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RESEARCH ARTICLE

Environmental impacts of enlarging the market share of electric vehicles

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Abstract
We extend a multimodal transport model to simulate an increase of the market share of electric vehicles. The model, which is described in detail in Kilani et al. (Sustainability 14(3):1535, 2022), covers the north of France and includes both urban and intercity trips. It is a multi-agents simulation based on the MATsim framework and calibrated on observed traffic flows. We find that the emissions of pollutant gases decrease in comparable proportion to the market share of the electric vehicles. When only users with shorter trips switch to electric vehicles, the impact is limited and demand for charging stations is small since most users will charge by night at home. When the government is able to target users with longer trips, the impact can be higher by more than a factor of two. But, in this case, our model shows that it is important to increase the number of charging stations with an optimized deployment for their accessibility.

Keywords Transport modeling and simulation · Electric vehicles · Deployment of charging stations · Local pollution · North of France · Spatial distribution · Decision support · CO_2 emissions

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1 Introduction

The first prototypes of electric vehicles were developed and used in the nineteenth century, but their market share remained negligible until recently. In fact, electric vehicles in France currently represent a small share of the market with 0.85%, but when we look at registrations over the past 2 years, we observe an exponential curve (see Fig. 1, data is limited to October 2021 from https://www.avere-france.org/publication/barometre-malgre-la-crise-les-vehicules-electriques-et-hybrides-rechargeables-poursuivent-leur-progression/.

The charging time of the batteries and their low autonomy are thought to be the main features that have prevented large-scale deployment of electric cars (see Rouhana and Saber 2020). 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 an important increase in several European countries and worldwide. 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) during use. While some skepticism is pointed out with respect to the production of batteries and electric engines, which are based on

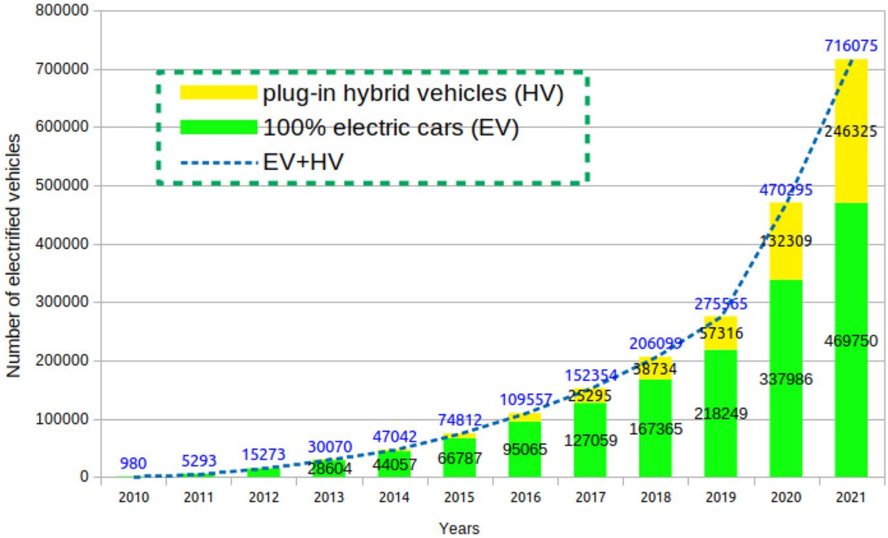

Fig. 1 Evolution of electric vehicle registrations in France

materials whose extraction is polluting, local policies generally focus 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 Kilani et al. (2022). The model includes four modes "walk" "bike", "car" and "public transport" and covers the north of France. 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 cars. We are particularly interested in the spatial deployment of charging stations and the extent to which it may affect polluting gas emissions and energy consumption. We then distinguish between a scenario (a) where the charging stations follow the observed actual locations and another scenario (b) where the deployment is optimized to improve accessibility to these stations.

