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Environmental impacts of enlarging electric vehicles market share

Daniel De Wolf^{1,2,3*}, Ngagne Diop^{1,2} and Moez Kilani^{1,4†}

^{1*}Département Economie Gestion, Université du Littoral Côte d'Opale, 59140 Dunkerque, France.

²Territoire Villes, Environnement & Société, 59140 Dunkerque, France.

³Center for Operations Research and Econometrics, UCLouvain, 1348 Louvain-La-Neuve, Belgium.

⁴Lille Economie Management – LEM CNRS, UMR 9221 Dunkerque, France.

*Corresponding author(s). E-mail(s):

daniel.dewolf@uni-littoral.fr;

Contributing authors: ngagne.diop@univ-littoral.fr;

moez.kilani@univ-littoral.fr;

[†]These authors contributed equally to this work.

Abstract

We extend a transport model to simulate an increase of the market share of electric vehicles. The main results of our model is that the increase in the share of electric cars in the network must then be accompanied by the implementation of charging stations in sufficient quantity and optimal location, to reduce, not only the waiting times for charging the electrical vehicles, but also to reduce the polluting gas emission of other vehicles. The simulation framework we use is based on the model developed [1].

Keywords: Transport modeling and simulation, Electric vehicles, Deployment of charging stations, Local pollution, North of France

JEL Classification: H23 , Q5 , R4

1 Introduction

The first prototypes of electric vehicles were developed and used in the nineteenth centuries, but their market share remained negligible until recently. The charging time of the batteries and low autonomy are thought to be the main features that have prevented large scale deployment of electric cars. During the last decades, several important technological advances has been made to produce much more efficient batteries and propose faster charging equipment. At the same time, several regions and governments are investing to improve the deployment of charging stations. During the pandemic, the sales of electric vehicles recorded important increase in several European countries and world-wide. This trend is expected to continue in the future as several governments are targeting the progressive elimination of combustion engines.

The support for electric vehicles is based on their zero emissions (greenhouse gases and particulate matters) features. While some skepticism is pointed out with respect to the production batteries and electric engines, which are based on rare materials whose extraction is heavily polluting, local policies generally focusing on local pollution where electric cars perform very well. In this paper, we adhere to this view, focus on local impacts, and do not consider the whole life cycle of electric cars and batteries.

Our objective is to evaluate the environmental impacts and energy consumption when the market share of the electric cars increases. Our analysis is based on a multimodal transport simulation framework described in [1]. The model covers the North of France, but in this study we focus on the Lille metropolitan area since electric vehicles are particularly relevant for urban and suburban transport. We consider a base case scenario, corresponding to the actual observed situation, and compare with several other configurations by varying the market share of the electric car. We are particularly interested by the spatial deployment of charging stations and the extent to which it may affect emissions and energy consumption. We then distinguish between scenarios where the charging stations follow the observed actual locations and other scenarios where the deployment is optimized to improve accessibility to these stations.

Our results show that the optimal deployment of the charging stations is fundamental to reach a significant decrease in pollution and fuel energies. The intuition for this is that electric cars require frequent charging and spend a significant distances to reach the charging stations. These extra distances increase congestion level leading to a decrease in average speed. The level of pollution by unit distance is then higher. When the charging station are not set optimally, this extra trips related to charging electric vehicles are high. An optimal deployment of the charging stations will reduce significantly the length of these trips and reduces the level of external costs (congestion and pollution).

To find optimal locations of charging station we formulate and solve a network optimization problem using `cplex`. The objective function of the problem

is the total distance to charging stations, which we minimize, and the constraints reflect realistic requirements in the process (each car should find a charging station, the number of charging stations, etc.).

The paper is organized as follows. Section 2 reviews other studies that have considered electric cars and the optimal deployment of charging stations. Section 3 briefly describes the multimodal transport model we use as a framework [1] and describes how electric vehicles have been taken into account. The results of our analysis are reported in Section 4 and we conclude in Section 5.

