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A pricing-based location model for deploying a hydrogen fueling station network

Daniel Thiel

CEPN, UMR-CNRS 7234, Université Sorbonne Paris Nord
99 Avenue Jean Baptiste Clément, 93430 Villetaneuse, France
daniel.thiel@univ-paris13.fr

Abstract

We propose an innovative two-step *Pricing-Based Location* strategy for the rollout of new hydrogen fueling stations. A first model maximizes the profit of a new station with a price p^* which corresponds to a design capacity supplying a given market share (n^* customers). According to these findings and with the objective of deploying an extensive network, a second model searches for a suitable location as remote as possible from existing competitors, but as close as possible to just n^* demand locations. This problem is solved by an agent-based model integrating the *Particle Swarm Optimization* metaheuristic and a *Geographic Information System* representing the geospatial distribution of customer demand. We apply this model to the city of Paris by locating additional stations across the city one by one to supply a growing captive fleet of taxis and other transport operators in the future.

Keywords

Hydrogen car, filling station, location problem, price optimization, agent-based model, particle swarm optimization.

1. Introduction

The development of *Fuel Cell Electric Vehicles* (FCEVs), which contributes to green mobility, depends on there being a convenient hydrogen (H_2) refuelling infrastructure (Ball & Weeda, 2015). But the number of new hydrogen refuelling stations (HRSs) to set up also depends on the expected demand for this type of vehicle. Schwoon (2007) shows that there must be at least some initial HRSs to overcome this chicken-and-egg problem while keeping upfront infrastructure investments as low as possible (see also Köhler et al., 2010). Stephens-Romero et al. (2010) and Brown et al. (2012) show how systematic planning can optimize early investments in hydrogen infrastructure. Their case study optimizes the number, location, and rollout of HRSs and it determines the environmental impact for the city of Irvine in California. Dagdougui (2012) reviews the current state of the available approaches for planning and modelling H_2 infrastructure and notices that most papers develop cost minimization models while only a few of them focus on minimizing environmental impact. Lin et al. (2008) observe in their optimal station roll-out model that early HRSs are mostly spread out over a network that grows quickly. Other papers tackle the problem of new HRS locations more globally by modelling the entire supply chain to be deployed (Stiller et al., 2010).

Although these models are interesting at the theoretical level, the present barrier to the adoption of FCEVs is their relatively high purchase price which influences sales forecasts depending on consumer behavior and willingness-to-pay (Hardman et al., 2017). Some researchers integrate diffusion sub-models in their FCEV location models to estimate the change in demand for H_2 (Shafiei et al., 2013); Zhao & Ma, 2016). Nevertheless, facing the uncertainty about future demand for FCEVs and in order to improve the process of rolling out new HRSs, the strategy of most suppliers is to target first a captive fleet of vehicles with predictable driving and refueling patterns (Element Energy, 2018).

In the case of gasoline station location problems, the distances or durations of trips made by motorists to reach the stations are often considered as the main criteria but few studies take into consideration the fuel price. In operations management, authors usually consider that location and pricing decisions are made separately, as locations are long-term decisions while prices can change overtime (Hanjoul et al., 1990). Moreover, the importance of location as a key decision factor is surprisingly absent from the retail pricing literature (Heppenstall et al., 2013). Aboolian et al. (2008) demonstrate that a joint location and pricing scheme is helpful in maximizing profit. Given the high level of infrastructure investment (Kurtz et al., 2019) and the expected evolution of FCEVs, we assume that each decision-maker has to site a new HRS with a competitive price and to size its H_2 capacity according to expected demand. Our case study consists in proposing new HRS locations within the city of Paris to supply a growing captive fleet of taxis which will be gradually supplemented after 2023 by FCEVs from other transport operators.

Our research questions are:

- What price will maximize the total profit of a new HRS faced with existing competitors? What is the expected market share and what H₂ capacity is needed to meet the corresponding demand?
- Where should the new station be sited given the location of existing stations and the spatial distribution of customer demand?

We propose to solve this multi-objective optimization problem in two steps. First, to maximize profit and calculate the optimal H₂ price for a new station, we consider a static oligopoly (only one decision is taken) made up of a new station in competition with existing stations offering the same product (hydrogen). We assume that: (i) customers care only about price, (ii) demand is known (i.e. to supply a given number of FCEVs with H₂), (iii) capacity is flexible (H₂ gas cylinders can be ordered according to demand) and, (iv) the relationship between demand and price is linear (i.e. the station's attractiveness is inversely proportional to the H₂ price). Second, we propose to base a location model on the results of the previous pricing model. In our case of setting up an extensive HRS network and trying to reduce customer travel costs to the stations, we choose to site the new HRS as far as possible from existing competitors but as close as possible to a chosen number of customers. In his multi-objective model used for both dispersing services and having localizations close to demand areas, Daskin (1995, p. 313) proves that the more we try to minimize the distance to a facility, the lower the coverage of demand, and vice versa. In our case study, demand is defined by an optimal price and we consider that the customer takes into account the price difference between a new station and the average price of the existing stations in the different districts of Paris. To solve the location problem, we develop an *Agent-Based Model* (ABM) which integrates a *Particle Swarm Optimization* (PSO) metaheuristic. As proposed by Crooks et al. (2018), we also integrate a *Geographic Information System* (GIS) into the ABM.

What makes this research original is, to the best of our knowledge, the lack of papers:

- Combining a price optimization model and an operational model for solving fuel station location problems. While the two-step approach proposed by Chan et al. (2007) tackles the problem in a similar way, even so, the context where many stations are already established in this city is different as are the methods for solving the problem.
- Comparing fuel price differences and travelling costs to allocate a station to a customer.
- For taxis, addressing the problem of the risk of losing customers during the trip to a filling station.

Section 2 presents a review of the literature on location and price competition. The models are developed in Section 3. Section 4 describes the case study, the experimental conditions, and the simulation results. We conclude this paper in Section 5.

2. Literature review

Most location models focus on cost minimization, return, or revenue maximization (Revelle et al., 1970). For a situation where demand is known—which corresponds in our case study to the average H₂ consumption of a given FCEV fleet—the point and flow demand approaches are the ones most often used by many researchers (e.g. Agnolucci & McDowall, 2013). The point demand approach assumes that demand is located at specific places and the flow demand approach that consumers will search for a station during the trip to their destination.

The point demand location approach

The p -median or *minisum* problem (Hakimi, 1964) and the covering problem (Farahani et al., 2012) are the commonest models in discrete location theory. The p -median problem consists in locating p stations so as to minimize the distance from consumer nodes to their nearest refuelling stations. Our specific problem consists in searching for a location for a new station which has to be as far as possible from the competitors and which covers a given number of customers representing demand. This location problem is similar to a discrete p -dispersion problem (Erkut, 1990) which aims to maximize the minimum distance between pairs of facility sites in some space with the aim of having as “dispersed” a set as possible. Moreover, Garcia & Marin (2015) and Murray (2016) solve a maximal covering problem for a given number of stations in order to maximize the demand covered. Some publications deal with the specific case of electric taxi charging stations to be located in a city (Jung et al., 2014; Islam et al., 2015; Tu et al., 2016; Asamer et al., 2016). Electric vehicles (EVs) and FCEVs are both in full development but the EV stations location problem focuses on maximizing availability in relation to battery recharging time, which is not transposable to the HRS location problem.

The flow demand location approach

In the case of refuelling cars during long journeys, Kuby et al. (2009) advise that it is more important to locate the initial set of HRSs along the routes people travel rather than near their homes. They justify this approach by the fact that the customers generally refuel their vehicles when they make their trips to work, shopping, or other activities and do not make a specific trip just to refuel.

