Evolutionary optimization of the gas/charging stations topology for the Electric Vehicle Market

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Abstract

This study applies Evolutionary Algorithms (EAs) to optimize the profitability of a hybrid refueling network for conventional and electric vehicles. Three strategies are explored: reconfiguring existing stations, siting new ones, and combining both methods. A multi-agent simulation models stakeholder interactions in a Spanish city, incorporating behavioral dynamics between users and operators. The approach features problem-specific objective functions, a compact encoding scheme, and a heuristic to reduce computational cost. Results show that small, strategically located mixed-use stations maximize profitability and support EV adoption.

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 Electrical Vehicle (EV) market has experienced huge growth in the last five years. In 2020, 5% of all sold vehicles were electric. This market expansion causes big changes in how the users (drivers), energy companies, car sellers, and other main actors relate to each other. In this sense, Multi-agent systems (MAS) for simulating the EV market are required as tools to analyze such interactions empirically. In this paper, we propose Evolutionary Algorithms (EAs) to optimize different simulation parameters that permit the maximization of some agents' internal goals. In our Multi-agent system, the *company agents* have the possibility of creating new stations and deciding on the configuration of each of them to maximize the benefits, but taking into account that they are part of the market ecosystem being, at the same time, influenced by it.

This paper assesses the problem of optimizing the EV middle-size infrastructure in terms of refueling or recharging stations location and configuration to promote the development of the EV market sharing. The main contributions of this paper are:

- The optimization processes integrated into a multi-agent system where the various agents actively interact.
- This paper analyzes the problem through three optimization processes: locating new charging stations, reconfiguring existing infrastructure, and combining both, enhancing efficiency, revenue, and scalability of the EV charging network.
- This work explores the impact of energy companies' policies while emphasizing the need for broader studies collaborating with governments to drive EV market growth.

2 Related Work

Genetic algorithms (GA) have been widely applied to the allocation of electric charging stations in road networks. For example, Jaramillo et al. [4] found GA to outperform other methods in facility location problems. Celik and Ok [2] provide a summary of various solution approaches, including GA-based ones. In contrast, little work addresses the configuration of mixed gas-electric charging stations. However, decentralized optimization of charging/discharging processes has been studied under both cooperative Li et al. [8] and non-cooperative Alghamdi et al. [1] frameworks

Multi-agent approaches to this problem using intelligent agents are scarce. The work by Jordán et al. [5] presents a multi-agent system where agents do not represent real characters but are in charge of system functionalities like collecting environment information, managing the user interface, etc. In the paper Kangur et al. [6], the authors use a multi-agent system to model EV market diffusion via social simulation. Our work differs from the previous ones in that we present a bottom-up multi-agent system approach, where agents represent the main stakeholders of the EV Market, and the system dynamics are based on the complex relationships between

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them. In this environment, the agents that represent gas and electric suppliers use GA for optimizing the locations and configurations of gas/electric stations which allows us to analyze the impact of the network configuration change in the ecosystem.

3 Multi-agent architecture description

Our model presents a framework to simulate the interactions between various agents involved in the electric vehicle and energy sectors. It is capable of modeling intra-urban or inter-urban environments, their populations, and service stations, as well as the interactions among them. It is based on the closed systems paradigm, where every trip's origin and destination fall within the environment. The system defines how people take trips and decide where to refuel and when and which model of vehicle to buy. The primary objective of this framework in this study is to provide a tool for assessing the long-term effects of different policy decisions on energy company profitability. By capturing both individual behaviors and synergistic interactions, the framework offers insight into how factors such as infrastructure investments influence the transition to electric mobility. Specifically, we are interested in assessing the influence of the location and configuration of gas/electric stations on the EV market share.