2 Literature review

Mathematical models, for optimal deployment of charging stations, are advancing rapidly in this decade. In addition to considering the optimal location of charging stations in an area, the latest optimization models have also determined the number of charging outlets per station, which is necessary to allow for maximizing the service levels of electric vehicles [2]. These authors adopted an approach that is based on three steps, after subdividing the Ohio region into sub-regions, which can correspond to communes in the case of Northern France.

Models on energy transition scenarios are more and more considered by policy makers. They can be used as valuable tools to evaluate the effectiveness in the reduction of negative externalities. For example, the Greater Berlin model has shown that population exposure to road traffic noise depends largely on intra-day travel patterns of the citizens [3]. The combination of these transport models with vehicle emission models can be used to identify relevant policies that can be used by local authorities [4].

Agent-based models operate at the level of the individual who chooses the transport mode, the route between the origin-destinations pairs and the departure time. These agents are allowed to change their decisions when they are offered better alternatives. Since all trips information are available, it is straightforward to use energy and environmental models to evaluate fuel consumption and pollution under each scenario.

Including electric vehicles does not raise any particular challenges, but to be useful in practice and to fall in the scope of energy transition objectives, distinctive attributes of these vehicles should be taken into account. In particular, they should take into account the charging process and the limitation in travel distances that electric vehicles provide by comparison with vehicles that run on fossil energies. One of the most elaborated case studies that has considered electric mobility in Sweden is reported in [5]. The model has freight and person transport. The data is collected from GTFS and OSM data files.

In general, the automotive industry is expanding to satisfy the human addiction to the private car. As far as electric vehicles are concerned, there has been several major innovations in the recent years, even the progress in the main challenge for more efficient batteries has progressed at slower pace. Issues with respect to the autonomy of the batteries (autonomy and charging time) has

been for a long time blocking points. A large research effort has been deployed with respect to these issues (See Saber et al [6]).

There exist three main charging technologies [2]. Level 1 batteries use a standard wall outlet producing a 110V/15A connexion. The power provided by these batteries varies from 16 to 25 kWh, and full charging time varies from 12 to 18 hours. Level 2 batteries use more powerful circuits, generally based on 220V between 15 and 30A. Quick charge uses a continuous electricity under high voltage system (400 to 500V), and full charging time can take less than half an hour. This charging system is based on a relatively sophisticated equipment and cannot be deployed in residential locations.

For example, for a Lithium-Ion battery with capacity 22 kWh, the charging duration is between 3 and 8 hours in single phase alternating current with power 3.7 kW and voltage 230V, 16 to 32 A. With three-phase current, the charging time drops to 1 to 2.5 hours with a voltage of 400 V, and could even be with 20 to 30 mins with 63 A. The performances in this case are almost similar to those provided by continuous current with charging power 50 kW and voltage 400 V/100 A.

In general, full charging requires 13 hours, but 80% charging could take about 30 mins using advanced the most advanced technologies (See De Wolf [7]).

Charging stations are either private, generally located at hotels and shopping malls, or public as those located in motorways, in particular the quick charging stations. The accessibility of a charging station is an main factor to improve is usage. The optimal location of a given charging station will depend on its performance and charging time, in particular. Clearly, slow charging station will be not used at a satisfactory level when they are not accessible. With slow charging stations users will generally prefer partial charging [2]. Slow charging stations are well convenient when located at home, where charging of the private car is processed at night, but requires that the houses are equipped with a garage. One of the main challenges related to the deployment of slow charging stations in urban areas is the management of the difficult trade-off between the supply of charging time and parking space.

The location of fast charging stations shows a concentration in wealthy residential areas in the North of France. This pattern in the deployment of fast charging station is explained by the fact that it is mainly conducted by private operators [11].

A further difficulty in the deployment of charging stations is the interoperability of the used equipments. If each operator uses a specific and non standard system of plugin, the attractiveness of the charging stations will be limited. Broadly speaking, this will not favour the transition to electric vehicles.