Metaheuristic methods

Large-scale location problems are classified as NP-hard (Mladenovic et al., 2007). Such classes of problems are not solvable in realistic time by using a polynomial time algorithm. Metaheuristic methods can efficiently find good solutions but cannot guarantee global optimality. We choose *particle swarm optimization* PSO (Kennedy & Eberhart, 1995) among different heuristic or metaheuristic methods. PSO is a stochastic optimization technique inspired by the social behaviour of

bird flocks or fish schools. It is based on the collaboration of individuals with each other and has some similarities to ant colony algorithms relying on the concept of self-organization. Predicated on simple displacement rules (in planar space), the particles (each candidate location solution) can gradually converge towards a local minimum (nearest distance from the customers). Sun et al. (2017) apply PSO to locate five HRSs in Shanghai with a multi-source H_2 supply.

Agent-based modelling and location optimization

ABM is a class of computational models consisting in autonomous agents and an environment in which the agents act (Gilbert & Doran, 1993). Agents are situated in space and time and are placed in lattice-like neighbourhoods. In our case, the HRSs (the suppliers) can be considered as agents as can the cars (the customers), who are independent rule-based agents who can decide to choose an HRS according to their own criteria. Davidsson et al. (2007) and Ahmad et al. (2007) suggest integrating conventional optimization techniques into ABM as other researchers like Huang & Levinson (2011) or Bruno et al. (2010) have done to solve the p -median problem and the p -maximal covering-like problem in an ABM framework. The advantage of ABM is also that geographic data may be used for setting up the initial location of the agents and as a background layer (Crooks et al., 2018). In a recent literature review relating to the techniques for optimal placement of electric vehicle charging stations (Islam et al., 2015), Han et al. (2015) develop an ABM combined with a GIS using *NetLogo* software (Wilensky, 1999). Their model, applied to the municipality of Eindhoven, solves the location problem as a multi-objective partial covering problem where charging station availability and profitability are the objectives to maximize.

Location and pricing optimization

As part of the earliest research in location science, Hotelling (1929) shows the relationship between location and the pricing behaviour of firms. (Ottino-Loffler et al., 2017) propose an ABM to a case of more than two firms choosing both price and location to maximize profit. In the specific case of gas filling station location problems, only a few papers take into account the fuel price. According to Dan et al. (2018), many authors have addressed joint location and pricing problems in a hierarchical manner by specifying locations first, and then defining price competition. For instance, Chan et al. (2007) propose a two-step approach for solving a location-based gas station pricing problem in Singapore. First, they develop a retailer's location model based on an econometric model of potential demand and the consumer's decision rule for choosing a station. They solve the p -median problem by using the *Lagrangian* method. Second, they build a pricing model based on Bertrand's competition model (1883) and on the previous optimal locations. As our context is different, we propose a reverse two-step approach which consists (i) in maximizing the profit of a new HRS based on a constant absolute price difference between existing stations and (ii), on searching for a profitable location depending on the price difference and on the distances from the customers under the condition of

being placed as far as possible from the competing locations and as close as possible to an optimal number of potential customers.

3. Presentation of the models

In this section, we present a two-step *Pricing-Based Location* approach. In the first step, we assume that demand depends not on the location but only on the price considering constant price dispersion among the stations. An optimal price p^* corresponds to a given market share and an expected number n^* of customers to satisfy. In the second step, the location model assigns these n^* customers to a new station according to its price attractiveness which satisfies the previous assumption and also according to a distance/price ratio (see assignment condition in §3.3).

3.1. A two-step modelling approach

To illustrate our method, we present the case of two competing stations, an existing one and a new one, both serving a certain number of FCEVs. Given that we consider that the H_2 demands are positioned at fixed places, each station will draw customers according to its H_2 price and location. Fig. 1 illustrates the approach in two steps.

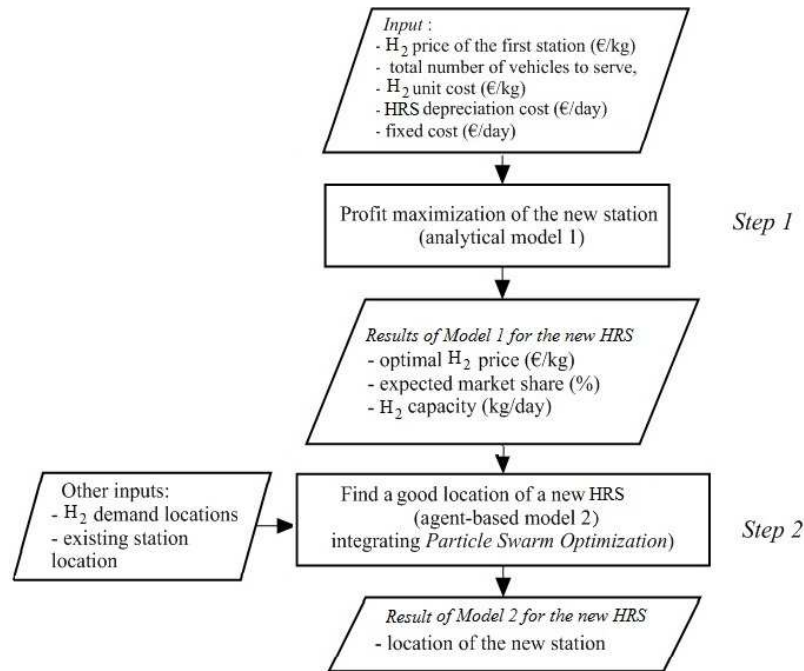


Fig. 1. A two-step modelling approach

Step 1: Regardless of the location of each car and depending on market size, the variable costs, the depreciation costs, the fixed costs, and the H_2 selling price of the existing station, Model 1 finds the optimal price which maximizes the profit of a new HRS. From this model we deduce a market share and an H_2 capacity that satisfies the corresponding demand.

Step 2: Given that the customers will always choose the station based on distance and price, the objective of Model 2 is to attract an optimal number of vehicles to serve, while siting the new station as far as possible from the existing station (cf. objective of an extensive construction of an H₂ infrastructure for FCEVs).

3.2. Pricing model (model 1)

We assume that all car drivers have the same attitude toward price: the lower the price, the greater the quantity sold by each station. In Paris, we observe that the price differentials between gasoline and diesel stations in different districts remain stable which can be explained by the difference between the operating costs (Gautier & Le Saout, 2017). In fact, in a large city such as Paris, fuel prices are very high and some people choose to refuel their cars in the suburbs or during an external trip. People who live in Paris and do not look for a better price, will refuel at the nearest station to their home. In the case of taxis, price comparison is advisable although it is out of the question to waste time searching for a station far from the city with better prices because there is a high risk of customer's loss and a kilometric excess that will not be offset by the expected savings on the price difference. Nevertheless, the driver will look for a station within the city close enough of his place but cheaper. However, it turns out that the price dispersion between traditional gasoline stations is stable simply because the consumer who has chosen to buy his gasoline in Paris, which is much more expensive than outside, is looking first and foremost for near his parking place. This is not the case for taxi drivers moving around the city who may choose to compare prices when they are trying to refuel their vehicles. There is currently no horizontal competition on the traditional gasoline market in Paris. For all these reasons, we do not treat the case of dynamic H₂ pricing. Hereafter, we take the case of a static duopoly with two HRSs in which each customer chooses the HRS offering the lower price. To set up a new station, an optimal price is calculated according to the price of the competitor. At this stage, distance is ignored, demand is known, and capacity is not considered a constraint in the model. We assume that the new station's market share depends linearly on price alone. To define this function, we consider two points corresponding to a market share of 0.5 if the price of the new station is equal to the competitor's price and of 0 if the price is equal to or greater than a maximum price calculated according to the price elasticity of demand. According to this demand function, the model has to find the optimal H₂ price for the new station which maximizes its profit and corresponds to a market share and to a daily H₂ capacity that has to be set to meet expected demand.

