Systems & Control Transactions

Research Article - Peer Reviewed Conference Proceeding
ESCAPE 35 - European Symposium on Computer Aided Process Engineering
Ghent, Belgium. 6-9 July 2025
Jan F.M. Van Impe, Grégoire Léonard, Satyajeet S. Bhonsale, Monika E. Polańska, Filip Logist (Eds.)

PSE PRESS

Optimization of Sustainable Fuel Station Retrofitting: A Set-Covering Approach considering Environmental and Economic Objectives

Daniel Vázquez*, Raul Calvo-Serrano

IQS School of Engineering, Universitat Ramon Llull, Via Augusta 390, 08017 Barcelona, Spain
* Corresponding Author: daniel.vazquez@iqs.url.edu.

ABSTRACT

In this work, we propose a mixed-integer linear programming (MILP) model that optimizes economic and environmental objectives by retrofitting fuel stations for the case study of Spain. The model contains set-covering constraints that ensure that there is at least one retrofitted fuel station within a radius of 20 kilometers of each retrofitted fuel station. The results indicate that by retrofitting fuel stations to allow for electric vehicles, both economic and environmental objectives improve, while showing which power plants would be tasked with the increase in electricity production to satisfy the increased electric demand.

Keywords: Life Cycle Assessment, Supply Chain, Optimization, Renewable and Sustainable Energy, Technoeconomic Analysis

INTRODUCTION

To improve the sustainability of the transport sector, there is a global tendency to promote more environmentally friendly modes of transportation, in alignment with the Sustainable Development Goals (SDGs), particularly SDG 13, which focuses on climate change action. This shift is essential given that the transport sector is one of the largest contributors to greenhouse gas emissions globally, and transitioning to cleaner transportation options is a critical step toward mitigating climate change. Electric vehicles (EVs), if powered by renewable energy, are a promising solution to reduce emissions significantly. In response to these developments, many countries are implementing policies and incentives to encourage the adoption of EVs, including subsidies for EV purchases, investments in charging infrastructure, and stringent emission standards for conventional vehicles. This trend has led to a surge in EV adoption, which may reduce the reliance on traditional fuel stations in the future. However, the existing network of fuel stations, strategically located and familiar to consumers, offers a unique opportunity to support the EV transition. Retrofitting these fuel stations into EV charging stations not only profits from their advantageous locations and existing infrastructure but also facilitates a smoother transition for current consumers [1].

We propose a mixed-integer linear programming (MILP) optimization model based on the set-covering problem to determine which fuel stations are best suited for retrofitting and to evaluate the impact of this conversion on economic and environmental objectives compared to a baseline scenario with no retrofitting. The set-covering approach ensures that the retrofitted stations can adequately serve EVs within a specified radius, addressing the limited range issue of current electric vehicles. These types of models are common in supply chain and energy systems modelling [2].

This methodology is applied to a case study in Spain, utilizing a comprehensive dataset of all existing fuel stations. Given the NP-hard nature of the set-covering problem, an initial filtering step is employed to reduce the problem's size. Subsequent optimization is performed under various assumptions, such as the source of electricity and local demands of transport usage, using bi-objective optimization techniques. The model aims to minimize economic costs and CO_2 equivalent emissions, employing a life-cycle assessment (LCA) framework [3].

The results indicate that retrofitting a relatively small fraction (~10%) of the fuel stations satisfies set-covering constraints, ensuring sufficient coverage for EV users. Notably, even considering retrofitting costs, both the economic and environmental optima coincide in a full electrification of the vehicle float.

PROBLEM STATEMENT

The objective is to model and optimize the economic and environmental impacts of retrofitting existing standard fuel stations into EV charging stations in Spain, compared to a baseline case where no retrofitting is allowed. Thus, part of the energy system of the country is also modeled through the locations and capacities of existing power plants. The problem can be summarized through the following bi-objective optimization problem (1).

$$\begin{aligned} &\min\ \{obj^{eco}(x,y), obj^{env}(x,y)\} \\ &s.t. \\ &h(x,y)=0 \\ &g(x,y)\leq 0 \\ &x\in\mathbb{R}^n, y\in\{0,1\} \end{aligned} \quad (1)$$

where obj^{eco}, obj^{env} represent economic and environmental objectives, x represent continuous variables, y represent Boolean variables, $h(x,y)$ indicate equality constraints, and $g(x,y)$ indicate inequality constraints. Boolean variables are required to include set-covering constraints and other logical requirements detailed in the modeling section. For the economic objectives we consider the total cost, and for the environmental objective, we use the global warming potential from the IPCC2021 method (GWP). The temporal scope is one year.