Our simulation framework is based on the deployment of charging stations setted up by BOUYGUES ENERGIES ET SERVICES (60%) and DRIVECO (31%). The powerful charging stations (22 kVA) are more frequent (78%) and the fast public charging stations haven't gained a large market share (2.6%). Notice that this small value should yield a higher contribution to charging services.

A proposal for the distribution of charging stations would allow the selection of the most suitable locations. It could be based on a more equitable distribution, on the one hand, between city centers and the countryside and, on the other hand, between high and low income people. The study case of an electric cab fleet in Beijing showed that an optimal deployment of public charging stations can increase the electric cab fleet by 59% for the slow charging stations and 88% for the fast charging stations (See Shahraki et al [12]).

Mathematical models for optimal deployment of charging stations are advancing rapidly in this decade. In addition to considering the optimal location of charging stations, the latest models also determine the number of charging outlets per station needed in order to maximize the service level (See Xi et al [13]). These authors adopted a three-step approach, after subdividing the Ohio region into sub-regions, which may correspond to communes in the case of Northern France. Their methodology consisted of:

- First, they determine, for an agent, the probability of having an electric vehicle on the base of socio-demographic and macroeconomic data for the sub-region. Then they determine electric vehicles flows between the sub-regions.
- Then, they develop a simulation model of the vehicles likely to be recharged at potential charging stations according to the number of slots.
- Finally, they use an integer linear programming model to determine the location and size of charging stations.

The model for locating charging infrastructure in the Seattle area was also based on a linear program (See Chen et al [14]). The objective is to minimize the costs of access to these infrastructures computed by the distance traveled.

Li et al [15] integrate the monitoring of the state of charge of vehicles into the charging station location model. [16] applies this model in South Carolina assuming the knowledge of the origin-destination matrix of the population's trips. The same author develops a model for a cab fleet in Montreal based on various assumptions. The study perimeter is divided into different areas that may or not receive a charging station. The charging stations are located at the ends of the trips (origin or destination).

3 The transport model

The start by briefly describing the simulation framework (subsection 3.1) and then discuss how electric vehicles are taken into account (subsection 3.2).

3.1 The basic setup and calibration

This research is based on a multimodal transport model that we have developed for the North of France. The total population in this region is about four million inhabitants. The North of France connects northern Europe to Paris Metropolitan area and to southern Europe. Several policies have been considered to alleviate congestion and reduce the emissions of polluting gases.

Several steps have been made to develop attractive public transport and reduce the usage of the private car. For example, Lille was the first city worldwide to implement a fully automated metro line in early eighties of the last century, and Dunkerque is now the largest agglomeration in France where public transport is free.

Lille is a metropolitan area with more than 1.1 million inhabitants. Other major cities include Valenciennes, Dunkerque (Dunkirk), Calais, Boulogne-sur-Mer and Arras (See Fig. 1). The historical mining activities explain part of the trip patterns observed between the mining area and other cities, Lille, in particular.



Fig. 1: The Nord Pas de Calais.

Motorways around this city are severely congested during the peak hours. Also, the “A1” motorway, linking Lille to Paris, is a main connection for freight transport between northern Europe, Paris region and other southern cities in the south of France and Spain. The study area is a main place for logistics activities, including warehousing, since it connects several ports (Dunkerque, Calais and Boulogne-sur-Mer) and multimodal platforms (for example, Dourges which is located in the south of Lille).

The model includes four modes “walk”, “bike”, “car” and “public transport”, and allows for their combinations (to some extent). It covers both urban and intercity trips. Survey data from the Regional Household survey of 2016 is used to build daily trips. The usage of the private car is the dominant mode, and most short trips, less than one kilometer, are made by walk. Public transport modes are used for urban (bus and metro) and intercity (train) trips. Other modes, like tramways and intercity buses, have a very small share and

are not reported here. The data we use covers all trips departing and arriving inside the study region, but also inflows and outflows with other regions in France. Our simulation model includes all these trips. As we explain below, the model is complemented, at the calibration stage, by the census data, to include cross-border traffic and freight transport.