Model formulation

Notation:

j	index of a station, $j=1$ for an existing station and $j=2$ for the new station
n	the total number of cars
m	the total number of stations (in our following example, $m = 2$)
c	the H ₂ unit cost in €/kg ($c > 0$), we assume that each HRS uses the same infrastructure

p_1	the initial selling price per kg of H ₂ at the station HRS 1 ($p_1 \geq c$)
p_2	the selling price per kg of H ₂ at the new HRS 2 j ($p_2 \geq c$)
ε	the short-run demand elasticity ($\varepsilon < 0$)
$D(p_j)$	the market share corresponding to a price p_j ($0 \leq D(p_j) \leq 1$)
p_{max_1}	the price at station 1 corresponding to $D(p_1) = 0$
p_{max_2}	the price at station 2 corresponding to $D(p_2) = 0$

Given the linear demand function, the market share $D(p_2)$ of the new station is:

$$D(p_2) = (p_{max_1} - p_2) / 2(p_{max_1} - p_1)$$

with $0 < D(p_2) \leq 1 \rightarrow (2p_1 - p_{max_1}) \leq p_2 < p_{max_1}$ and $p_1 < p_{max_1}$

The demand elasticity is: $\varepsilon = -1/2(p_{max_1} - p_1)$ and $p_{max_1} = (p_1 - \varepsilon^{-1}/2)$

$$\rightarrow D(p_2) = \varepsilon (p_2 - p_1 + \varepsilon^{-1}/2) \quad (1)$$

Under the conditions that $D(p_2) \geq 0 \rightarrow p_2 \geq p_1 - \varepsilon^{-1}/2$ and $D(p_2) \leq 1 \rightarrow p_2 \leq p_{max_1}$

Given that $D(p_1) = 1 - D(p_2)$, then:

$$D(p_1) = \varepsilon (p_1 - p_2 + \varepsilon^{-1}/2) \text{ and } D(p_1) > 0 \quad (2)$$

The daily average consumption of the n cars is: $K = \gamma n$ with γ the average H₂ fueling volume in kg per day for each car.

The daily H₂ consumption in kg of the new station is:

$$q_2 = K D(p_2) = K \varepsilon (p_2 - p_1 + \varepsilon^{-1}/2) \quad \text{with } q_2 \leq \gamma n \quad (3)$$

The daily income of each station $SALES_2$ is:

$$SALES_2 = p_2 q_2$$

As the H₂ capacity z_2 has to be greater than or equal to the total quantity sold by each station, we assume that each station has a flexible capacity equal to the volume sold: $z_2 = q_2 \leq 200$ (we assume that a “city” HRS that uses H₂ delivered as a gas, has a maximum capacity of 200 kg/day).

The daily direct cost of the new station is: $DCOST_2 = cz_2 = cq_2$

The fixed cost is defined by the depreciation cost of the investment DEP_2 and the real estate cost FIX .

As the amount INV of the initial investment is the same for all new HRSs, the depreciation cost depends on the amortization period of the equipment (approximately 20 years) based on a maximum capacity of 200 kg/day which has to be weighted by the annual consumption $365q_2$.

Accordingly: $DEP_2 = 2INV/73q_2$

The total profit of the new station is:

$$\begin{aligned} M_2 &= (SALES_2 - DCOST_2 - DEP_2 - FIX) \\ &= [q_2 (p_2 - c) - 2INV/73q_2 - FIX] \\ &= [K \varepsilon (p_2 - p_1 + \varepsilon^{-1}/2) (p_2 - c) - 2INV/(73K\varepsilon (p_2 - p_1 + \varepsilon^{-1}/2)) - FIX] \end{aligned} \quad (4)$$

The objective function of the new station aims to maximize its daily profit M_2 according to a given price p_2 and a corresponding H₂ capacity z_2 .

$$\rightarrow \text{Argmax}_{p_2} M_2 = (\text{SALES}_2 - \text{DCOST}_2 - \text{DEP}_2 - \text{FIX})$$

The optimal price p_2^* is calculated by solving the following third-order equation:

$$\partial M_2 / \partial p_2 = 0 \rightarrow \partial (2 p_2^3 + p_2^2 (-5p_1 - c + 5\varepsilon^{-1}/2) + p_2 (\varepsilon^2 + 2c p_1 + 4p_1^2 - 4p_1 \varepsilon^{-1} - c \varepsilon^{-1}) - c p_1^2 + c p_1 \varepsilon^{-1} - c \varepsilon^2/4 - p_1^3 + p_1^2 \varepsilon^{-1} - 3p_1 \varepsilon^2/4 + \varepsilon^{-1} p_1^2/2 + \varepsilon^3/8) + 2INV/73K^2 \varepsilon^2) / \partial p_2 = 0 \quad (5)$$

From equation (1), we deduce the market share $D^*(p_2)$ and from equation (3), the quantity q_2^* , which is also the minimal H₂ capacity z_2^* to set up:

$$z_2^* = q_2^* = K \varepsilon (p_2^* - p_1 + \varepsilon^{-1}/2) \quad (6)$$

Given n the total number of cars and according to equation (1), the expected number of customers to supply with H₂ from the new station is:

$$n_2^* = n D^*(p_2) = n \varepsilon (p_2^* - p_1 + \varepsilon^{-1}/2) \quad (7)$$

Case of a new station faced with (m-1) existing competitors

If there is more than one existing station (i.e. an oligopoly context), our pricing model addresses the problem as a price competition between a new station and the average price of the existing competitors. The optimal price of a new station m is calculated by solving equation (5) after replacing in equation (4) p_1 by $\bar{p} = \sum_{i=1}^{i=(m-1)} p_i / (m-1)$ (\bar{p} is the average price of the existing stations).

The objective function is: $\text{Argmax}_{p_m} M_m = (\text{SALES}_m - \text{DCOST}_m - \text{DEP}_m - \text{FIX})$

The corresponding market share is:

$$D(p_m^*) = 2\varepsilon (p_m^* - \bar{p} + \varepsilon^{-1}/2)/m \quad (8)$$

The number of cars to attract to this new station is:

$$n_m^* = n D^*(p_m^*) \quad (9)$$

3.3. Pricing-based location model (model 2)

Based on the optimal price p_2^* provided by Model 1, the agent-based model (Model 2) searches for a good location by: (i) searching to be close to the customers to serve (i.e close to the fixed demand points corresponding to n_2^* car locations) and (ii) locating the new station as far as possible from the first ones (i.e. trying to design the most extensive HRS network). We present below the example of two stations, a station 1 which already exists and a new station 2 which is to be sited.

Given:

v the average speed of a car in the city

ϕ the average H₂ consumption of an FCEV in kg per 100 km

d_{ij} the distance from a car H₂ demand location i to a station j with $1 \leq d_{i1} \leq d_{max}$; $1 \leq d_{i2} \leq d_{max}$ and the hypotenuse of the rectangle corresponding to the grid space $d_{max} > 2$

t_{ij} the time needed to travel from a car location i to a station j : $t_{ij} = d_{ij} / v$

g the average number of customers per taxi per hour

r_{id} the distance ratio = d_{i2}/d_{i1}

r_p the price ratio = p_1/p_2 with $p_2 \neq 0$ and $p_2 \leq 2 p_1$

In the case of a price $p_2 < p_1$, a car driver located at a place i needing to fill her tank, chooses the new station 2 if the following conditions are satisfied:

- The cost of travel of the car to the new station has to be lower than the cost of reaching the first station. This condition corresponds to: $\phi d_{i2} p_2/100 < \phi d_{i1} p_1/100$ which is equivalent to the condition: $r_d < r_p$
- In the specific case of taxis, the loss of revenue due to the risk of losing customers during the trip to reach the new station has to be lower than the loss involved in reaching the first station.

The condition corresponds to: $g t_{i2} p_2 < g t_{i1} p_1$ which is also equivalent to: $r_d < r_p$

In conclusion, the algorithm will assign a station j to the H_2 demand of a car located in i , if $r_d < r_p$ is confirmed (i.e. distance ratio < price ratio) (10)

Local search heuristic

Fig. 2 illustrates the principle of searching for a new location.