Our analysis highlights the importance of (*i*) the traveled distance made by the users who switch to electric vehicles, and (*ii*) the optimal deployment of charging stations. Switching to electric cars reduces the emissions of pollutant gases (and fuel consumption) and the magnitude of this impact depends on the travel distance made by the cars that switch to electric energy. When only users with smaller distances switch to electric vehicles, the impact on emissions, as well as the demand for charging stations, is limited. Indeed, in this case most users can charge by night at home and do not need further energy for their daily trips. When the government is able to set incentives to target users with longer daily traveled distances, the impact on emissions can be much more important, but at the same time, the demand for charging stations increases significantly. The waiting time to access charging facilities are high and several users need to run extra trips to find charging stations. These trips are new sources of external costs. Our model shows that it is then important to increase the number of charging stations, and the geographical locations of these stations should be optimized to improve their accessibility. Otherwise, our model shows that congestion increases and the emissions of other vehicles also increase.

To find the optimal locations of charging stations, we formulate and solve a simplified network optimization problem using +Cplex+, a solver developed by IBM that implements the Simplex and the branch and bound method in the C language (see Anand et al. 2017) The objective of the problem is to minimize the total distance to charging stations and the constraints reflect realistic requirements in the process (each car should find a charging station, the number of charging stations is limited).

The paper is organized as follows. Section 2 reviews others 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 (see Kilani et al. 2022) and describes how electric vehicles are taken into account in our transport model. The results of our analysis are reported in Sect. 4. Finally, we conclude the paper in Sect. 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 (see Xi et al. 2013). After subdividing the Ohio region into sub-regions, which can correspond to communes in the case of the north of France, Xi et al. (2013) adopted a three-step approach. First, they determine the probability of owning an electric vehicle for an agent based on the socio-demographic and macroeconomic data for the sub-region. Second, they determine the flows of electric vehicles between the sub-regions. Then, they develop a simulation model of the vehicles that are likely to be charged at potential charging stations based on the numbers of outlets. Finally, they use a linear programming model to determine the location and size of the charging stations.

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 (see Kaddoura et al. 2017). The combination of these transport models with vehicle emission models can be used to identify relevant policies that can be used by local authorities (see Kickhöfer and Nagel 2016). The model used in MATsim and adopted in our anlysis is based on the Handbook on Emission Factors for Road Transport (HBEFA). More details on the implementation of the model are reported in Kickhöfer et al. (2013).

Agent-based models operate at the level of the individual who chooses its transport mode, its route between the origin–destinations pairs and its departure time. These agents are allowed to change their decisions when they are offered better alternatives. Since all trip information ia 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 within 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 to vehicles that run on fossil energies. One of the most elaborate case studies that has considered electric mobility in Sweden is reported in Bischoff et al. (2019). The model considers freight and person transport. The data are collected from GTFS (General Transit Feed Specification) and OSM (OpenStreetMap) data files.

In general, the automotive industry is expanding to satisfy the human addiction to private cars. As far as electric vehicles are concerned, there has been several major innovations in the recent years, and 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) have been for a long time blocking points. A large research effort has been deployed with respect to these issues (see Rouhana and Saber 2020).

There exist three main charging technologies (see Xi et al. 2013). Level 1 batteries use a standard wall outlet producing a 110V/15A connection. The power provided by these batteries varies from 16 to 25 kWh, and full charging time varies from 12 to 18 h. Level 2 batteries use more powerful circuits, generally based on 220 V between 15 and 30 A. Level 3 quick charge uses a continuous electricity under a high-voltage system (400–500 V), 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 due to technical problems with high voltage. On the other hand, at home, the recharging time is not a problem because the vehicles can stay for a sufficient time at night to recharge on a slow plug.

For example, for a lithium–ion battery with capacity 22 kWh, the charging duration is between 3 and 8 h in single phase alternating current with power 3.7 kW and voltage 230 V, 16–32 A. With three-phases current, the charging time drops to 1–2.5 h with a voltage of 400 V, and could even be in 20–30 min 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 h, but 80% charging could take about 30 min using the most advanced technologies (see De Wolf and Smeers 2018).

Charging stations are either private, generally located at hotels and shopping malls, or public such as those located in motorways, in particular the quick charging stations. The accessibility of a charging station is a main factor to improve its 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 (see Xi et al. 2013). Slow charging stations are convenient when located at home, where charging of the private car is processed at night, but requires that the houses are equipped with a private parking space. 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. The spatial distribution of existing stations can be observed in Fig. 8 (green points), and a more detailed discussion of the relation between this distribution and households' welfare is given in Frotey and Castex (2017).