For each trip, the survey data reports several activities as the trip purpose, at the origin or at the destination. The most frequent ones are “home”, “work”, “shopping” and “accompaniment” (family or friends). These values are reported for the whole population and should, of course, significantly differ when we focus on specific groups with respect to age or job qualification.

To obtain realistic traffic flows we need to add cross-border trips and freight transport. Unfortunately, there are no comprehensive datasets available to use for this purpose. Cross-border trips are important since the study region is adjacent to Belgium and cross-border commuting is central to several regional policies focusing on the development of European metropolitan Areas.

To overcome the lack of available information on cross-border traffic flows, we use census data for home-to-work trips, which is available at the scale of the “commune”. The database reports only flows departing from France to Belgium and not trips in the opposite direction. We assume a symmetric distribution of the trips and generate a random flow from Belgium to the study region in France. At the destination, these trips are directed towards most important agglomerations, i.e. activity zones.

Freight transport is not yet fully implemented in our model. The main reason is again the lack of an available database for these trips. Freight transport remains an important part of traffic flows since several logistic activities are taking place in the North of France. This region is crossed by the A1 motorway that connects the countries in the North (Netherlands, Belgium) to Paris and southern regions in Europe. To include representative traffic flows we produce freight transport, along the motorways crossing the study region, that matches counting data for trucks running on the corresponding links. We check that the calibrated model produces realistic patterns of congestion.

To run large-scale simulations, it is difficult to include the whole population. Each iteration would need a long time, and the calibration, which requires a large number of iterations, becomes unpractical. It is a usual practice, including in MATSim, to work with a synthetic population, instead of all [17]. The idea is to consider only a proportion of the population, uniformly drawn from the initial population, and scale down the network capacity, so that traffic congestion and public transport flows remain consistent. Several sampling levels, ranging from less than 1% to 50%, were used in our simulations (See Kilani et al. [1]). With a very small population, the simulations can be run quickly but it does not produce very representative outputs. At this level, the simulation was mainly designed for testing and checking the code. Large samples produce realistic traffic flows but require more time to run. The results reported here are produced with a 10%.

For the road network, we have used the open database provided by IGN¹, which is derived from **OpenStreetMap** databases with some corrections and standard formatting. This database provides the attributes of each link (speed limit, capacity, number of lanes, etc.) and is globally satisfactory for the road network. The road network has a large number of links that are grouped with respect to their importance (motorways, main links, secondary roads, etc.). The main limitation is the incomplete rail network which is composed of a dozen of service lines. We have then manually added the train lines, and the corresponding stations, directly in the **MATSim** format.

Public transport includes several urban bus networks, the TER (and TERGV) network, metro and tramway in Lille. The public transport fleet consists of 14748 vehicles spread over the conurbations of Lille (Fig ??), Dunkerque, Boulogne sur Mer, Calais, Valenciennes and Saint Omer, in addition to the region's rail network.

Public transport services include buses, operating at the urban and suburban areas, tramways, in Lille and Valenciennes, the two automated metro lines in Lille and the regional trains. Fast train lines also connect Lille to Dunkerque and Boulogne-sur-Mer. Most bus services are available in **GTFS** files provided by local operators. Some small local operators have not yet published the timetables of their services (Cambrai, Lens, Douai, Arras), but this does not have an important impact on simulated traffic given the relative size of the flows. The model will be updated when the corresponding data is made available.

The completed network (including roads and public transports) reflects the actual situation and is composed of 218 438 nodes and 485 072 links.

A topic issue in traffic modeling is the calibration of the model. The objective of the simulation is to produce realistic traffic flows over the study region and with respect to the set of transport modes considered (Fig ??). We focus on mode shares and optimize modes specific constants so that after several iterations the model converges to observed mode shares [1]. A plan is a sequence of activities, each one except the last, is followed by a trip (Fig. 2).