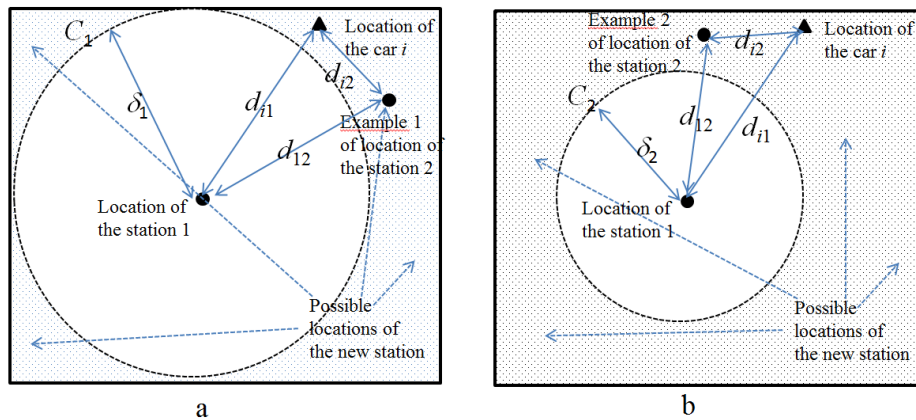


Fig. 2. Local search heuristic based on concentric circles

1. Initialization:

- The city of Paris is represented by a rectangular grid (space R) where each cell represents the possible placement of an agent.
- n passive agents (car H_2 demand locations) are positioned in R in the likely locations.
- One passive agent (station 1) is placed according to its current location.
- π active agents (PSO particles) are generated and randomly placed in R .
- N_{it} is the maximum number of iterations.

2. We define concentric circles $C \subset R$ which delimit the locations of the new station 2. The location of the existing station 1 is included in a first circle C_1 which has the largest possible radius δ_1 within the city represented by R . Fig. 2a shows the possible locations of the new station outside this first circle

C_1 . To guarantee this constraint, the algorithm checks whether the distance between the two stations d_{12} is always greater than δ_1 , the radius of the circle C_1 .

3. Within this restricted area (the complement of C in R), the PSO algorithm (see appendix A) initiates the movement of the particles step by step according to three components: their current speed V , their best solution, and the best solution obtained in their neighbourhood. Each particle representing a possible location of the new station 2, will attract a car i only if the distance ratio d_{i2}/d_{i1} is greater than the price ratio p_1/p_2^* cf. previous condition (10).

4. As long as the number of cars is lower than n^* (the optimal number of cars calculated in model 1), the PSO algorithm searches for a location outside the circles C_k . The model stops after a given number of iterations N_i or if the number of cars choosing the new station 2 is equal to n^* . The best location for the new station is considered to be at the centre of gravity of the particle locations. If there are not enough customers for the new station $n < n^*$, the algorithm returns to step (3) after reducing the radius δ_k by one cell length $\delta_{k+1} \rightarrow (\delta_k - 1)$ (Fig. 2b shows the example of a smaller circle C_2). If the new radius is less than the length of two cells, the algorithm will keep searching to attract n^* customers without reducing this radius. If the algorithm does not manage to attract n^* customers after N_{it} iterations, it will stop and the result will not be optimal in terms of profit.

Remark: In the case of more than two stations, the model compares the distances and prices of each station using the same local search heuristic.

4. Case study

In this Section, we first describe the context. Second, we expose the assumptions that define the H_2 demand locations of the taxis within the city of Paris. Third, we present the input data used in the modelling applications and fourth, the experimental conditions. Fifth, we show and discuss the results of the pricing model and new HRS location proposals.

4.1. Context

Given that a captive fleet approach for the rollout strategy for H_2 mobility facilitates the introduction of FCEVs, we assume two possible HRS development phases in the city of Paris. The first phase should consist in locating two new stations to supply a given captive fleet of taxis growing from 100 to 600 taxis between 2020 and 2022. In 2023, we suppose a second phase which corresponds to a progressive expansion to other transport operators (taxis, chauffeur driven cars,...) in Paris¹ with the introduction of new FCEV and the beginning of price competition among stations.

¹ <https://www.paris.fr/pages/ces-taxis-qui-roulent-a-l-hydrogene-7115> accessed 08/05/2020.

4.1.1. Phase 1 during the period 2020–2022

Fig. 3 shows six HRS locations already installed by the companies Air Liquide, ENGIE, and McPhy to serve captive fleets throughout the Paris Region but only one in the center of Paris (AFHYPAC, 2019).

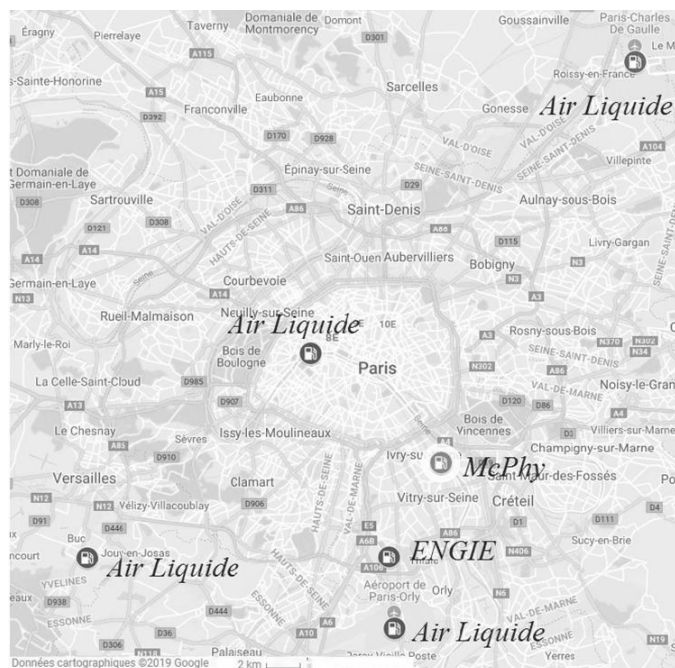


Fig. 3. Map of the existing HRSs in the Paris Region (AFHYPAC, 2019; Google Map, 2020)

Our study focuses on the possible development of new HRSs within the city of Paris. Currently, the only station is near the *Alma Bridge* and was launched thanks to the support of FCH JU (2018)² and a partnership between *Air Liquide* and the *Societe du Taxi Electrique Parisien*. This single station supplies the *Hype* taxi fleet³ composed of *Toyota Mirai* and *Hyundai Nexo* cars. H_2 gas is delivered by *Air Liquide* to this station in cylinders at a pressure of 200 bars and a maximum storage of 200 kg/day⁴. Since there are currently 100 *Hype* taxis in service in 2019, we estimate an average need of 160 kg H_2 per day.⁵ This fleet will increase from 100 to 600 taxis at the end on 2020 (Toyota Europe Newsroom, 2019). Given that 51.6% of taxi trips took place within the city of Paris in 2018 (OMNIL 2018), we consider that more than half of the fleet will fill its tanks in the city and the other half in the HRSs located in the suburbs. In the future, for the equivalent of 300 taxis (out of an expected fleet of

² *Fuel Cells and Hydrogen Joint Undertaking* is a public-private partnership that supports research, technological development, and demonstration activities in the field of energy technologies, fuel cells, and hydrogen in Europe. The *Hype* network was launched on December 7, 2015 during the COP 21 by the *Societe du Taxi Electrique Parisien*. This fleet of taxis is a member of the ZEFER network 2017–2022 *Zero Emission Fleet vehicles For European Roll-out*. (FCH HU 2018).

³ The *Hype* network was launched on December 7, 2015 during the COP 21 by the *Societe du Taxi Electrique Parisien* (Air Liquide, 2018). This fleet of taxis is a member of the ZEFER network 2017–2022 *Zero Emission Fleet vehicles For European Roll-out* (FCH JU, 2018).

⁴ This typical station is composed of an H_2 compressor and a cooler. Hydrogen is produced upstream in a *Steam Methane Reforming* unit and delivered to the fueling stations by trucks in H_2 gas cylinders of 80 litres at 200 bars (California Fuel Cell Partnership, 2019).