OPTIMIZATION MODEL

Sets

We will use three main sets to model the system, these being, the set of fuel stations that can be retrofitted, $s\in S$, the set of power plants that could provide electricity to the retrofitted fuel stations, $p\in P$, and the set of autonomous regions in Spain, $r\in R$.

We define subsets depending on the type of power plant, specifically, if they are wind-offshore (P^{WO}), coal (P^C), gas (P^{NG}), waste (P^W), biomass (P^B), hydropower (P^H), solar (P^S), oil (P^O), or nuclear (P^N). We define a multi-set, $GS_{s,r}$, which maps which fuel stations are in each autonomous region.

Variables

The model includes the following continuous variables: $e^{RF}_{p,s}$ indicates the amount of electricity produced in power plant p that will be sent to retrofitted fuel station s [GWh], e^{DE}_p refers to the electricity produced in power plant p to satisfy the country's demand of electricity [GWh], e^{TP}_p refers to the total amount of electricity produced in power plant p [GWh], e^{EC}_r refers to the electricity available in autonomous region r to be used to charge electric vehicles, e^{SEC}_s refers to the electricity available in fuel station s to be used to charge electric vehicles, d^{EC}_r refers to the amount of kilometers traveled using electric cars in autonomous region r [$\times 10^3$ km], and d^{NC}_r refers to the amount of kilometers traveled using conventional combustion engine cars in autonomous region r [$\times 10^3$ km].

Regarding binary variables, we consider two. w indicates if we activate or de-activate the set-covering constraints, while y_s indicates if we retrofit fuel station s ($y_s=1$) or not ($y_s=0$).

Parameters

$D^{SC}_{s,s'}$ refers to a binary parameter that has a value of 1 if fuel stations s and s' are within a given distance valid for the set-covering problem, $D^S_{s,s'}$ refers to the distance between two fuel stations [10^3 km], $D^{PS}_{p,s}$ refers to the distance between each power plant and each station [10^3 km], GWP^{PP}_p refers to the GWP of generating electricity in power plant p [tCO_2eq/GWh], GWP^{EC} refers to the GWP of using an electric car without counting the fuel [$tCO_2eq/10^3$ km], GWP^{NC} refers to the GWP of using a standard car [$tCO_2eq/10^3$ km], $\bar{E}_p$ refers to the maximum amount of electricity that power plant p can produce [GWh], E^{EC} refers to the required electricity for traveling using an electric vehicle [GWh/10^3km], B^D_r refers to a demand of distance that must be fulfilled in each autonomous region r [10^3 km], B^E refers to the demand of electricity of the country, not counting inclusion of new electric vehicles [GWh], C^{RF} refers to the cost of retrofitting a fuel station [M€], C^{NC} refers to the cost of traveling using a standard vehicle [M€/10^3 km], and C^{WO}, C^C, C^{NG}, C^W, C^B, C^H, C^S, C^O, and C^N refer to the levelized cost of each type of electricity [M€/GWh].

Equations & Constraints

Objective functions

We consider both an economic and an environmental objective, calculated as shown in (2) and (3).

$$obj^{eco}=\sum_{s\in S}C^{RF}y_s+\sum_{r\in R}C^{NC}d^{NC}_r+\sum_{p\in P^{WO}}C^{WO}e^{TP}_p+\sum_{p\in P^C}C^Ce^{TP}_p+\sum_{p\in P^{NG}}C^{NG}e^{TP}_p+\sum_{p\in P^W}C^We^{TP}_p+\sum_{p\in P^B}C^Be^{TP}_p+\sum_{p\in P^H}C^He^{TP}_p+\sum_{p\in P^S}C^Se^{TP}_p+\sum_{p\in P^O}C^Oe^{TP}_p+\sum_{p\in P^N}C^Ne^{TP}_p \quad (2)$$

$$obj^{env}=\sum_{r\in R}d^{NC}_rGWP^{NC}+\sum_{r\in R}d^{EC}_rGWP^{EC}+\sum_{p\in P}GWP^{PP}_pe^{TP}_p \quad (3)$$