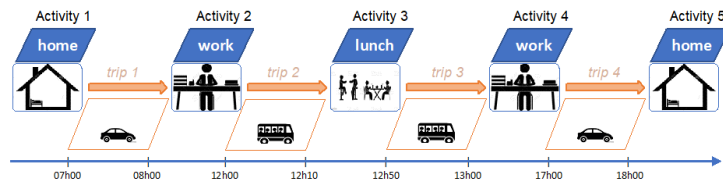


Fig. 2: Example of an agent's sequence of activities in a normal situation (car and bus journeys).

In the utility function, a constant is attached to each mode. An increase in the value of the constant increases the share of the corresponding mode

and vice versa. The utility related to an activity depends on its duration and the schedule delay cost if the user arrives early or late to the activity. Several formulations are possible to reflect the interactions between these variables.

The calibration's objective is to adjust the parameters of the model so that it replicates observed traffic flows. Usually, we focus on mode shares and travel duration. With several modes, the calibration may not be straightforward since several parameters must be adjusted smoothly and each iteration is time consuming.

The idea here is to increase (resp. decrease) the value of the shift parameter when mode m is underused (resp. overused) in the output of the last completed iteration. More sophisticated techniques to find the best values of the shift parameters can be used. We intend to improve this step in future research.

When the model produces a distribution of mode shares close to the observed distribution we check if traffic flow and travel times reflects realistic trends. In our case, the calibration process was satisfactory with respect to this test. It displays traffic flows for cars and public transport modes, and shows an important congestion on the main road links (See Figure 3).

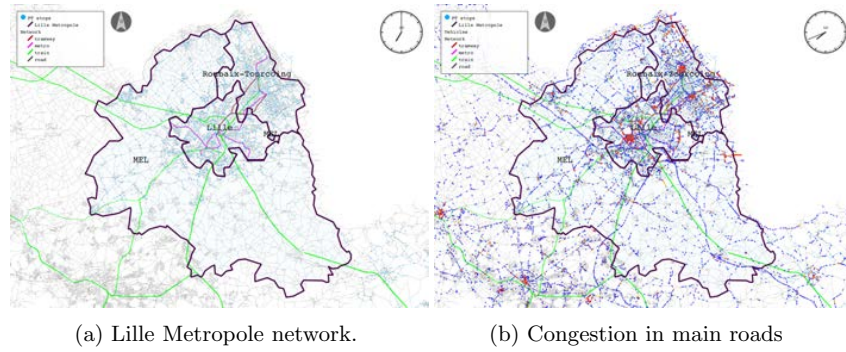


Fig. 3: Transport model focused on Lille Metropole area

3.2 Electric vehicles and charging stations

In our standard model to simulate the daily transport in the North of France (See Kilani et al [1]), the data for electric mobility is taken into account in the demand, supply and configuration parameters. In the present model, we have added the supply of charging stations and the demand for electric vehicles.

The electrical supply is materialized by the chargers defined on the network links. They include attributes on their power and the number of plugs. On the other hand, the demand lists the vehicles to be charged among the cars of the initial demand whose daily travel plans remain unchanged. The electric vehicles are also characterized by an initial state of charge, the battery capacity, and

by the type of charging to be assigned to them. Once the data is generated, the configuration parameters of the simulation will be adapted to take into account the electric vehicles that were not included in our preceding model.

The minimum charging time must be defined.

The optimization of the location of charging stations performed in the present model is based on the origin-destination matrix of car trips in the network at the regional level, noted here $trips(i, j)$. The objective of the model is to minimize the total travel distance of the cars from their origin area to the potential charging site.

We note by S , the set of potential areas for locating a charging Station and by A , the Area's set which correspond is the set of communes in the study. This implies that $S \subset A$. We impose a maximum number of different sites where the stations can be deployed. We computed the distance between a potential location $k \in S$ and an origin or destination $j \in A$ as follow :

$$dist(k, i) = \begin{cases} \text{mean distance for the cars traveling between } k \text{ and } i & \text{if } i \neq k \\ \text{mean distance for the cars traveling inside } i & \text{if } i = k \end{cases}$$

The distance is weighted by the predefined number of inter-zone trips. The considered zones represent the set of municipalities generating or receiving flows. We obtain thus the following objective function:

$$\min z = \sum_{k \in S} \sum_{(i, j) \in A \times A} \frac{trips[i, j] + trips[j, i]}{2} dist(k, i) y(k, i)$$

where $y(k, i)$ a binary variable indicating if station k is accessible to cars starting from area i .