A further difficulty in the deployment of charging stations is the interoperability of the used equipment. If each operator uses a specific and nonstandard system of plugin, the attractiveness of the charging stations will be limited. Broadly speaking, this will not favor 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 have not 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. 2015).

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 to maximize the service level (see Xi et al. 2013). These authors adopted a three-step approach, after subdividing the Ohio region into sub-regions, which may correspond to communes in the case of the north of 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 vehicle 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. 2013). The objective is to minimize the costs of access to the infrastructure computed by the distance traveled.

Li et al. (2016) integrate the monitoring of the state of charge of vehicles into the charging station location model. Moreso (2017) 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).

By taking into account the fleet of electric vehicles in the transport model, we can evaluate the environmental benefits concerning the reduction in GHG and fine particles, and the decrease in consumption of fossil fuel energy. The evaluation of these impacts is based on the traveled distances, vehicles speeds and the emission profiles of the existing vehicles (see Márquez-Fernández et al. 2019), and the information on the vehicles entering and exiting the network links. This allows us to evaluate the energy consumption of all the vehicles and update the battery charge levels of the electric vehicles. The details of these computations are handled within the `MATSim` framework.

Fig. 2 The Nord Pas de Calais

3 The transport model

We start by briefly describing the simulation framework (Sect. 3.1) and then we discuss how electric vehicles are taken into account (Sect. 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. A detailed description of this model is given in Kilani et al. (2022). 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 private cars. For example, Lille was the first city worldwide to implement a fully automated metro line in the early 80s 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, Calais, Boulogne-sur-Mer and Arras (see Fig. 2). The historical mining activities explain part of the trip patterns observed between the mining area and other cities, Lille, in particular.

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

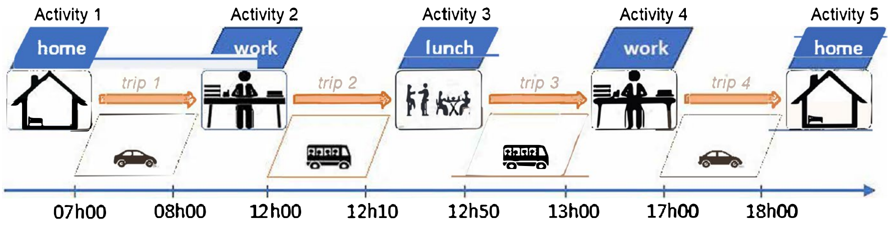

Fig. 3 Example of an agent's sequence of activities in a normal situation (car and bus journeys)

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, Dourge which is located in the south of of Lille).

As previously said, the model includes four modes "walk", "bike", "car" and "public transport", and allows for their combinations (to some extent). For instance, the model does not include shared mobility, but we plan to include this feature, at least partially, in the near future. Both urban and intercity trips are condidered. Survey data from the Regional Household survey of 2016 is used to build daily trips (see Fig. 3 for a agent's typical sequence of activities).

The usage of the private car is the dominant mode, and most short trips, less than 1 km, are made by walk. Public transport modes are used for urban (bus and metro) and intercity (train) trips. Other modes, like intercity buses, have a very small share and are not reported here. The data we use cover 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" (see Fig. 3 for a typical sequence of activities). These values are reported for the whole population and should, of course, significantly differ when we focus on specific group with respect to age or jobs 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 toward 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`,[1] to work with a synthetic population instead of the whole population (see Ben-Dor et al. 2021). 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 1–50%, were used in the simulations (see Kilani et al. 2022). With a very small population, the simulations can be run quickly but it does not produce very representative outputs. At this level, the simulation were 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 Institut Géographique National[2], 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 in this database 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 14 748 vehicles spread over the conurbations of Lille, Dunkerque, Boulogne sur Mer, Calais, Valenciennes and Saint Omer (see Fig. 2), 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 connecting the main agglomerations. Fast train lines also connect Lille to Dunkerque and Boulogne-sur-Mer. Most bus services are available in `GTFS` files provided by local operators (the latest version of this data is dated

[1] `MATSim` is a large-scale simulator that has been used for several cities around the world (https://www.matsim.org/). A general reference for this simulation framework is Horni et al. (2016).