The economic objective includes the cost of retrofitting plants, producing electricity required both for the country's demand and for the electric vehicles, and the cost of using standard combustion cars for traveling distances. The environmental objective includes the emissions from the electricity production, the emissions of using standard combustion cars for traveling distances, and the emissions of electric vehicles for traveling distances, without counting the electricity itself to avoid double counting.

Set-covering constraints

The set-covering constraints make use of the Boolean parameter $D^{SC}_{s,s'}$ to make sure that there each retrofitted fuel station has at least one another retrofitted fuel station at the stipulated distance. In this work, the stipulated distance is 20 km. We also allow the model to not retrofit any station at all, thus ignoring the set-covering constraints. For this, we use the following equations (4,5):

$$\sum_{s'\in S} D^{SC}_{s',s} \geq w \quad \forall s \in S \tag{4}$$

$$w \geq y_s \quad \forall s \in S \tag{5}$$

Electricity balances

The total electricity produced in a power plant is given by (6).

$$e^{TP}_p = e^{DE}_p + \sum_{s\in S} e^{RF}_{p,s} \quad \forall p \in P \tag{6}$$

The electricity that can be used in a retrofitted fuel station is the amount that is sent from each power plant, subtracting a 3%/1000 km loss in transport (7).

$$e^{SEC}_s = \sum_{p\in P} e^{RF}_{p,s} \cdot (1 - 0.03 D^{PS}_{p,s}) \quad \forall p \in P \tag{7}$$

The aggregation of electricity produced for electric vehicles in an autonomous region is given by (8).

$$e^{EC}_r = \sum_{s\in GS_{s,r}} e^{SEC}_s \quad \forall r \in R \tag{8}$$

We also limit the amount of electricity that each retrofitted gas station can receive from non-dispatchable technologies (wind and solar) to a 40% of the total it receives (9), in order to at least simulate part of the availability problems that non-dispatchable technologies present.

$$\sum_{p\in (P^{WO} \cup P^S)} e^{RF}_{p,s} \leq 0.40 \cdot \sum_{p\in P} e^{RF}_{p,s} \quad \forall s \in S \tag{9}$$

If a fuel station is not retrofitted, it cannot be used to fuel electric vehicles (10)

$$e^{RF}_{p,s} \leq \bar{E}_p \cdot y_s \quad \forall s \in S, p \in P \tag{10}$$

You cannot produce more electricity in a power plant than its maximum capacity (11)

$$e^{TP}_p \leq \bar{E}_p \quad \forall p \in P \tag{11}$$

A lower bound of 1 GWh is set to the electricity used to charge electric vehicles, so to ensure that all retrofitted stations are used to charge electric vehicles (12).

$$e^{SEC}_s \geq y_s \quad \forall s \in S \tag{12}$$

Demand constraints

The demand of electricity of the country must be fulfilled notwithstanding the introduction of electric vehicles (13).

$$\sum_{p\in P} e^{DE}_p = B^E \tag{13}$$

To fulfill the transportation demand, we must specify how electricity is converted through kilometers in electric vehicles, using (14).

$$d^{EC}_r = e^{EC}_r / E^{EC} \quad \forall r \in R \tag{14}$$

The transportation demand is fulfilled through electric and non-electric vehicles (15).

$$B^D_r = d^{NC}_r + d^{EC}_r \quad \forall r \in R \tag{15}$$

Domain of the variables

All continuous variables, except for obj^{eco}, obj^{env}, are positive real variables ($\mathbb{R}^+$). The objective function variables are real variables ($\mathbb{R}$). Variables w and y_s are binary variables ($\{0,1\}$).

