Where is the nearest EV charging station? Evolutionary optimization of the gas/charging stations topology

Extended Abstract

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ABSTRACT

Electric vehicle (EV) adoption depends heavily on the availability and accessibility of charging infrastructure. In this work, we propose a multi-agent framework for optimizing the placement of gas and charging stations. The multi-agent system models drivers' behavior with varying goals and constraints, interacting in a shared environment. Preliminary results using a baseline genetic algorithm demonstrate the feasibility of our approach and provide insights into optimal station distributions. This framework can be extended to incorporate more sophisticated evolutionary algorithms or real-world datasets.

CCS CONCEPTS

• **Computing methodologies → Genetic algorithms**; **Multi-agent systems**; *Interactive simulation*; • **Applied computing →** Multi-criterion optimization and decision-making.

KEYWORDS

Electric Vehicle Market; Charging facility location; Genetic algorithms; intelligent agents

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1 INTRODUCTION

The Electric Vehicle (EV) market has grown significantly in the last five years, with 5% of all vehicles sold in 2020 being electric. This growth has transformed interactions between drivers, energy companies, car sellers, and other stakeholders. Multi-agent systems (MAS) are essential for simulating and analyzing these interactions. For instance, studying how the placement and number of charging stations influence EV adoption can guide the optimization of station topologies to boost market growth or company profits.

This paper proposes using Evolutionary Algorithms (EAs) to optimize simulation parameters. Company agents can create and configure charging stations in our MAS to maximize benefits. Unlike previous works focusing solely on station allocation [2, 11], our approach incorporates interactions between agents. We introduce domain-specific heuristics to avoid full simulations and the computational challenges of calculating fitness functions, significantly reducing computation time. We demonstrate that combining EAs with fitness estimations enables effective parameter optimization.

2 RELATED WORK

Building an efficient network of electric stations is crucial for increasing EV adoption. Most studies use a top-down approach, leveraging data like economic and geographic information with optimization algorithms. For instance, Erbaş et al. [3] rank sites in Ankara using a fuzzy analytical hierarchy process, while Zhao and Li [14] apply a fuzzy Delphi method in Tianjin. Genetic algorithms (GA) are also widely used; Jaramillo et al. [5] showed GA's advantages in facility location problems, influencing works like Tu et al. [11], who optimize spatial-temporal demand for electric taxis in Shenzhen, and Dimitrios Efthymiou and Aifantopoulou [1], who evaluate station demand near Thessaloniki.

Multi-agent approaches are less explored. Jordán et al. [6] use agents for tasks like data collection and GA-based station location in Valencia, while Miranda et al. [8] develop virtual agents for electricity allocation in charging stations. However, these systems lack representation of real-world EV market actors and their interactions. This is tackled in the work by Kangur et al. [7] that uses the consumer model to simulate market diffusion.

Our work introduces a bottom-up multi-agent system in which agents represent EV market stakeholders. Supplier agents use GA to optimize station locations and configurations, enabling analysis of network changes in the market ecosystem.

3 THE MULTI-AGENT ARCHITECTURE

Our model provides a framework to simulate interactions among electric vehicle (EV) and energy sector agents. It models urban environments, populations, and service stations, capturing how people

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travel, refuel, and decide on vehicle purchases. All trips occur within the environment, with no external inflow or outflow. The framework assesses the long-term effects of policy decisions on energy company profitability, analyzing how infrastructure investments impact EV adoption and market dynamics.

The Multi-agent simulation includes key agents representing EV market stakeholders. **Vehicles** simulate energy consumption, deterioration, and breakdowns, influencing consumer satisfaction and decisions. **Consumers** maximize their satisfaction by deciding where to refuel, which vehicle to purchase, and when to travel or refuel. **Service stations** manage queues, service delivery, expenses, and revenue, while energy companies optimize station configurations and locations using Genetic Algorithms (GA) to maximize profits. **The energy market** reflects dynamic energy price changes driven by market rules, and the environment provides spatial and demographic data that influence agent decisions. This allows the simulation of the complex dynamics of the EV market.

The system operates synchronously with discrete daily time steps, combining decentralized and hierarchical structures[9, 12, 13]. Service stations implement policies set by their parent energy companies while maintaining operational independence. Energy companies respond to market-driven energy prices and adjust station configurations. Vehicles and consumers act autonomously, making decisions based on observed features and individual goals. This mixed structure allows reactive agents, like vehicles, to interact with deliberative agents, such as energy companies, which possess advanced decision-making and optimization capabilities.