[2] https://geoservices.ign.fr/ consulted on March 2020

March 2020). 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 relatively small size of these flows. The model will be updated when the corresponding data will be 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. We focus on mode shares and optimize modes specific constants so that after several iterations the model converges to observed mode shares (see Kilani et al. 2022). A plan is a sequence of activities, each one except the last, is followed by a trip (see Fig. 3).

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 Fig. 4 for the traffic at 7 h and Fig. 5 for the traffic at 7:45).

3.2 Electric vehicles and charging stations

In our previous model, to simulate the daily transport in the north of France (see Kilani et al. 2022), the data for electric mobility were not taken into account. 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 the initial model.

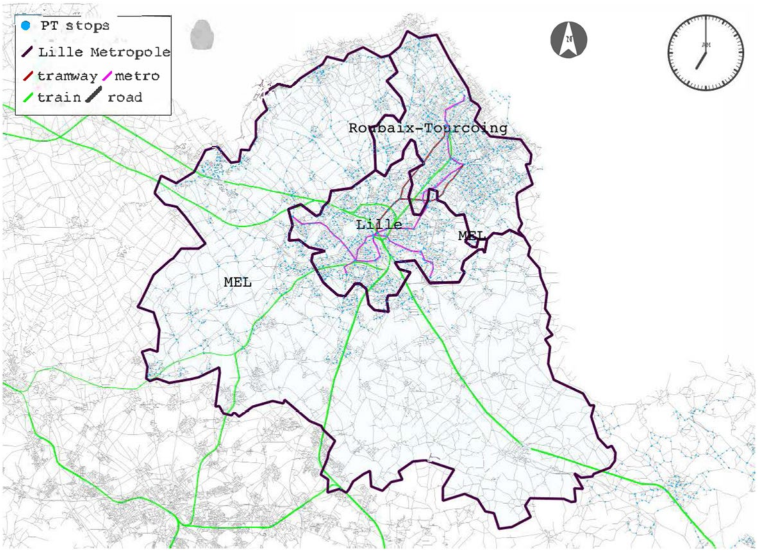

Fig. 4 Lille Metropole network

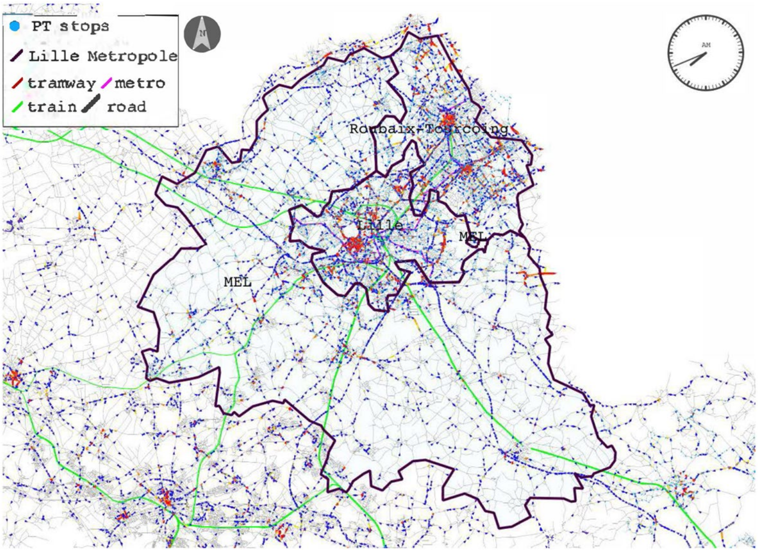

Fig. 5 Congestion in the main roads

Depending on the network characteristics, we need to set a minimum charging time before a vehicle continues its journey. We set this value to 25 min that corresponds to currently available technologies. The optimization of the location of charging stations performed in the present model is based on the origin–destination

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

Electric vehicles share	0.85%	3%	5%	10%	20%	100%
Electric vehicles	1175	4144	6906	13,813	27, 439	138,130
(a) Current stations	1079	1079	1079	1079	1079	1079
+ New stations	100	100	100	400	1800	13,000
(b) Stations simulated	1179	1179	1179	1479	2879	14,079

matrix of car trips in the network at the regional level, that we denote as $trips(i, j)$. The objective of the model is to minimize the total travel distance of the cars from their origin area i to the potential charging site k.

