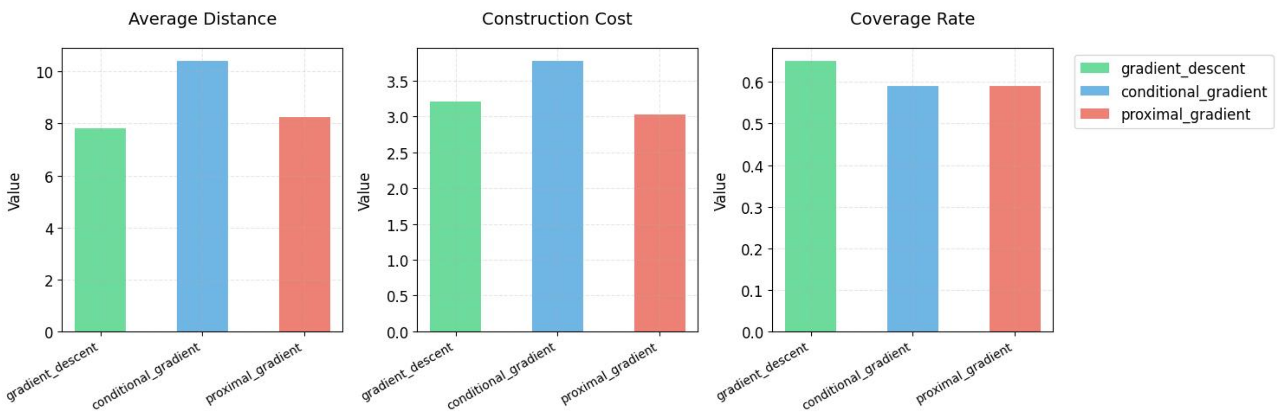


Figure 3 Cost Comparison of Charging Base Stations Generated by the Three Algorithms

In order to evaluate the scalability and robustness of the three optimization approaches, we conducted extensive experiments across four key problem dimensions: region size, demand point density, population center distribution, and charging station capacity. Each dimension was tested with four increasing scales to assess algorithmic performance under varying computational loads, as demonstrated in Table 1. Table 2 shows the mean and variance of results from five independent runs were reported.

Table 2 Performance Comparison of Different Algorithms in Varying Cases

Optimizer	Case (a)	Case (b)	Case (c)	Case (d)
Adaptive	5.26261± 0.732883	**9.938685± 0.905996**	**19.331808± 0.841872**	40.866991± 1.618788
Conditional	**5.213003± 0.748442**	10.623469± 0.214425	20.686607± 0.908285	41.086251± 1.783154
Proximal	5.290131± 0.703791	10.015033± 0.990372	19.625276± 1.278735	**40.536592± 1.609049**

The results revealed distinct performance patterns for each algorithm across different problem scales. The adaptive gradient demonstrates robust performance across medium to large-scale problems, while the conditional gradient excels in small-scale optimization scenarios. The proximal gradient becomes increasingly competitive as problem dimensions grow.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

CODE AVAILABILITY

The code to implement this project is available at https://colab.research.google.com/drive/1Ct4LfFBUKfm3Pmncx0OVWmOsO7RF4YqO?usp=sharing.

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