Our Multi-agent simulation framework is structured into several core agent types, each representing a stakeholder. **Vehicles** simulate energy consumption, deterioration, and breakdowns, influencing consumer satisfaction and decisions. **Consumers** maximize a utility function based on a cognitive satisfaction model. This is achieved by deciding where to refuel, which vehicle to purchase, and when to travel or refuel. **Service Stations** simulate the operation of refueling and charging stations by managing queues, service delivery, expenses, and revenue. **Energy Companies** optimize station configurations and locations using Evolutionary algorithms (EAs) to maximize profits. The **Energy Market** reflects dynamic energy price changes driven by market rules. The **Environment** provides spatial and demographic data that influence agent decisions and interactions, and their initialization.

We consider a synchronous Multi-agent framework to tackle operational issues [10]. Agents operate in a specified order and time is discretized into days. At the organizational level, our framework features a mixed structure, combining elements of decentralized and hierarchical systems [12, 13]. A service station must implement the changes decided by the energy company that owns it, and the energy company must adhere to the energy market prices. At the same time, all agents retain some independence to perform other actions, and no central coordinator dictates how all agents should behave. The energy company agent uses EA to make decisions about the configuration and location of the gas stations.

4 Optimization based on EAs

EAs are stochastic search algorithms that use a heuristic based on natural selection and evaluation. They consist of several elements: the genome coding which is used to represent each solution; the population generation, the fitness function that is used to evaluate each possible solution and guide the search process; the selection procedure to determine the best solutions; the modification of each solution to create new individuals with the crossover and mutation operators; and the stop criteria. We opt for the Differential evolution [11] algorithm for our optimization processes. This is a popular EA with convenient properties: it converges well, handles non-differentiable cost functions, and has few parameters to tune.

4.1 Problem Formalization

We propose three optimization strategies: distributing pumps in existing stations, selecting locations for a limited number of new stations with predefined supply types, and a combined approach optimizing both. All strategies use clear profit functions based on revenue-cost differences, as followed by Gan et al. [3].

Definition 1 (Optimizing the Distribution of gas-electric pumps). *Let $S = \{s_1, s_2, \ldots, s_n\}$ represent the set of refueling stations, where each station s_i can have p_i^G gas pumps with an associated cost and revenue (C_i^G, $R_i^G(p_i^G)$), p_i^E electric pumps with associated cost and revenue (C_i^E, $R_i^E(p_i^E)$) and a maximum capacity Cap_i. Then the objective is to maximize the profit P:*

$$\max_{p_i^G, p_i^E} P = \sum_{i=1}^{n} \left(R_i^G(p_i^G) + R_i^E(p_i^E) - p_i^G \cdot C_i^G - p_i^E \cdot C_i^E \right)$$

where $p_i^G + p_i^E \leq Cap_i$ and $p_i^G, p_i^E \geq 0$.

Definition 2 (Optimizing the Location of gas-electric stations). *Let $S = \{s_1, s_2, \ldots, s_m\}$ represent the potential locations for new refueling stations. Each station can be either fully gas, fully electric, or 50% gas and 50% electric with a specific capacity Cap_i. Each station has a fuel cost associated and some revenue (C_i^G, $R_i^G(p_i^G)$) and an electric cost associated and some revenue (C_i^E, $R_i^E(p_i^E)$). Additionally, we have a maximum number of new stations N_{max} and some decision variables:*

- $x_i^G \in \{0, 1\}$*: 1 if a station has gas pumps at i, 0 otherwise*
- $x_i^E \in \{0, 1\}$*: 1 if a station has electric chargers at i, 0 otherwise*

Hence the objective is to maximize the profit P:

$$\max_{p_i^G, p_i^E, x_i^G, x_i^E} P = \sum_{i=1}^{n} \left(R_i^G(p_i^G) + R_i^E(p_i^E) - p_i^G \cdot C_i^G - p_i^E \cdot C_i^E \right)$$

where:

- $p_i^G = Cap_i \cdot (\frac{1+x_i^G - x_i^E}{2})$
- $p_i^E = Cap_i \cdot (\frac{1+x_i^E - x_i^G}{2})$
- $\sum_{i=1}^{m} max(x_i^G, x_i^E) \leq N_{max}$