⁵ We assume the average taxi in Paris covers 200 km daily. Given that the average consumption of *Mirai* and *Nexo* cars is 0.80 kg H_2 per 100 km, then for 100 taxis, the daily consumption is 160 kg.

600 taxis)⁶ refilling in the city of Paris, we suggest installing two additional HRSs within the city to supply a total average of 480 kg H₂ per day. During this first phase, our study consists in proposing to locate these two new HRSs without price competition by taking into account fixed demand points corresponding to the taxi locations when the drivers decide to fill up. This location problem can be solved by using the model presented in §3.3 with the following simplifications: (i) we just take into account the distances without price considerations and (ii) we assume an equitable market share between the HRSs.

4.1.2. Phase 2 in 2023

Following the first rollout period based on a captive fleet of FCEVs, we assume a second phase starting in 2023 where the HRSs will compete on price and 100 new FCEVs (taxis and chauffeur driven cars) will complete the total fleet of 600 taxis. We apply our pricing-based model to locate a fourth HRS in Paris based on the H₂ price differences between competitors and their proximity to the fixed demand points (i.e. the taxi demand locations).

4.2. Assumptions about taxi H₂ demand locations

We consider that the taxi H₂ refuelling demand is located at a fixed place and does not occur during a trip. We assume that a taxi driver decides to fill her tank when the gauge is almost at the level of ¼. We consider that these demand location points correspond to the customer's drop-off locations on the condition that the taxis do not have another customer to pick up (according to the *Institute of Planning and Development*, a taxi is available 42% of its working time on average (Predali 2008)). We also assume that during all trips from Paris to the suburbs and from the suburbs to Paris, taxi drivers refuel their car outside Paris which corresponds to 48.4% of the trips taking place outside the city of Paris according to OMNIL (2018). The H₂ demand locations in Paris are thus places of taxi customer final destinations where the probability of picking up a new customer is low. We choose to distribute these demand points according to the existing major and district taxi bays in Paris. These stations were established in the city of Paris according to the customer potential for taxis. We also consider that the customers' destinations are located within a radius of around 200 m around these bays. The 120 main stations (27 major bays and 93 district bays) cover 80% of the taxi activity in taxi ranks (Predali 2008).

As shown in Fig. 4, we split the city of Paris into k zones z_k in which we allocate n_{z_k} taxis to each zone k . The zones $z_{k \neq 21}$ include major and district bays and z_{21} corresponds to the complement of these zones in the whole city, which includes the remaining bays.

Considering that, on average, a major bay hosts three times more taxis than a district bay, we calculate the values of n_z for the total fleet N of *Hype* taxis to supply in Paris. On this basis, we determine the

⁶ More precisely and for simplification reasons, we choose 300 taxis corresponding to a fleet of 582 taxis on the basis of 51.6% of trips taking place within the city of Paris.

relative frequencies of taxis present in these 21 zones and locate $f_z N$ taxis randomly in each zone. Then, referring to Han et al. (2015) who randomly distribute electric taxis in the city of Eindhoven, we use GIS software to extract the map of Paris and to locate the taxis.

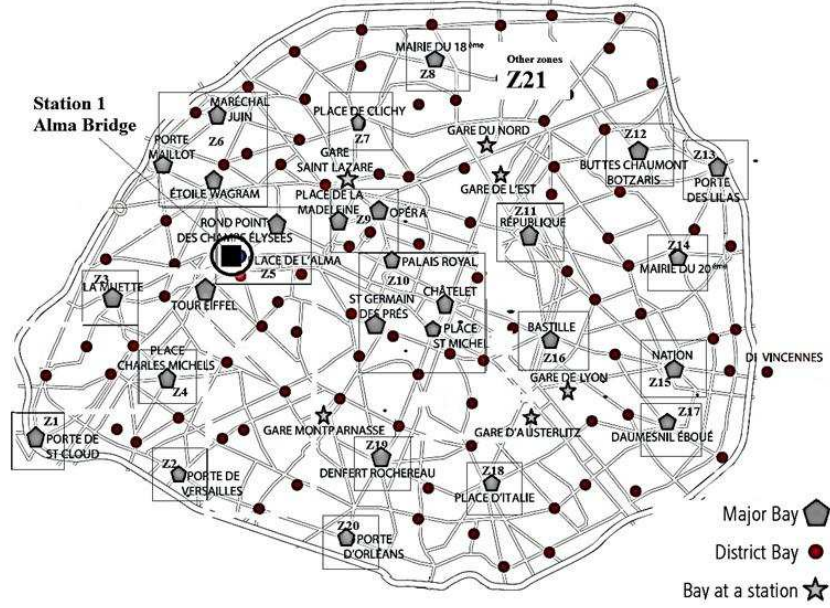


Fig 4. Location of taxi stands and H₂ demand zones (map reference: OMNIL 2015)

Remark: In the second development phase from 2023, we complete Fig. 4 by distributing the 100 new FCEVs in the same areas as the first 600 *Hype* taxis.

4.4. Data

- The unit cost of H₂ including production, distribution, and operating costs is: $c = €5.10$ per kg excluding the rental costs for the space occupied in the city (see appendix B).
- The real estate cost *FIX* of each station is €65.75 per day⁷.
- The investment of a station j is assumed to be €350,000 for a maximum capacity of 200 kg/day (see appendix B) and the daily depreciation cost is: $9589q_j$ depending on the H₂ quantity sold daily by each station j .
- The price elasticity of demand is chosen at $\varepsilon = -0.1$ (Zelege 2016).
- Each car driver fills up her tank with an average daily quantity of $\gamma = 1.6$ kg/car⁸.
- Referring to the H₂ selling prices in different countries (see Appendix C), we choose average prices \bar{p} in 2023 of €9.50 and €8.50 per kg. Each station in Paris is located in what is termed an “influence zone” calculated according to the *BD Topo* provided by the *Institut Geographique National* (APUR, 2013). We observe an average price dispersion of SP E5 gas over a long period of time which seems to be constant between the stations of the different

⁷ The cost of renting and maintaining an industrial building in Paris is €10/m²/month on average. For a floor area of 200 m² = €24 k/year or €65.75/day.

⁸ We consider that the average H₂ refilling volume is 4.36 kg when the H₂ gauge is on 1/4 (mean value of three-quarters of a full tank of *Mirai* and *Nexo* cars). Given that the average consumption of these cars is 0.80 kg H₂ per 100 km and the average distance a taxi in Paris covers is 200 km per day, the average time between refuelling stops is 2.725 days.

districts. We assume that the H₂ absolute price differences will be similar to the present gasoline price differences, which can be explained by the real-estate cost and the social environment of each district. Referring to recent gasoline prices collected on May 3, 2019 (French Ministry of Economy and Finance, 2019), we deduce the possible H₂ prices based the average \bar{p} (see Table 2).

Table 2

Gasoline prices in Paris and H₂ price assumptions

	Gas price (SP E5)	H ₂ price assumptions $\bar{p} = €9.50/\text{kg}$	H ₂ price assumptions $\bar{p} = €8.50/\text{kg}$
<i>Paris district 1</i>	€1.98 per l	€9.85 per kg	€8.81 per kg
<i>Paris district 7</i>	€1.94 per l	€9.65 per kg	€8.63 per kg
<i>Paris district 8</i>	€1.78 per l	€8.85 per kg	€7.92 per kg
<i>Paris district 10</i>	€1.76 per l	€8.75 per kg	€7.83 per kg
<i>Paris district 11</i>	€1.95 per l	€9.70 per kg	€8.68 per kg
<i>Paris district 13</i>	€1.71 per l	€8.52 per kg	€7.62 per kg
<i>Paris district 14</i>	€1.97 per l	€9.80 per kg	€8.77 per kg
<i>Paris district 15</i>	€1.76 per l	€8.74 per kg	€7.82 per kg
<i>Paris district 16</i>	€1.76 per l	€8.74 per kg	€7.82 per kg
<i>Paris district 18</i>	€1.73 per l	€8.58 per kg	€7.68 per kg

4.5. Experimental conditions

Agent-based model design and GIS data

We consider the city of Paris as a rectangle of length 11 km and height 9 km. We use *NetLogo* 6.0.4 software and build a grid space of 55 x 45, corresponding to 2475 cells and possible locations of the different agents. Like Han et al. (2015), we use the *Netlogo* GIS extension to load vector GIS data (*Geographic Information System*) and raster GIS data (grids) corresponding to the geographic space of the city of Paris and the taxi bay locations. These geospatial data are created by using QGIS software⁹ and transferred from the GIS data space to the *NetLogo* space (Crooks et al., 2018).