The number of charging stations is defined as 10% of the number of electric vehicles, in accordance with European recommendations (See European Directive [8]).

The present model will have to integrate the existing fast and slow charging stations. It will simulate two different scenarios for each different market share of electric vehicles. The first scenario (a) will deal with the existing charging stations and the provisional number of vehicles in circulation in the study area. The second scenario (b) is based on the provisional number of electric vehicles and on the number of charging stations optimized to satisfy the demand (See Tab. 1). Note that we have added 100 new stations for the electric vehicles share of 0.85%, 3% and 5% to allow the model to define locations which are better than the locations of the existing stations.

4 Results

In this section we report the main results of our simulations. The actual situation is considered as a base-case scenario (subsection 4.1). We then consider an increase in the market share of electric vehicles in subsection 4.2 and optimized deployment of charging stations in subsection 4.3.

Electric vehicles share	0.85%	3%	5%	10%	20%	100%
Electric vehicles	1175	4 144	6 906	13 813	27 439	138 130
(a) Current stations	1 079	1 079	1 079	1 079	1 079	1 079
+ New stations	100	100	100	400	1 800	13 000
(b) Stations simulated	1 179	1 179	1 179	1 479	2 879	14 079

Table 1: Basic scenario (a) and scenario with optimized number of charging stations (b).

4.1 The base-case

The basic scenario of the electric model incorporates, in addition to combustion engine cars, 1 175 electric vehicles. This randomly generated sample comes from the number of cars in the previous model (See Kilani et al [1]). Indeed, 0.85 % of the car fleet in the Hauts-de-France are composed of electric vehicles and plug-in hybrids in January 2021 (See Statistiques du Développement Durable [9]). The current location of 1 666 electric vehicle charging stations is available at Open-data Réseaux-energies (See [10]). The data also provides informations on the number of slots and charging power, which are very important for the simulation of electric vehicles. The charging stations are assigned to links in the network where car traffic is possible. The assignment is based on the proximity between the charging point and the link. For the Nord-Pas-de-Calais, 1 079 charging stations are assigned to the network, of which 90 are located in the European Metropolis of Lille.

4.2 Expanding market share of VE

By integrating the actual number of electric vehicles into the transportation network, the environmental gains are relatively small. Indeed, the modal share of electric vehicles is too low (less than 1 %) to have a significant impact on pollutant emissions. The inclusion of these electric cars reduces the carbon emissions of the other vehicles (diesel and engine car) by only 2 % since their number has decreased. In addition, the current location of the charging stations does not allow for optimal charging of electric vehicles. Indeed, many vehicles are waiting for available charging stations, especially during morning and evening rush hours (See Fig. 4a). Increasing the market share of electric vehicles to 5% while keeping the same number of charging stations (See Fig. 4b) results in a 14 % decrease in pollutant emissions, which is more significant.

We will see here after, that the increase in the share of electric cars in the network must then be accompanied by the implementation of charging stations in sufficient quantity, to reduce, not only waiting times for charging, but also to reduce the polluting emission of other vehicles.