Definition 3 (Optimizing the Location and Distribution of gas-electric pumps). *Let's consider a unified set of stations $S = \{s_1, s_2, \ldots, s_{n+m}\}$, where $s_1, \ldots, s_n$ are existing stations and $s_{n+1}, \ldots, s_{n+m}$ are potential new stations. Each station s_i can have gas pumps (p_i^G) with an associated cost and revenue (C_i^G, $R_i^G(p_i^G)$), electric pumps (p_i^E) with associated cost and revenue (C_i^E, $R_i^E(p_i^E)$) and a maximum capacity (Cap_i). Additionally, we have a maximum number of new stations N_{max} and some decision variables:*

- $p_i^G \geq 0$*: Number of gas pumps at station s_i*
- $p_i^E \geq 0$*: Number of electric pumps at station s_i*
- $x_i \in \{0, 1\}$*: 1 if station s_i is active ($1 \forall i \leq n$), 0 otherwise*

Then the objective is to maximize the profit P:

$$\max_{p_i^G, p_i^E, x_i} P = \sum_{i=1}^{n+m} \left(R_i^G(p_i^G) + R_i^E(p_i^E) - p_i^G \cdot C_i^G - p_i^E \cdot C_i^E \right) \cdot x_i$$

where $p_i^G + p_i^E \leq Cap_i$ *and* $\sum_{i=n+1}^{n+m} x_i \leq N_{max}$.

4.2 Representation of the solutions

Solution representations are a key factor in EAs. Codification must be unique and with few redundancies. Thus we generate a different codification for each optimization process.

Distribution optimization. We consider a set of stations $S = \{s_1, s_2, \ldots, s_n\}$ where each station s_i is represented by a vector $\mathbf{v}_i = [v_i^1, v_i^2, \ldots, v_i^{P-1}]$, representing the cumulative sum of pumps by type in ascending order, including an extra slot for empty pumps. This representation comes with some restrictions:

- $v_i^{j+1} \geq v_i^j$
- $c_i^1 = v_i^1$, where c_i^j is the of pumps of type j in station i
- $c_i^j = v_i^j - v_i^{j-1}$ for $j > 1$ and $j < P$
- $c_i^P = \text{Cap}_i - v_i^{P-1}$

We relax the sorting constraint to allow an unordered version $\mathbf{v}'$, expanding the search space and avoiding invalid solutions. For example, with 3 stations and capacity 8, the vector {[0,4],[2,3],[5,7]} represents the distribution of empty, fuel, and electric pumps. This corresponds to using 0, 2, and 5 pumps as empty pumps respectively, 4, 1, and 2 for fuel, and 4, 5, and 1 for electric pumps.

Location optimization. We define a set of possible stations $S = \{s_1, s_2, \ldots, s_n\}$ using vectors $\mathbf{l}_i = [\text{pos}_i^x, \text{pos}_i^y, p_i^f, p_i^e]$, where the position ($\text{pos}_i^x, \text{pos}_i^y$ coordinates) and type $p_i^f, p_i^e \in \{0, 1\}$ (fuel $(1, 0)$, electric $(0, 1)$, mixed $(1, 1)$ or not placed $(0, 0)$) are encoded. For example, with up to 4 stations, {[134.72, 19.81, 0, 0],[130.18, 50.25, 1, 0],[99.32, 79.01, 0, 1], [119.84, 63.99, 1, 1]} shows the first station is not placed while the rest are placed as fuel, electric, and mixed respectively.