Data gathering and assumptions

For the geographical coordinates, enumeration, and label of the existent fuel stations in Spain, we use the API offered by the Spanish Ministry of Industry and Tourism[4], through `GET` requests. A total of 11,733 fuel stations were found in the original dataset. Due to the set-covering problem being NP-hard, we reduced the size of the dataset by filtering out the fuel-stations that do not belong to major companies in Spain in order to reduce the solving time. The reduced dataset contains 5,866 fuel stations.

We obtain the geographical coordinates, primary fuel, and capacities of the power plants from the World Resources Institute [5]. We assume 8,000 h of possible production of electricity per year for the power plants. We model intermittency through the assumption that only 40% of the electricity used in electric vehicles can come from non-dispatchable technologies (9).

To calculate the distance among the different fuel stations, as well as between power plants and fuel stations, we use Haversine equation. While this distance is the shortest distance between two points in the Earth, and due to that is not really the distance that vehicles would have to traverse between two fuel stations, we balance that through the fact that for the set-covering, a small limit of 20 km is set for two fuel-stations to be able to fulfill the constraint. Considering that electric vehicles have an autonomy of >200 km, we consider that this proximity between retrofitted fuel stations would be enough to ensure availability.

The cost parameters for the electricity are sourced from a work by the European Commission [6], and the amount of kilometers traveled in the country per autonomous region has been calculated from a Spanish

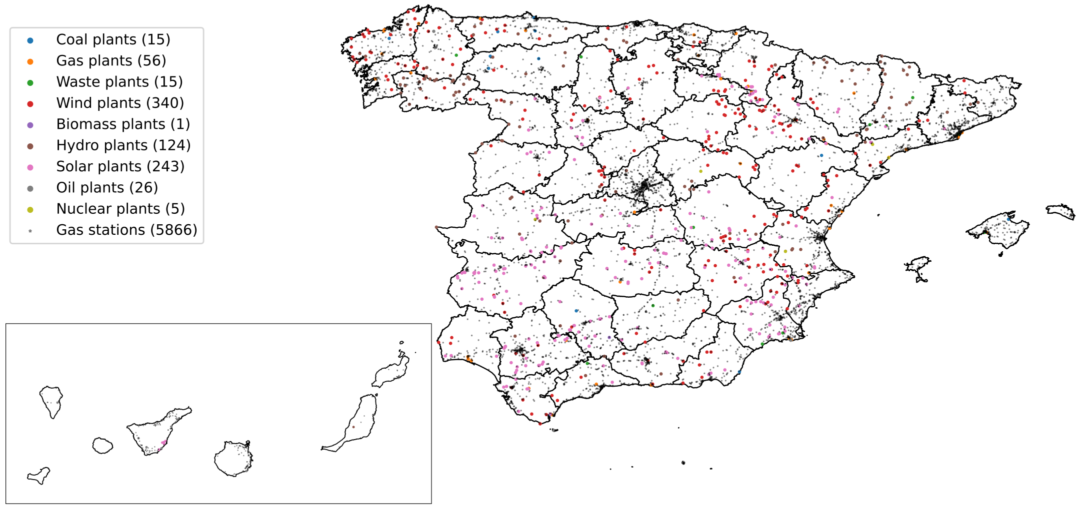

Figure 1. Map showing the location of the possible gas stations to retrofit, as well as the power plants available to produce the electricity required in them. The legend indicates the types of power plant and gas stations. The number between parenthesis indicates the number of plants/gas stations that are considered in the study.

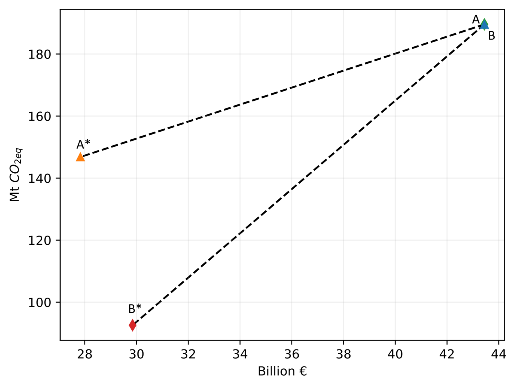

Figure 2. Results of the four optimization problems run. A and A* refer to the optimization of the economic objective without and with retrofitting, respectively. B and B* refer to the optimization of the environmental objective without and with retrofitting, respectively.