Let S denote 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 sites where the stations can be deployed. We compute the distance between a potential location $k \in S$ and an origin or destination $i \in A$ as follow :

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

We define $y(k, i)$ a binary variable indicating if station k is used by cars starting from area i or arriving to area i. The distance is weighted by the total number of interzone trips starting from i or arriving to i. The considered zones represent the set of municipalities generating or receiving flows. We obtain thus the following objective function:

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

The number of charging stations is set to 10% of the total number of electric vehicles, in accordance with European recommendations.[3]

The present model will have to integrate the existing fast and slow charging stations. It will simulate two different scenarios for each market share of electric vehicles. The first scenario (a) will deal with the existing charging stations and the previsional number of vehicles in circulation in the study area. The second scenario (b) is based on the previsional number of electric vehicles and on the number of charging stations optimized to satisfy the demand (see Table 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.

Regarding the choice of the 1175 vehicles that switch to electricity, we initially chose them randomly. Obviously with the 1079 charging stations available, even if they are not optimally located, no queues are formed at these charging stations since

[3] See European Directive at https://eur-lex.europa.eu/legal-content/FR/TXT/PDF/?uri=CELEX:32014L0094&rid=1

most trips are less than the autonomy of the batteries of the vehicles. In this case, charging at home by night is generally sufficient for the daily trips. Also, to force the use of charging stations by new electric vehicles, we have decided to allocate electric vehicles to agents with the greatest travel distances. So when we say 10% of electric vehicles in Table 1, we mean the 10% with the greatest travel distance switch to electricity.

4 Results

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

4.1 The base-case

The basic scenario of the electric model incorporates, in addition to combustion engine cars, 1175 electric vehicles. As stated above, the sample is not generated randomly from the number of cars in the previous model, but we choose the agents with the greatest travel distances. Indeed, 0.85% of the car fleet in the Hauts-de-France are composed of electric vehicles and plug-in hybrids in January 2021.[4] The current location of 1079 electric vehicle charging stations is available at Open-data Rseaux-energies[5]. The data also provides useful information 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, 1079 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 benefits 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 2.26% since their number has decreased (see Table 2). Recall that the multiplicative effect is due to our choice of agents with the greatest travel distances. This explains why, for example, 0.85% of electric vehicles allows more than 2% of CO_2 reduction. The multiplicative effect obviously comes

[4] See Statistiques du Dveloppement Durable at https://www.statistiques.developpement-durable.gouv.fr/donnees-sur-le-parc-automobile-francais-au-1er-janvier-2021