Combined optimization. To meet both objectives, we combine distribution and location optimization. We define stations $S = \{s_1, s_2, \ldots, s_{n+m}\}$, where n are existing and the rest are potential new ones. Each station uses $\mathbf{l}_i = [\text{pos}_i^x, \text{pos}_i^y, p_i, v_i^1, v_i^2, \ldots, v_i^{P-1}]$ where $p_i \in \{0, 1\}$ indicates if it is placed and v_i^j defines its configuration applying the same transformation used in the distribution problem. For example, {[0,4],[2,3],[134.72, 19.81, 0, 0, 3],[99.32, 79.01, 1, 4, 6]} represents two existing stations and two potential ones, with only the second new station placed and configured with 4 empty slots, 2 fuel pumps, and 2 electric pumps.

4.3 A Heuristic for Fitness Computation

Evaluating solutions is challenging due to the high cost of running full 10-year simulations. To overcome this, we created a heuristic that estimates long-term profit by simulating only the first month to gather queue data. Then, we estimate how often and where agents would refuel with optimal vehicles, allowing us to approximate the average profit. This approach speeds up evaluation by a factor of 50. Additionally, we use a solution dictionary that maps ordered solution vectors to their costs, avoiding redundant calculations.

5 Experimental Setup

This section defines the baseline and evaluation metrics followed by three optimization strategies: individual station configuration, spatial distribution, and a combined approach.

Evaluation Benchmark: We apply EAs for optimization, and compare it using both informed and uninformed strategies. Informed methods leverage environmental data, while uninformed ones do not. Simulations run for ten years to assess long-term effects, with a baseline configuration for comparison. Key metrics include total profit, electric pump profit, and the percentage of electric cars. The baseline has no electric pumps, allowing us to evaluate the impact of their introduction.

Optimizing the Distribution of Gas-Electric Pumps: We optimize pump types (fuel or electric) at refueling stations using two approaches: one based on fixed percentages across all stations, and another where stations adjust their pump types based on the surrounding car type distribution.

Optimizing the Location of Gas-Electric Pumps: To place new refueling stations, we use k-means clustering [9], with centroids representing new station locations. The number of clusters reflects station size—larger clusters for high demand, smaller for specific points. The stations are configured either fully electric or as a mix of fuel and electric pumps.

Optimizing the Position and Distribution of Gas-Electric Pumps: We combine the previous objectives by using methods like k-means with proportional distribution, pseudo-LVQ (a version of the original LVQ [7]) for engine-type-based centroids, and a refined pseudo-LVQ with proportional distribution. These methods simultaneously address station placement and pump type distribution, ensuring the system aligns with demand.

6 Experiments and Results

This study compares EA optimization to benchmark strategies and a baseline over a 10-year simulation, focusing on company profit, relative electric market gain, and EV adoption. Set in Alcorcón, Spain, the simulation uses real-world data on demographics, infrastructure, and vehicle types. Initially, the energy company owns 7 of 31 stations, none with EV charging. Results appear in Figure 1.

EA achieves the highest profit in the distribution optimization task, where pump types are reassigned within existing stations, especially when its allocations align with the actual vehicle distribution in the simulation. Configurations increasing electric pumps tend to encourage greater EV adoption, though benchmarks with fixed percentages also show strong results in electric market gains.

Location optimization explores two station addition strategies: a few large or many small stations. Results indicate that mixed-supply stations are generally more profitable, serving traditional and electric vehicles. From the EA perspective, this rule is not followed. Big stations tend to be principally fuel-based not coupling with the electric demand. On the contrary, small stations promote higher EV adoption, as they address local demand more effectively.

When optimizing both location and distribution simultaneously, pseudo-LVQ methods outperform electric market share and profitability, particularly with small stations. EA continues to maximize profit but may underperform in EV-related metrics due to its objective being solely profit-driven. Even without explicitly targeting