Remark: To finalize the model given the particularities that can be encountered in a city, different spatial constraints can be introduced into the ABM such as impossible or forbidden locations such as risk areas, rivers, streets...

Distance metrics

Following the recommendations of Peeters & Thomas (1997) and Brimberg & Love (1992), we define a metric for estimating the distances between all the agents. According to Heran (2009), a *Euclidian* distance of 7 km within Paris corresponds to an actual distance travelled at the shortest of 8.5 km. We can deduce an order $p = 1.31$ of the lp Minkowski distance $D(lp) = (|dx|^p + |dy|^p)^{1/p}$ where dx represents the distance between two points along the first axis, and dy along the second axis (Midler 1982)¹⁰.

⁹ <https://qgis.org/en/site/about/index.html>

¹⁰ Midler (1982) illustrates different possible values of the order p : $p < 1$ for a straight-line distance justified in certain empirical cases, such as a vehicle avoiding traffic, $p = 1$ for a *Taxicab* or *Manhattan* distance empirically validated in New York City, where the displacements are made in two perpendicular directions, $p = 2$ for Euclidean distance, which

PSO model calibration

The probability of obtaining a poor quality solution is low but like other metaheuristic, it has first to be calibrated to avoid a premature convergence toward sub-optimal solutions. Given that a PSO algorithm is also sensitive to its parametric evolution, we performed the following parameter sensitivity analysis.

- We choose a number of particles $\pi = 200$.
- V_{max} is the maximum velocity and ω the inertia weight of the metaheuristic. Shi & Eberhart (1998) and Eberhart & Shi (2001) observe that when V_{max} has a low value (≤ 2), an inertia weight ω of almost 1 is a good choice, while when V_{max} is not low (≥ 3), an inertia weight $\omega = 0.8$ is advised. In our simulation, we choose $V_{max} = 4$ and $\omega = 0.8$.

We run the simulations several times by changing the random distribution of the demand locations in the 21 zones in order to observe any differences in the location found by Model 2. Since the final best locations are presented by 100 particles, we choose the best location of each new station in the centre of a circle of radius equivalent to 3 cells in the grid. According to the initial conditions and particularly to the p order of the lp Minkowski metrics, simulation results can propose different best locations which all corresponds to a maximal profit and to n^* customers.

4.6. Results of the pricing model 1

The following results correspond to the second development phase of FCEVs with 400 FCEV taxis refuelling within the city of Paris. Given the uncertainty of the average price of the HRSs in 2023, we apply our pricing Model 1 for different initial values of \bar{p} (see Table 3). The optimal price of the new station p_{new}^* is calculated by solving the third-order equation (5) and by replacing p_1 by \bar{p} . We deduce the daily profit of the new station M_{new}^* , the corresponding H_2 capacity $z_{new}^* = q_{new}$, the market share $D(p_{new})$ and the optimal number of customers n_{new}^* to attract to the new station.

Table 3

Optimal results of Model 1 for different initial values of \bar{p} in 2023

Average price of the existing stations \bar{p}	€15/kg	€14/kg	€13/kg	€12/kg	€11/kg	€10/kg	€9/kg	€8 /kg	€7/kg	€6/kg
New station										
Optimal price p_{new}^* (€ per kg)	€12.53	€12.00	€11.47	€11.02	€10.51	€10.00	€9.49	€9.00	€8.45	€7.94
M_{new}^* (€ per day)	€1 670	€1 437	€1 219	€1 017	€830	€658	€501	€359	€230	€114
z_{new}^* (kg/day)	239	224	209	191	176	160	144	128	114	98
D_{new}^* (% market share)	37%	35%	33%	30%	27%	25%	23%	20%	18%	15%
n_{new}^* (number cars)	149	140	131	120	110	100	90	80	71	61
Average values of the existing stations										
M (average € per day)	€1 186	€1 099	€1 003	€902	€785	€658	€521	€373	€213	€44
z (average kg/day)	134	139	144	150	155	160	165	171	175	181
D (average % market share)	21%	22%	22%	23%	24%	25%	26%	27%	27%	28%
n (average number cars)	251	260	269	280	290	300	310	320	329	339
price ratio = p_1/p_2	1.197	1.167	1.133	1.089	1.047	1.000	0.948	0.889	0.828	0.756

corresponds to the distance as the crow flies often used as an estimator of real distances over a very dense network, for $p > 2$, the lp distance is shorter than the Euclidean distance. It is empirically justifiable for some individual, subjective evaluations.

For initial average prices \bar{p} between €6 and €15 per kg, the corresponding capacity to set up at the new station should be between 98 kg/day and 239 kg/day. Given that an H₂ station has a maximum capacity of 200 kg/day, in case of $z > 200$, the station will only be able to supply 200 kg/day and the profit will be lower. This is the case if $\bar{p} > €12$ per kg in 2023. Fig. 5 shows the daily profit M_{new}^* of the new station and the average profit \bar{M} of the existing stations for an optimal price range of p_{new}^* between €7.94 and €12.53 per kg depending on the average price \bar{p} . It can be seen that the new station will have a better profit than the average profit of its competitors if its optimal price is less than about €8 per kg or greater than about €10 per kg. The average profit of the existing stations will be higher than the expected profit of new station if their average initial price \bar{p} is between €7 and €10 per kg.

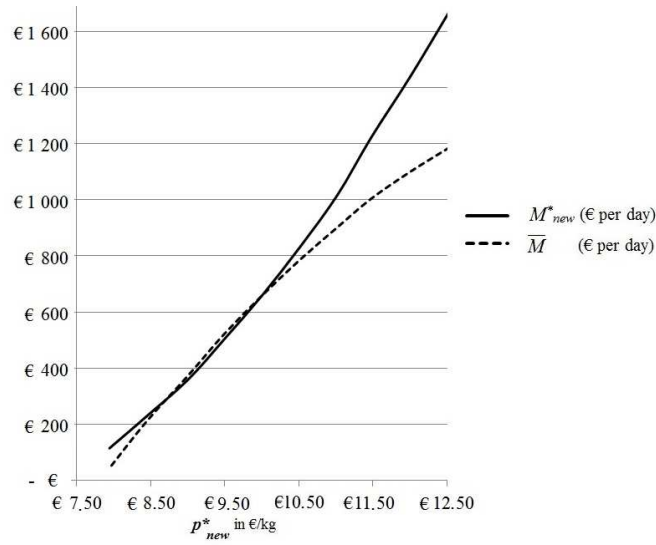


Fig. 5. Daily profit evolution M_{new}^* and \bar{M} vs optimal price $p_{new}^* = f(\bar{p})$

4.7. Results of Model 2

4.7.1. Phase 1. Location of two new stations without price competition

For the first FCEV development phase between 2020 and 2022, we apply Model 2 for a fleet of 200 taxis which implies starting up a second station within the city. Then, we increase the fleet to 300 taxis with a third station to locate. We also assume an equitable market share among the stations. Figs 6a and 6b show possible locations for the second and the third HRSs to be set up in Paris. We find different possible locations but after changing the random distribution of the demand locations in the different zones several times, 64% of the simulations propose the same locations as presented in Fig. 6. These locations correspond to the centre of a circle with a radius of 600 m (3 cells), which is near the centre of gravity of the particles.