[5] https://opendata.reseaux-energies.fr

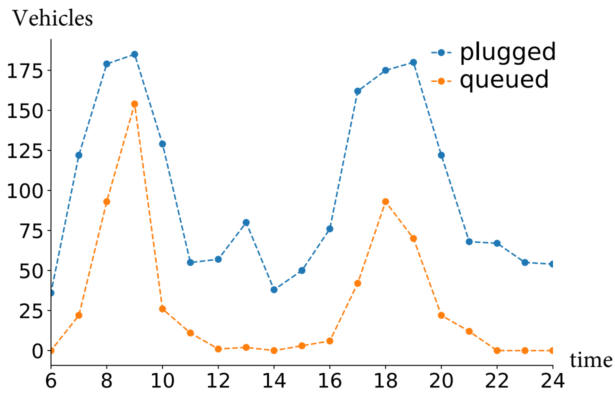

Fig. 6 Occupation of charging stations for 0.85% electric vehicles

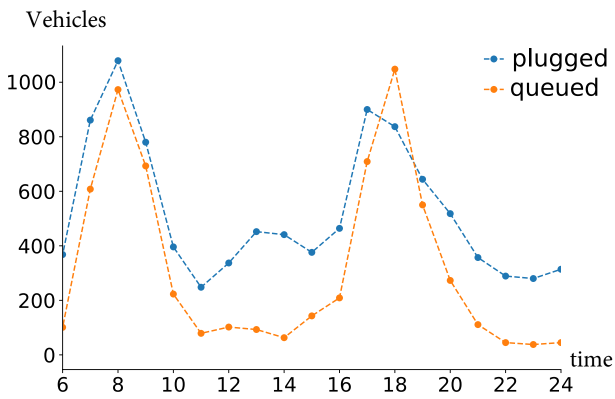

Fig. 7 Occupation of charging stations for 5% electric vehicles

from the fact that the vehicles emitting the most CO_2 are chosen. In addition, the current location of the charging stations does not allow for optimal charging process of electric vehicles. Indeed, many vehicles are waiting for available charging stations, especially during morning and evening rush hours (see Fig. 6). Increasing the market share of electric vehicles to 5% while keeping the same number of charging stations (see Fig. 7) yields 12.45% decrease in CO_2 emissions, which is more significant.

4.3 Optimal deployment of charging stations

We will now show that it is important that the deployment of new charging stations takes into account existing traffic flows. Indeed, as we observed in the previous simulation, the number of waiting cars can be large making the whole charging process time consuming and tedious. In such situations, some users may

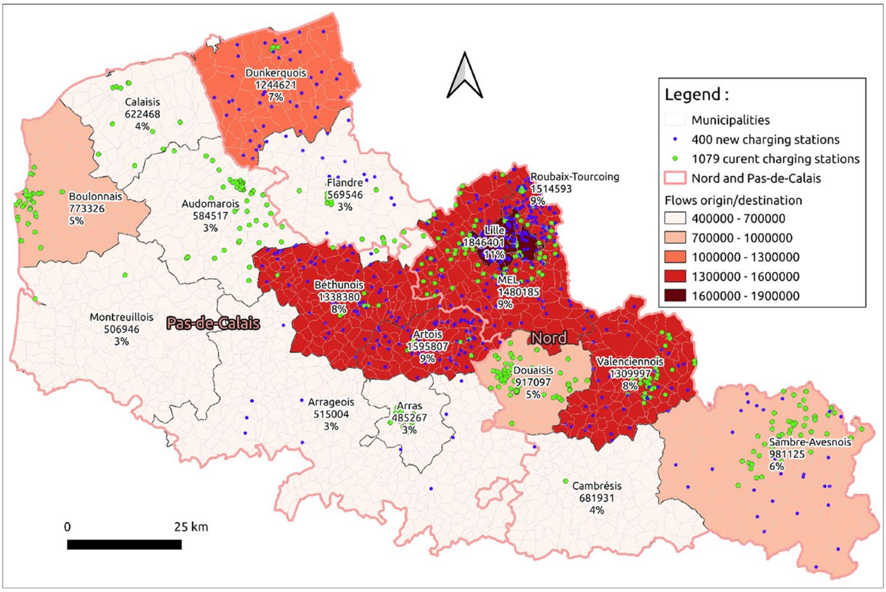

Fig. 8 Optimal charging stations proposed vs current deployed

Table 2 Reduction of CO_2 and PM emissions and of fuel consumption when optimizing the number and locations of charging stations

Electrical vehicles share	Impacts in %		
	CO_2 Scenarios *a*/*b*	PM Scenarios *a*/*b*	FUEL Scenarios *a*/*b*
0.85%	– 2.26/– 2.31	– 2.11/– 2.16	– 2.24/– 2.27
3.0%	– 8.84/– 9.69	– 8.21/– 8.94	– 8.70/– 9.49
5.0%	– 12.45/– 14.22	– 11.58/– 13.15	– 12.40/– 13.89
10.0%	– 22.10/– 28.46	– 20.81/– 26.40	– 22.00/– 27.90
20.0%	– 33.10/– 48.70	– 31.11/– 45.44	– 32.19/– 47.82

In each case, the percentage of replacement targets users with longest travel distances and this yields the multiplicative impacts

drive to far away charging stations generating a supplementary traffic, inducing high external costs, that can be controlled and limited if the charging stations are located efficiently. Considering the impact of congestion on pollutant emissions, a better distribution of charging stations, in sufficient quantity (see Fig. 8 for a electric vehicles share of 10%), will reduce waiting times and the environmental consequences of combustion engine vehicles.