This MAS framework enables detailed simulations of market dynamics and policy impacts, offering insights into the interplay between infrastructure, consumer behavior, and EV adoption.

4 OPTIMIZATION USING EAS

Evolutionary algorithms, such as Genetic Algorithms (GAs), are powerful optimization tools introduced by Holland [4]. GAs mimic natural selection, making them ideal for exploring large search spaces handling non-differentiable functions, strong convergence, and minimal parameter tuning. A GA starts with a population of solutions, evaluates them using a fitness function, and iteratively refines them through selection, crossover, and mutation. This process continues until a stopping criterion is met. In our work, we utilize the Differential Evolution algorithm [10] to optimize gas and electric pump configurations and station locations.

We define three optimization processes tailored to company needs: (1) redistributing pump types at existing stations; (2) selecting optimal locations for new stations using clustering techniques, with different configurations; and (3) a combined approach optimizing both station locations and pump distributions. Each solution is uniquely encoded to reduce redundancy and improve search efficiency. To address computational challenges, we devised a heuristic that approximates long-term profit by simulating consumer behavior over a short period, significantly reducing evaluation times. Metrics such as total profit, electric pump profitability, and market impact are analyzed over ten-year simulations.

Experimental results highlight the strengths of informed and uninformed approaches, comparing baseline configurations with optimized setups. For pump redistribution, strategies include fixed percentages or adapting to surrounding car types. Location optimization leverages k-means clustering for station placement, balancing large centralized stations against distributed smaller ones. The combined optimization integrates these methods.

Type	Settings	Total Profit	Electric Gain	% EVs
	baseline	$7.49\text{x}10^7$	-100%	3.42
Distrib.	50%	$7.20\text{x}10^7$	-89.40%	**5.18**
	70%	$8.22\text{x}10^7$	61.45%	4.57
	prop	$7.94\text{x}10^7$	-109.36%	3.35
	GA	$\mathbf{8.62x}10^7$	**172.28%**	5.02
Location	B|E	$7.22\text{x}10^7$	78.78%	**4.39**
	B|50%	$14.24\text{x}10^7$	**217.88%**	4.24
	B|GA	$\mathbf{14.99x}10^7$	-79.32%	4.02
	S|E	$6.48\text{x}10^7$	-2.42%	5.74
	S|50%	$13.38\text{x}10^7$	194.54%	**6.38**
	S|GA	$\mathbf{15.31x}10^7$	**219.66%**	3.99
Combined	B|lvq|C	$8.87\text{x}10^7$	**195.02%**	4.04
	B|lvq|prop	$9.20\text{x}10^7$	171.96%	4.84
	B|kmeans|prop	$7.43\text{x}10^7$	28.64%	**5.39**
	B|GA	$\mathbf{14.15x}10^7$	83.42%	5.31
	S|lvq|C	$\mathbf{15.44x}10^7$	**137.63%**	5.11
	S|lvq|prop	$15.25\text{x}10^7$	107.13%	5.70
	S|kmeans|prop	$6.92\text{x}10^7$	-20.61%	**6.75**
	S|GA	$12.71\text{x}10^7$	-19.83%	5.99

Table 1: Comparison of Total Profit, Electric Gain, and % Cars for different configurations in the final simulation step. Here we use *50%* to determine half of pumps of each supply type, *70%* for 30% electric and the rest fuel, *E* for all electric and *prop* for proportional to people nearby. Big stations are referenced as *B* and small stations as *S*. LVQ algorithm uses *lvq* abbreviation and K-means uses *kmeans*. The solutions regarding the genetic algorithm are called *GA*.

Table 1 shows that GA optimizations consistently achieve the highest overall profit, with large stations addressing overall demand and small ones focusing on local demand. While profit maximization sometimes reduces electric gains or EV fleet size, GA still tends to include EV dispensers, even without explicit optimization. Benchmark methods that force all-electric stations to improve electric gains but reduce profits due to higher maintenance costs. Although GA struggles with small stations due to a larger search space, all optimizations outperform the baseline across all metrics.

5 CONCLUSIONS

This study uses multi-agent simulations to evaluate the impact of optimizing gas and charging station networks on energy company revenue. Key findings reveal that station quantity, configuration, and placement significantly influence EV market growth and company profits. High-density electric station networks foster EV adoption, while small, well-placed mixed-type stations yield the highest profits, especially in markets transitioning to electric vehicles with a still-large fuel vehicle presence.

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