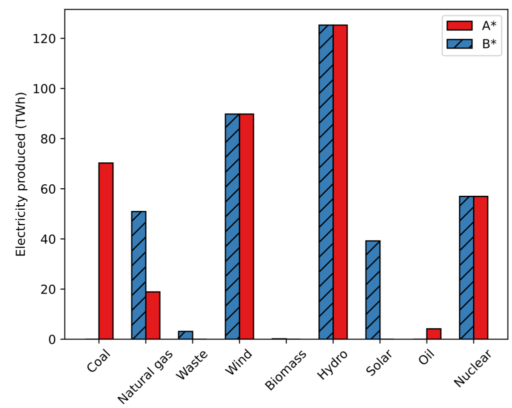

Figure 3. Electricity mix obtained for the economic optimum scenario (A*) and the environmental optimum scenario (B*).

newsletter [7], considering an average consumption of six liters of gasoline per 100 km traveled. The price of fuel for standard cars is considered as 0.771 €/l, without counting taxes. The cost of retrofitting a fuel station ($3,988,900) is sourced from the work of Feng and Khan [8], and does not consider on-site power storage. For the environmental impacts, we use the Ecoinvent database[9] 3.9.1 cutoff, using the IPCC2021 GWP method. For the case of electric cars, we take the GWP of the car subtracting the electricity needed to fuel it, since we are considering it in the model through equation (14).

In **Figure 1**, we show the location of each power plant and fuel station considered in this work.

RESULTS AND DISCUSSION

We perform two optimizations per objective, for a total of four optimization runs. For each objective, we consider a scenario where we forbid retrofitting ($w \leq 0$) in order to obtain a comparison of how much the inclusion of electric vehicles modifies the results. The scenarios considered are therefore A and A*, where we optimize the economic objective without and with retrofitting, and B and B*, where we optimize the environmental objective without and with retrofitting. The results obtained are shown in Error! Reference source not found..

As shown in the figure, when we do not allow retrofitting in the model, both solutions (points A and B) are very close, changing only a bit the optimal electric mix obtained. However, when we allow retrofitting (points A* and B*), and thus, electric vehicles, both solutions immediately get better in both objectives. Compared to their base cases, A* improves 36% its economic objective and 22% its environmental objective, while B* improves 31%