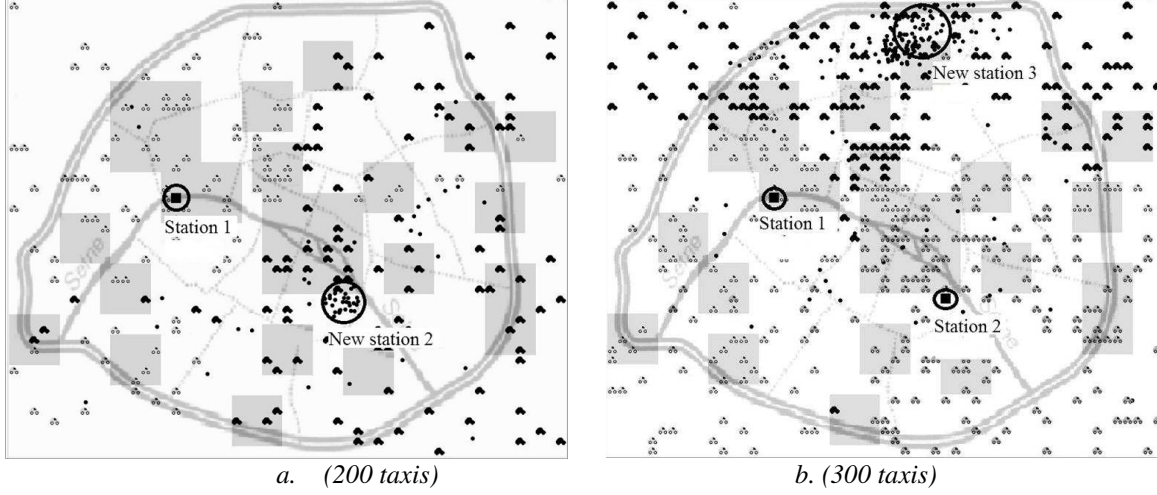


Fig. 6. Possible locations of two new HRSs in Paris during the period 2020–2023

4.7.2. Phase 2. Location of a fourth station with price competition

Depending on the results provided by the previous Model 1, Model 2 searches for a location for a fourth station based on a fleet of 400 FCEVs in 2023 (300 *Hype* taxis and 100 other transport operators). Table 2 estimates the H_2 price for each district with a likely average price of €9.50 per kg for the whole city. Given the proposed HRS locations shown in Fig. 6, we assume that the first three stations will choose a “district price” policy. This means that the H_2 price is, respectively for each station, $p_1 = €8.85$ per kg (district 8), $p_2 = €9.80$ per kg (close to district 14) and $p_3 = €9.85$ per kg (district 1). For $\bar{p} = €9.50$ per kg, the optimal price of the new station 4 should be $p_4^* = €9.76$ per kg. This price corresponds to a market share $D_4^* = 24\%$ and to a number of cars to attract to this new station $n_4^* = 95$, a profit $M_4^* = €578$ per day, and a necessary H_2 capacity of $z_4^* = q_4^* = 152$ kg H_2 /day¹¹ (the expected *Return On Investment* (ROI) should be 60%). Fig 7a shows the likely location of the fourth HRS for $\bar{p} = €9.50$ per kg.

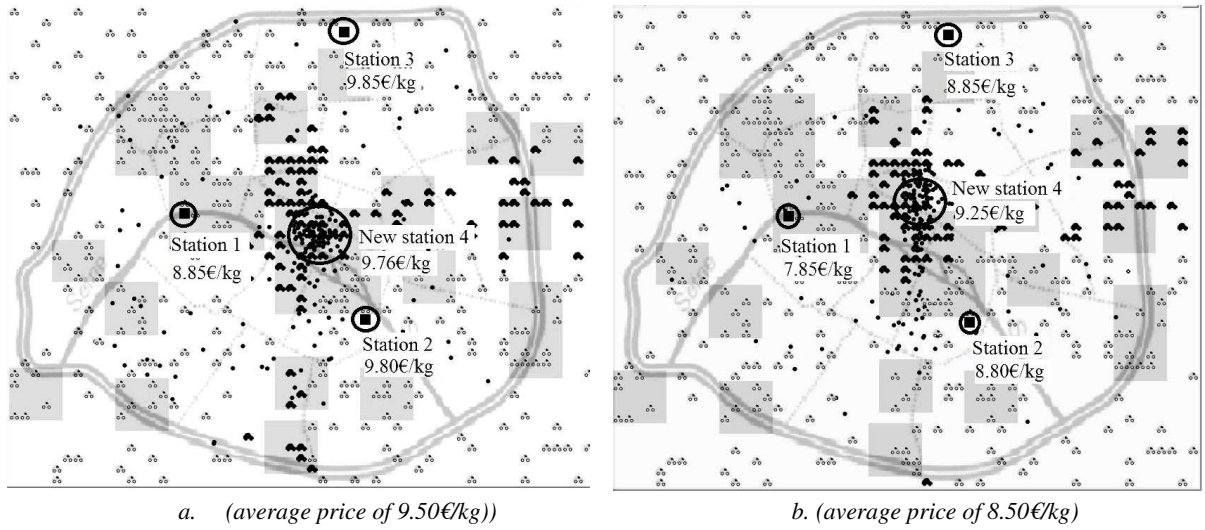


Fig. 7. Possible location of a fourth HRS in Paris in 2023

¹¹ This value is compatible with the current maximum capacity of 200 kg/day for this type of station.

If the initial average price in 2023 is lower than €9.50 per kg for instance, $\bar{p} = €8.50$, the location of the fourth HRS will be different (see Fig. 7b). For this option, we choose the same dispersion price as in Table 2 so that $p_1 = €7.85$ per kg, $p_2 = €8.80$ per kg, and $p_3 = €8.85$ per kg. The optimal price $p_4^* = €9.25$ per kg corresponds to $n_4^* = 85$ customers to attract, a profit $M_4^* = €428/\text{day}$ (ROI = 45%) and an average capacity $z_{new}^* = 136$ kg H₂/day. In that case, the location of the fourth station will be different as for the case of $\bar{p} = €9.50$ per kg (Fig. 7b). These two cases show the importance of \bar{p} on “optimal” station location. The higher the value of this initial average price \bar{p} and consequently, the optimal price p_4^* , the greater the number n_4^* of cars to attract (cf. Table 3) and the more the location of the fourth station tries to catch customers close to the other HRSs. Given the hypothesis of constant price dispersion between Paris districts and depending on the location of the fourth, Table 4 compares the market share and the profit between a price p_4 depending on the district (cf. Table 2 and Fig. 7) and the optimal price p_4^* which is independent of the location (cf. Model 1 and Table 3). If a decider chooses to maximize the profit, prices will no longer comply with the usual price dispersion between the different districts. However, if she chooses to fix a price p_4 instead of p_4^* , the profit M_4 is always lower than M_4^* but the number of customers to attract n_4 may be higher or lower than n_4^* . In the case of $n_4 < n_4^*$, Model 2 looks for a new location further from other stations without leaving this district (new constraint to add to the model), seeking a more extensive HRS network. If $n_4 > n_4^*$, Model 2 will look to be closer to other stations to catch more customers.

Table 4

Comparison between a price p_4 depending on the district and the optimal price p_4

Location	Price p_4	Number of customers n_4	Profit M_4	Average initial price \bar{p}	Optimal price p_4^*	Optimal number of customers n_4^*	Optimal profit M_4^*
<i>District 8</i>	€8.85/kg	113	€559/day	€9.50/kg	€9.76/kg	95	€578/day
<i>District 11</i>	€9.70/kg	76	€415/day	€8.50/kg	€9.25/kg	85	€428/day

To summarize, price optimizing behaviour will lead to fuel station networks being re-organized as the development of FCEV taxis progresses.

5. Uncertainties in the models

In the present case study, the simulation results must be considered in light of some experimental uncertainties and assumptions made on travel distances, demand locations and pricing policies. We will discuss each of these points in this section.