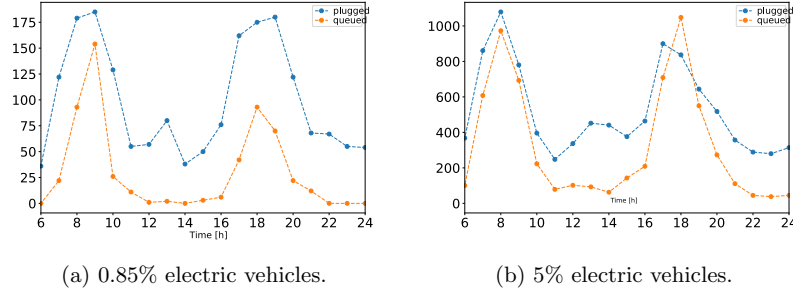


Fig. 4: Occupation of sharing stations for modal share of electric vehicles

4.3 Optimal deployment of charging stations

The increase of charging stations to satisfy electric vehicles demand is an opportunity to propose a more adequate location, based on the origin-destination flows. Indeed, previous simulations have shown that despite the low modal share of electric vehicles in the fleet, the expectations of available charging stations are high. This causes time loss for vehicles and affects congestion in general. Considering the impact of congestion on pollutant emissions, a better distribution of charging stations, in sufficient quantity (See Fig. 5 for a electric vehicles share of 10%), will reduce waiting times and the environmental consequences of combustion engine vehicles.

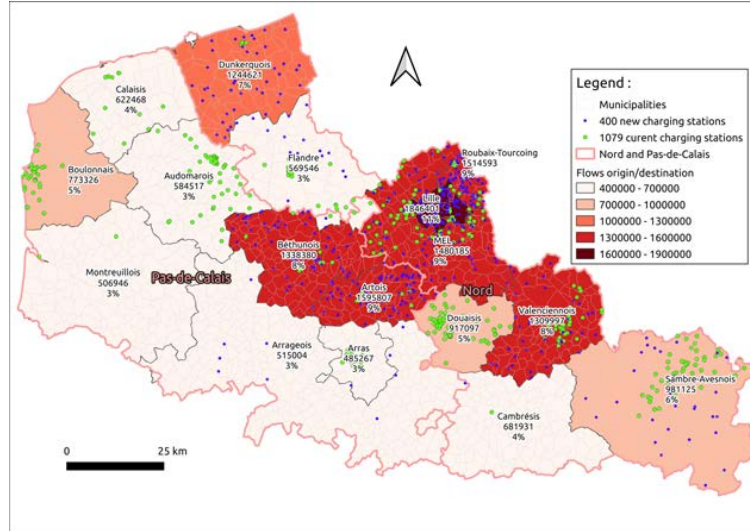


Fig. 5: Optimal charging stations proposed vs current deployed.

One of the main results of our simulation is quite suprising. The installation of new charging stations, in addition to the current ones, makes traffic flow more smoothly. This means that cars with combustion engines pollute less. For example, an optimization of the charging stations for the reference situation (0.85 % of electric vehicles), results in a 2.3 % decrease in fuel consumption and pollutant emissions (CO₂ and PM). Moreover, the decrease in emissions and fuel consumption is even greater as the penetration of electric vehicles increases. Table Tab. 2 presents the reduction the emissions of CO₂, PM obtained when comparing the emissions of this polluting gas with the actual number of charging stations with the optimized number and locations of charging stations. The same comparison is made for the fuel consumption of the vehicles.

Electrical vehicles share	Impacts in %		
	CO ₂	PM	FUEL
0.85%	-2.31	-2.16	-2.27
3.0%	-9.69	-8.94	-9.49
5.0%	-14.22	-13.15	-13.89
10.0%	-28.46	-26.40	-27.90
20.0%	-48.70	-45.44	-47.82

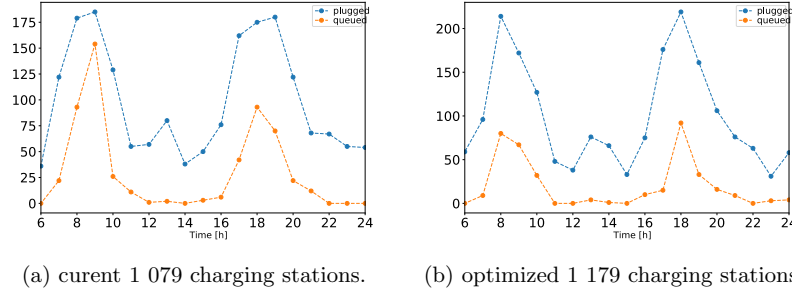
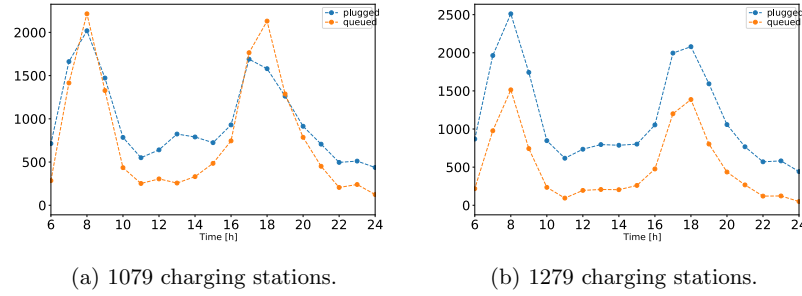
Table 2: Reduction of CO₂ and PM emissions and of fuel consumption when optimizing the number and locations of charging stations