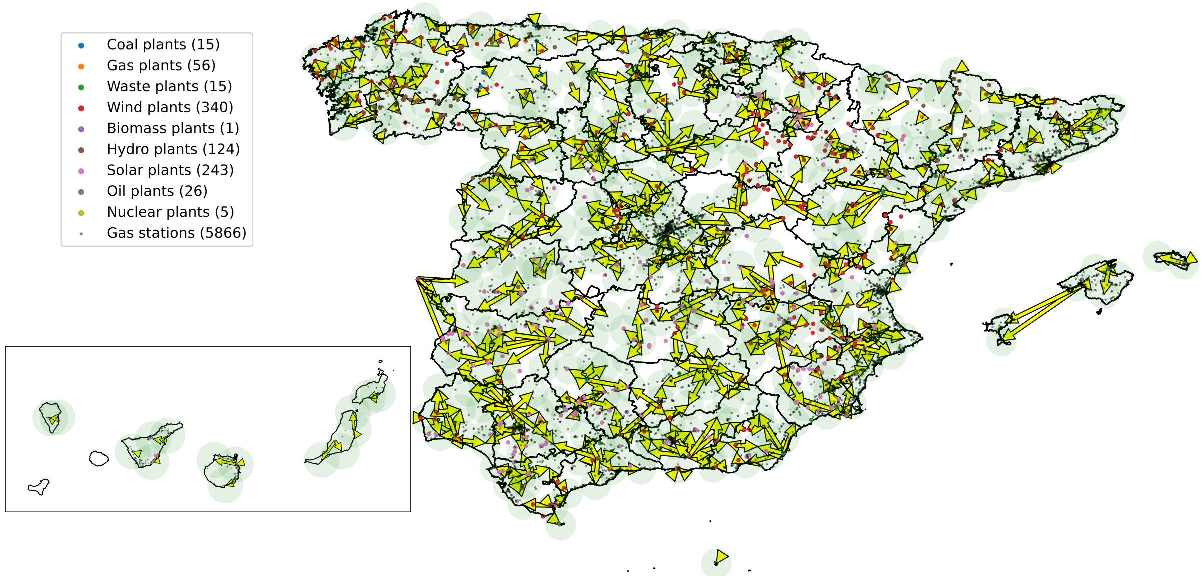

Figure 4. Economic optimum result (A*). Green circles indicate service area of each retrofitted station. Yellow arrows indicate from which power plant is electricity generated for each retrofitted fuel station.

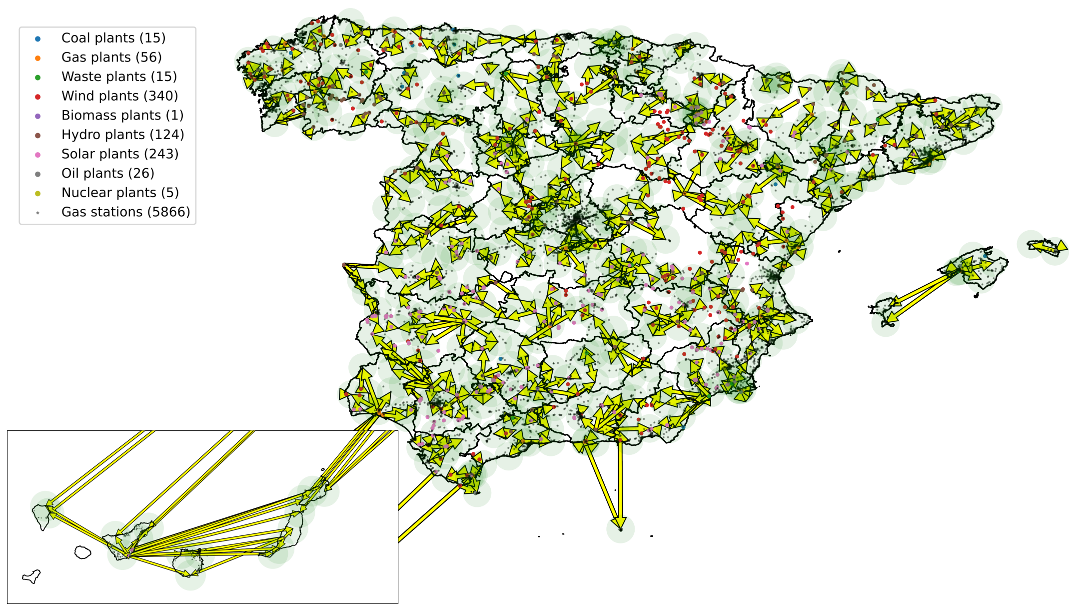

Figure 5. Environmental optimum result (B*). service area of each retrofitted station. Yellow arrows indicate from which power plant is electricity generated for each retrofitted fuel station.

its economic objective and 51% its environmental objective.

Notably, in both A* and B*, the model chooses to electrify the vehicle fleet completely, since that alternative is cheaper and more environmentally friendly than standard combustion vehicles, even with the cost of retrofitting the fuel stations needed.

Focusing on the scenarios where we allow retrofitting of fuel stations, the electric mix optimized to account for both the electricity demand of the country and the demand from the electric vehicles is shown in **Figure 3**.

While the electricity mixes are very similar, focusing on renewable energy available in the country with a low levelized cost of electricity, there certain differences between the environmental and economic optimums. While the economic optimum employs oil and coal, which are economic but contaminant, the environmental optimum uses solar and waste, as well as raising the use of natural gas, which while being a fossil fuel, has a lower GWP than that of coal and oil.