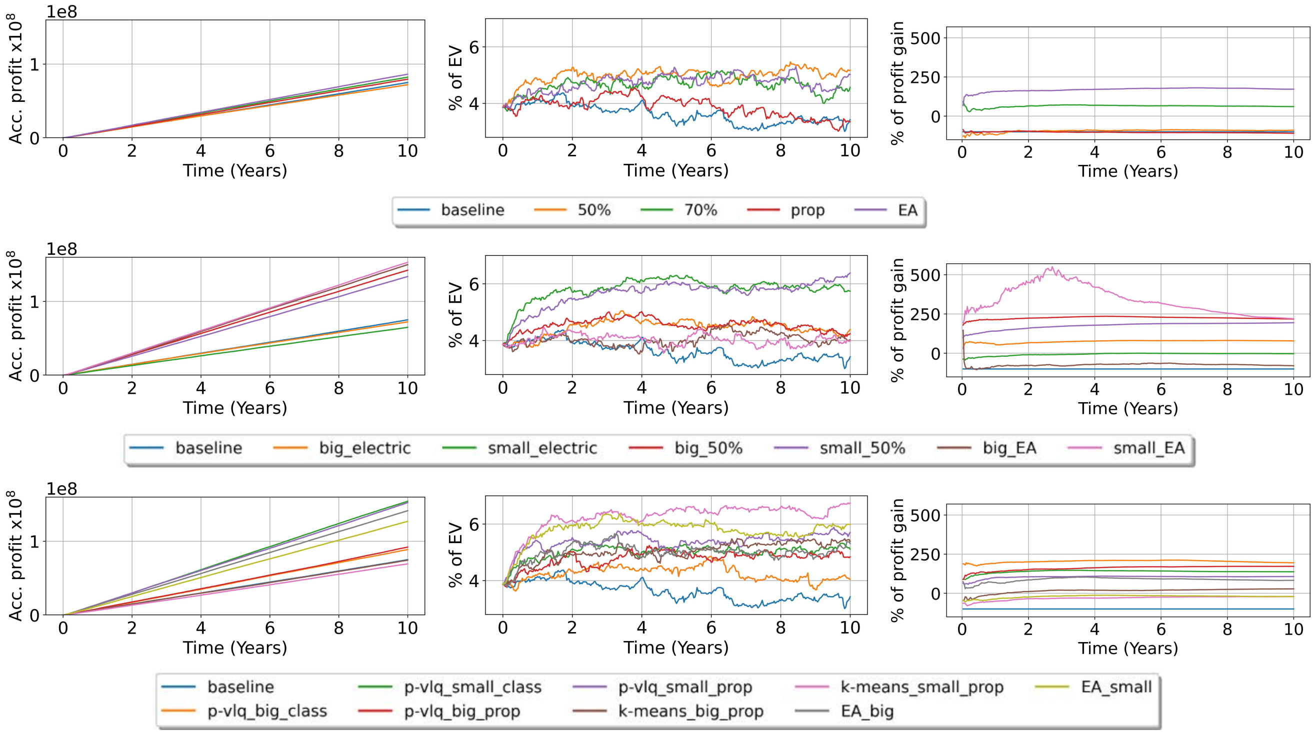

Figure 1: Comparison of total profit, EVs percentage in the fleet, and electric profit gain from left to right. Rows refer to distribution, location or combined problems from top to bottom. *Baseline* is the default configuration, *big* is for two 10 pump stations, *small* is for ten 2 pump stations, *prop* is for proportional to people nearby, percentages are for fixed values, and *class* is for pumps related to centroid's class. *k-means*, *p-lvq* and *EA* refer to each algorithm used.

EV expansion, EA solutions include electric pumps, highlighting the interdependence of demand and supply in a dynamic market.

7 Conclusions

This work shows that optimizing the location and configuration of refueling stations can significantly impact both company profit and EV adoption. Mixed-type stations placed in high-demand areas, especially when guided by pseudo-LVQ, offer the best balance between profitability and support for electrification. While EA focuses on maximizing profit, it still tends to include electric infrastructure, indirectly fostering EV growth. Overall, high-density networks of small stations are most effective in promoting EV uptake. Future work will expand the optimization objectives to include electric gains and relax constraints on station placement and capacity.

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