One of the main results of our simulation is quite surprising. The installation of new charging stations, in addition to the current ones, makes traffic flow smoother. 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 2.31% decrease in CO_2 emmissions (see Table 2, scenario b).

Recall that the decrease in emissions and fuel consumption is greater as the penetration of electric vehicles increases due to our particular choice of agent. Table 2 reports the impacts of the increase in the number of electric vehicles when the number of charging stations are unchanged (scenario *a*), and when new charging stations are deployed with optimized locations (scenario *b*). There are several pollutant gases, but their values are generally well correlated. For a representative picture, we only report values of carbon dioxide emissions (CO_2), a greenhouse gas, and emissions of particulate matter (PM), fine particles. We start with a market share of electric vehicles equal to 0.85%, that corresponds to the actual situation, and then consider several higher values to evaluate the impact of larger market shares up to 20% (see Table 2).

In each case, Table 2 reports the impacts on emissions and fuel consumption for Scenario (*a*) and Scenario (*b*). We may first notice the high correlation between CO_2 emissions, PM emissions and fuel consumption. This is because fossil fuels are the main sources of all pollutant gases, and not only those reported in Table 2. When the number of electric vehicles is small, and as expected, the supply of new charging station and their optimized localization are not that important as impacts under both scenarios are quite similar. But, as the market share of electric vehicles increases, the impacts for Scenario (*b*) are significantly better than those for Scenario (*a*). Indeed, even if the deployment of new charging station does not seem to be a major issue in the actual situation, it will play a key role in the development of the market of electric vehicles. We must also remind that value for Table 2 are obtained on the basis that the switch to electric vehicles is made by the users who have the longest travel distances. We did not report here the values for cases where users switch to electric vehicles independently with their daily travel distances, but the impacts are of comparable magnitudes to the market share of electric vehicles, e.g. a 10% market share of electric cars will lead to a reduction of emissions and fuel consumption to about 10% (unit elasticity). When only short distance users switch to electric vehicles the impacts are of smaller values, and charging stations are less used.

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 (compare Fig. 9 and Fig. 10).

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. 11). The optimal allocation of 400 additional charging stations reverses the situation (see Fig. 12), with a 30% decrease in vehicles waiting to charge and a 25% increase in vehicles charging.