In addition to the environmental benefits, the effect of optimizing charging stations is most felt in the reduction of waiting times for electric vehicles at free charging stations. In the reference scenario (0.85%), an optimal allocation of 100 additional charging stations in the North of France halves the morning peak waiting time and increases the number of vehicles charging (See Fig. 6).

The optimization of the location of new charging stations is more significant when considering the evolution of the modal share of electric vehicles. For example, with the current location of the charging stations, a simulation of 10% of electric vehicles results in more cars waiting for free charging stations than charging vehicles (See Fig. 7a). The optimal allocation of 300 additional charging stations reverses the situation (See Fig. 7b), with a 30% decrease in vehicles waiting to charge and a 25% increase in vehicles charging.

5 Conclusion

We have developed a model of transport simulation that includes several transport modes, including electric vehicles. The transport model has been coupled

**Fig. 6:** Occupation of charging stations for 0.85% modal share electric vehicles.**Fig. 7:** Occupation of charging stations for 10% modal share electric vehicles.

with an optimization module to find the most efficient locations of the charging stations. Our analysis has shown that, given the expected increase in the market share of electric vehicles, the public authorities and involved operators should be careful in the planning the location of charging stations to support energy transition policies. A non optimized deployment of the stations may generate extra traffic that increases congestion and pollution, since travel speed decreases even for cars equipped with combustion engines.

Indeed, an optimization of the number and of the location of charging stations produces two positive impacts. The first one is a direct impact for the users of electric vehicles. With no planning of new recharging stations, there will be more waiting vehicles for a free recharging station than vehicles loading even for small market share of electrical vehicles. The second positive impact is indirect to non electric vehicles. When optimizing the number and the location of charging stations, the traffic of other vehicles is smoother and there is an important reduction of emissions of polluting gases of other vehicles (28 % of reduction of CO₂ emission for only 10% of market share of electrical vehicles).

The model can be extended in several directions. In particular, one may consider a broader scope where several competing firms are choosing the locations of their charging stations. It is important to see whether competition improves the deployment of charging stations and how it compares with optimized one. A second extension that we plan to address in a future research is to improve the possibility of combining several transport modes for a given trip. Electric and light vehicles are particularly interesting in this case. Indeed, they could be used to feeder to a mass transport system that connect efficiently suburban areas to city center.

Acknowledgments.

Declarations

Some journals require declarations to be submitted in a standardised format. Please check the Instructions for Authors of the journal to which you are submitting to see if you need to complete this section. If yes, your manuscript must contain the following sections under the heading ‘Declarations’:

- Funding: ANR (Agence Nationale de la Recherche) under project fund ANR-21-HDF1-0014.
- Conflict of interest/Competing interests: None.
- Ethics approval: Not applicable.
- Consent to participate: Not applicable.
- Consent for publication: Not applicable
- Availability of data and materials: Data available in a publicly accessible repository. The data presented in this study are openly available at <https://murdasp.univ-littoral.fr>
- Code availability: Not applicable.
- Authors’ contributions: The three authors were directly involved in the analysis and in writing the paper.

If any of the sections are not relevant to your manuscript, please include the heading and write ‘Not applicable’ for that section.

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