Distance uncertainties. We have chosen a Minkowski distance of order $p = 1.31$ but actual travel-times heavily depend on the traffic congestion and unforeseeable events at different times of the day. Based on the depiction of journey time rather than distance, we propose to complete Facta Group’s spatial study of the taxi trips in Paris to improve our model (Facta Group, 2016). Moreover, in some

cases, drivers go around the ring road to reach a given place within Paris. In this case, we should estimate the mathematical expected distances using the model proposed by Hale et al. (2013).

Uncertainties about the location of the demand points. Our case study corresponds to the current context of a captive fleet of taxis and to its potential evolution over time. We assumed that the location of the demand points have been considered to be randomly distributed around the current taxi stands and that they depend on when each taxi driver decides to join a station. This simplification of reality led us to propose a prospect for future research following the advice of Miralinaghi et al. (2017) who recommend integrating demand uncertainty and driver route choice behaviour into the HRS location problem. Moreover, Tu et al. (2016) collected massive raw GPS data for the electric taxi service in the city of Shenzhen. We propose to adopt their method of recovering demand data by using a map-matching algorithm. Another simplification of reality consists in assuming that drivers decide to refill their tank when their fuel gauge is on $\frac{1}{4}$. Model 2 can easily be adjusted according to a new set of demand points.

Uncertainties about future H₂ prices. It is not known whether future HRS will be managed by the same distributor or not, which could also change the price competition context. However, within the city of Paris, there is no major reason for the price dispersion to change in the future. The price differences across districts are well-known by individuals and taxi drivers whose primary objective is to fill their tank at the station closest to their home or demand point. Besides, it is currently difficult to predict the demand elasticity and the future changes in H₂ prices but it is easy in Model 1 to modify the elasticity coefficient and to recalculate the optimal price for a new station by solving equations (5), (6) and (7). According to this price, Model 2 can propose another possible location for a new HRS.

Finally, we would like to state that Models 1 and 2 are easily configurable according to changes in initial prices, price elasticity, statistical distributions of taxi demand points, spatial constraints in the city and changes in HRS characteristics in terms of capacity and cost depending on H₂ production and distribution techniques.

6. Conclusion

The *Fuel Cell Electric Vehicle* is considered to be one of the key solutions of the energy transition. To guarantee this green evolution, there is currently the problem of locating *Hydrogen Refuelling Stations* in order to cover the countries. Moreover, given the significant infrastructure costs (Sprik et al., 2017), there is also the problem of the economic profitability related to location and price competition. Proximity and price differences become a major decision factor for car drivers although these are often neglected in current location research. The main contributions of this research are twofold. First, methodologically, this paper has addressed the HRS location problem by presenting a two-step modelling approach for optimal pricing and location. Second, at a more practical level, the results

propose to roll out new HRSs in Paris in response to the expected FCEV development phases from 2020 to 2023 starting with a captive fleet with known demand. In the first development phase, we suggest locating the new stations by minimizing the *lp Minkowski* distances between the HRSs and the different H₂ demand locations. In the second development phase, price competition between the stations will emerge and consequently a dual problem of profitable locations for the future stations will arise. The literature shows that it is more usual to tackle this problem in two stages consisting, first in trying to optimize the location and then to optimize the price in the framework of dynamic competition. Given that the dispersion of prices for gasoline and diesel fuel in the different districts of Paris remains almost constant over time, we assume in the future similar absolute H₂ price differences between districts. This justifies our approach consisting first in maximizing profit in an oligopoly framework with static pricing and then locating a new station according to an optimal market share to capture. Nevertheless, this approach also has its limitations. Hanjoul et al. (1990) demonstrate that separating location and price decisions leads to sub-optimality. Dan et al. (2018) advise a joint decision in some practical applications which can provide valuable insights into whether or not entry into a market is profitable (Dobson & Stavroulaki, 2007).

Research outlooks

In the specific context of rolling out new HRSs, we choose just price and proximity as the main customer decision-making factors. Several econometric models identify attractiveness factors of gasoline service stations other than price and proximity, such as brand name, opening hours, and other ancillary services that they might offer (e.g. Gagne et al., 2004). In a more mature phase of FCEV development integrating private cars and based on surveys to be conducted, we suggest developing a gravity model (Bucklin, 1971) integrating an HRS attractiveness function taking into account all explanatory factors and consistent with McFadden's *logit* model (1973) in order to calculate the probability of each consumer *i* choosing an HRS *j*.

What we claim as a contribution is that, provided that data is available, we have developed a simulation model that can be replicated to study other HRS location problems considering different capacity limitation and H₂ production-distribution methods, other initial H₂ price “at the pump” and more accurate statistical distributions of the taxi demand locations and the travel times.

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Appendix A

PSO pseudocode

1. Each particle k has a current position X_k , a current velocity V_k and a remembered best location P_k . Finally, all particles know the index g of the particle that corresponds to the best location so that P_g is the best location that anyone has found.

$P_k = X_k$ initial position of remembered best location

P_g = the position of one of particles (randomly chosen)

2. For each particle do:

2.1. Particles move according to the rule (update the velocity and position)

$$V_{k'} = \omega V_k + \phi_1 (P_k - X_k) + \phi_2 (P_g - X_k)$$

$$X_{k'} = X_k + V_{k'}$$

where ω is an inertia parameter

and ϕ_1 and ϕ_2 are random numbers uniformly distributed in $[0, 2]$.

2.2. Calculate for each particle at the position $X_{k'}$, the values of V_k and P_g .

3. For $k := 1$ to n_p (number of particles)

If $X_{k'} > P_k$ then $P_k = X_{k'}$

If $P_k > P_g$ then $P_g = P_k$

4. The algorithm will stop after a fixed number of iterations.

The best location P_k corresponds to the new station location.

Appendix B

José Solé, an expert in analytical costing for the PSA *Peugeot Citroen Group*, estimates the H₂ unit cost of €5.1 per kg for a 200 kg/day H₂ station composed by, (i) the unit cost of *Steam Methane Reforming* (SMR) with *Carbon Capture and Storage* (CCS), the transportation and compression costs, (ii) the investment of €350,000 for a 200 kg/day H₂ station (AFHYPAC 2016), the energy cost for H₂ compression from 200 bars to 1100 bars to more efficiently fill the tanks of cars at 700 bars, the energy cost for cooling and the maintenance cost (€5.4 per kg including the rental costs for the space occupied in Paris). This assessment applied to the context of French H₂ production and the city of Paris, is similar to calculations in other countries. For instance, Gigler & Weeda (2018) mention that in 2023 the price of H₂ delivered to an HRS should be in the range of €4.50 to €7 per kg excluding the HRS operating and depreciation costs. Reddi et al. (2017) estimate an H₂ cost between \$6 and \$8 per kg and observe that station capacity utilization strongly influences this cost (see also Melaina & Penev). Weinert et al. (2007) estimate a cost of \$5.7 per kg for a 300kg/day HRS capacity and Creti et al. (2015) forecast a cost of €5.7 per kg in 2020 including logistic cost for HRSs with H₂ produced by SMR CCS production technology. Moreover, by 2030, according to the *CertifHy* project report, the cost could reach between €5 and €7 per kg (Fraile et al., 2015). Today, there is a broad international consensus on the future need for clean hydrogen which still costs too much (IEA 2019). Researchers estimate that green H₂ prices may not come down sufficiently until the 2030s. For their location decisions and ROI estimations, the investors have therefore to consider a likely price evolution scenario. The H₂ price “at the pump” depends on these changes in cost, on value-added tax, and on possible excise duty on H₂, which could also have a significant impact on the final price (Gigler & Weeda 2018).

Appendix C

The H₂ price “at the pump” in Germany in 2019 is €9.50 gross per kg (Hydrogen Mobility Deutschland GmbH & Co KG, 2019). In California in 2015, the prices ranged from \$12.85 to more than \$16 per kg with a most common price of \$13.99 per kg (California Fuel Cell Partnership, 2015). In France, *Air Liquide* announced a price of €15 per kg in April 2019 at the *Orly* fueling station but the goal in France is to reach €10 per kg (Mobilite Hydrogene France, 2017).