In **Figure 4** and **Figure 5** the supply chain results of the economic (A*) and environmental (B*) optima are shown. It is important to mention that, in the model, certain electricity transport options which are currently not possible were not limited. For example, in the environmental optimum, there is transport from the mainland to the Canary Islands, which is not currently possible. However, it is noteworthy that even with losses that are proportional to the distance that electricity is transported, the model chooses to generate electricity in the peninsula and transport it to the islands. The number of retrofitted stations also varies between the solutions. For the economic optimum, 412 fuel stations are retrofitted, to fulfill the set-covering constraint. However, in the environmental optimum, this number rises to 477.

It is important to note that, due to data not being available, there was no upper limit to the number of cars that any fuel station can serve in a year. For a more precise model, an upper bound would need to be set to each fuel station that limits the amount of service that it can provide per year.

CONCLUSIONS AND LIMITATIONS

The model shows that it is possible to reduce both the economic and environmental objective through an implementation of retrofitted fuel stations and electric vehicles. Specifically, the cost and GWP are reduced from 43.44 billion € and 189.55 million tonnes of CO2eq. to 27.83 billion € and 146.80 million tonnes of CO2eq. when minimizing the cost (scenarios A and A*), and from 43.44 billion € and 189.55 million tonnes of CO2eq. to 29.85 billion € and 92.57 million tonnes of CO2eq. when minimizing the cost (scenarios B and B*).

However, the results of this study must be taken as an ideal case due to the assumptions followed during its modeling. Namely, the consideration of steady state indicates that although Spain has enough electricity production capacity to satisfy a full electric fleet, electricity demand and production dynamics are not considered, hence assuming that the country has the instantaneous capacity required to provide electric energy at a given point in time.

In summary, future work will focus on the dynamic aspect of the model, including generation profiles of the different electricity technologies, as well as realistic upper limits for the service that each fuel station can provide at a given time.

ACKNOWLEDGEMENTS

D.V. acknowledges financial support from grant PID2023-151826OA-I00 funded by MICIU/AEI/ 10.13039/501100011033 and ERDF/EU.

REFERENCES

1. N. Ghosh, S. Mothilal Bhagavathy, and J. Thakur. Accelerating electric vehicle adoption: techno-economic assessment to modify existing fuel stations with fast charging infrastructure, *Clean Techn Environ Policy* 24 10:3033–3046 (2022) https://doi.org/10.1007/s10098-022-02406-x
2. Á. Galán-Martín, D. Vázquez, S. Cobo, N. Mac Dowell, J. A. Caballero, and G. Guillén-Gosálbez. Delaying carbon dioxide removal in the European Union puts climate targets at risk. *Nature Communications* 12 1:6490–6490 (2021) https://doi.org/10.1038/s41467-021-26680-3
3. A. Azapagic. Life cycle assessment and its application to process selection, design and optimisation. *Chemical Engineering Journal* 73 1: 1–21 (1999) https://doi.org/10.1016/S1385-8947(99)00042-X
4. Ministry of Industry and Tourism, Spain. API fuel stations. Accessed: Dec. 20, 2024. [Online]. https://sedeaplicaciones.minetur.gob.es/ServiciosRESTCarburantes/PreciosCarburantes/help/operations/PreciosEESSTerrestres#response-json
5. L. Byers et al. A Global Database of Power Plants. Accessed: Dec. 20, 2024. [Online] https://www.wri.org/research/global-database-power-plants
6. European Commission. Directorate General for Energy. and Trinomics. Cost of energy (LCOE): energy costs, taxes and the impact of government interventions on investments : final report. *LU: Publications Office* (2020). https://data.europa.eu/doi/10.2833/779528
7. Cores. Boletín Estadístico de Hidrocarburos. Cores, Spain, 317, (2024). https://aop.es/wp-content/uploads/2024/06/boletin-est-hidrocarburos-317-abril-2024.pdf
8. J. Feng and A. M. Khan. Accelerating urban road transportation electrification: planning, technology, economic and implementation factors in converting gas stations into fast charging stations. *Energy Syst* (2024) https://doi.org/10.1007/s12667-023-00638-4
9. G. Wernet, C. Bauer, B. Steubing, J. Reinhard, E. Moreno-Ruiz, and B. Weidema. The ecoinvent database version 3 (part I): overview and methodology. *Int J Life Cycle Assess* 21 9:1218–1230, (2016), https://doi.org/10.1007/s11367-016-1087-8