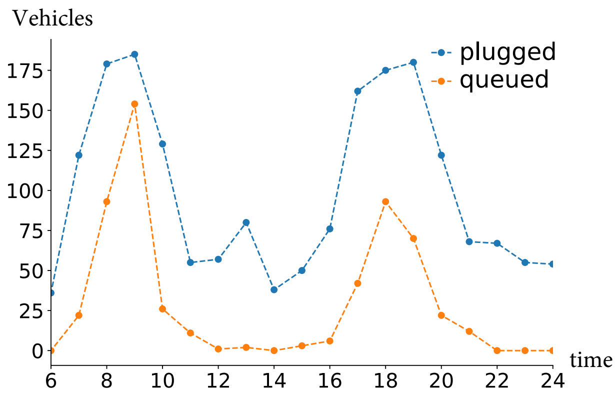

Fig. 9 Occupation of the curent 1079 charging stations for 0.85% modal share

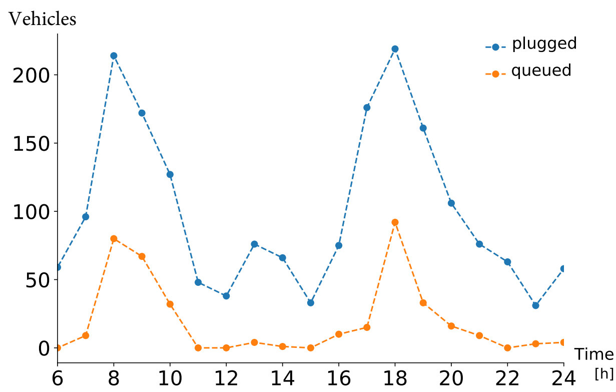

Fig. 10 Occupation of the optimized 1179 charging stations for 0.85% modal share

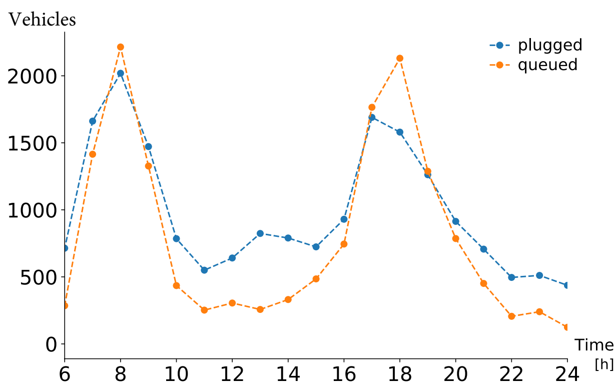

Fig. 11 Occupation of 1079 charging stations for 10% modal share

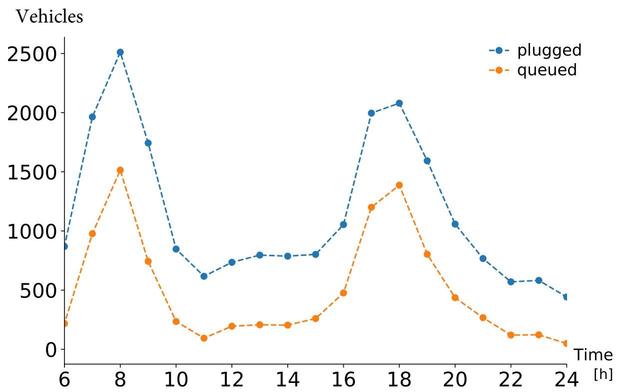

Fig. 12 Occupation of 1479 charging stations for 10% modal share

5 Conclusion

We have developed a model of transport simulation that includes several transport modes, including electric vehicles. The model covers a large area in the north of France with both urban and intercity trips. The transport model was combined 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, public authorities and involved operators should be careful when planning the location of charging stations to support energy transition policies.

Our results show that the traveled distance of the users who switch to electric cars is a main factor for the positive impact on this energy transition. Indeed, if the users who switch to electric cars have daily short trips (as one may comment the actual situation), the impacts on the emissions of pollutant gases and fossil fuel consumption will be small; more precisely, it will be significantly smaller than the proportion of users who switch to electric vehicles. Public policies aiming at ambitious environmental objectives need to target users with important daily traveled distance. This group of users is less likely to switch to electric vehicles for instance and given the available technologies. Specific incentives should be provided for this group of users and for the producers of electric vehicles to improve their supply of electric vehicles with large autonomy. In this case, however, the demand for charging stations will increase significantly. Without new charging stations, users will need to wait for a long time in queue to access the charging stations. They may consider using more available charging stations that are far away from their routes, diverting some traffic which may increase congestion and emissions. So, it is important in this case to increase the number of charging stations with optimized locations.

Indeed, an optimization of the number and of the locations of charging stations produces two positive impacts. The first one is a direct impact for the users of electric vehicles. With no planning of the new recharging stations, there will be more waiting vehicles for a free charging station than vehicles loading even for small market share of electrical vehicles. The second positive impact is indirect to nonelectric 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 CO_2 emission for only 10% of market share of electrical vehicles).

The model can be extended in some interesting directions. In particular, one may consider a broader scope where several competing firms choose the locations of their charging stations. It is important to see whether competition improves the deployment of charging stations and how it compares with the 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 as feeder to a mass transport system that connects suburban areas to the city center. Finally, for a more advanced examination of electric mobility, it will be interesting to include shared modes, a feature that we plan to consider in the near future.

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Code availability Not applicable

Declarations

Conflict of interest None.

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

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