batteries

Article

Battery Sharing: A Feasibility Analysis through Simulation

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Abstract: Nowadays, several alternatives to internal combustion engines are being proposed in order to reduce CO_2 emissions in freight transportation and citizen mobility. According to many experts, the use of electric vehicles constitutes one of the most promising alternatives for achieving the desirable reductions in emissions. However, popularization of these vehicles is being slowed by long recharging times and the low availability of recharging stations. One possible solution to this issue is to employ the concept of battery sharing or battery swapping. This concept is supported by important industrial partners, such as Eni in Italy, Ample in the US, and Shell in the UK. This paper supports the introduction of battery swapping practices by analyzing their effects. A discrete-event simulation model is employed for this study. The obtained results show that battery sharing practices are not just a more environmentally and socially friendly solution, but also one that can be highly beneficial for reducing traffic congestion.

Keywords: electric vehicles; mobility; battery sharing; battery swapping; discrete-event simulation

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1. Introduction

Electric vehicles (EVs) are among the most prominent and valid alternatives to internal combustion-based vehicles [1,2]. Even in industrialized and technologically advanced countries, some customers are insecure regarding the transition to EVs [3]. Some studies have assessed the life cycle of EVs and have concluded that greenhouse gas emissions are reduced when these vehicles are employed [4,5]. The life cycle of EVs includes their production, use, and recycling. However, toxicity level increases because of the higher exposure to chemicals and metals during the life cycle of EVs [4]. The initial cost of EVs is expected to be higher than conventional diesel or petrol vehicles. Still, in the long run, the cost of powering them is found to be much cheaper [6,7]. In addition, hydrogen vehicles seem to be an alternative in practice, but unfortunately they are still expensive to refuel. This is due to the fact that hydrogen is expensive to produce and refine [8]. They are similar in design to EVs, since they are also powered by fuel cells, which are characterized by an anode, a cathode, and a catalyst that triggers the separation of protons and electrons. Electrons are removed from the hydrogen, sent to the power motor, and combined with oxygen to form water vapor. The energy generated can be used both to power the electric engine directly or to recharge small lithium-ion batteries, which allows the vehicle to store the energy for later use.

Despite of their huge potential, the large-scale dissemination of EVs is hindered by low efficiency and long charging times. Charging times vary depending on the technology [9] used. These can range from around half an hour to several hours. Waiting for about half an hour (or even more) for vehicles to recharge is not handy, realistic, or compliant with modern commercial transportation requirements, including the car-sharing and ride-sharing mobility modes. In addition, charging at home is not an option for EV users that do not have home charger. Some representatives of the automotive sector and battery manufacturers are working to provide valid alternatives to lithium-ion batteries in terms of duration and charging time. However, this will require big investments and a consistent research effort.

To the best of our knowledge, given the urgency and rapid changes required, a more straightforward solution relies on the concept of battery sharing (BS) [10,11], which is also known as battery swapping. This refers to a situation where drivers of EVs, once arrived at a charging station, remove exhausted batteries and replace them with the charged batteries previously left by somebody else. This approach might be more convenient [12], and it gives rise to a scenario that may be enhanced by previously developed technologies provided by companies such as Ample in the US, Eni in Italy, or NIO in China.

The considered BS scenario has several requirements. First of all, batteries need to be standard or clustered in as few categories as possible. Secondly, they must be redistributed, since there might be more vehicles traveling in one direction rather than the other. Whenever these requirements are correctly fulfilled, BS may lead to an increase in efficiency of commercial travel, a reduction in waiting times at charging stations, and a more handy and user-friendly way to use EVs [13].

Battery sharing is also a more environmentally and socially friendly scenario for the following reasons:

- The service life of batteries is decoupled from the service life of vehicles. In this way, the use of batteries might significantly increase.
- Batteries would be managed by a few easy-to-control companies, thus reducing the risk of illegal disposal.
- The need to redistribute batteries may give rise to many new job positions.

The main goal of this work is to study the performance of some indicators when a BS strategy is employed. For this, we use a discrete-event simulation model that allows us to measure the benefits of employing such a strategy and gain insight into how BS can support the popularization of EVs. The remaining sections are distributed as follows. Section 2 discusses the current state of the art on EVs and battery sharing. Then, Section 3 introduces the main components and the architecture of our simulation model. This simulation model is available at https://github.com/mattianeroni/batteryswap (accessed on 8 April 2023). Section 4 describes the algorithms incorporated into the simulation, which allows the reader to better understand how it works. In Section 5, the BS scenario is validated and compared to a classic approach with no sharing in several road networks across Europe and considering dynamic conditions. Finally, conclusions and future research perspectives are discussed in Section 6.

2. Related Work

Researcher interest in studying energy consumption has increased exponentially during the last decade. According to the Scopus database, 205, 540 documents have been published between 2010 and 2022 concerning energy consumption. This trend is associated with the energy crisis, increased energy demand, and rising energy prices. Many of these documents focused on studying models to estimate energy consumption and investigate solutions to reduce this consumption. One of these solutions is to utilize EVs. These vehicles can substitute traditional fossil fuel vehicles and can also include so-called unmanned aerial vehicles (drones). EVs have a significant role in diminishing environmental pollution and counterbalancing the effects of fossil fuel-based energy [4,14]. However, there are several obstacles that make it difficult to complete the transition to sustainable transportation by utilizing electric power systems. These include the potential increase in electric power demand beyond current generation capabilities and the continued use of fossil fuel-based electric energy sources in the industry [15]. In addition, while EVs are emission-free, the batteries used in them are not environmentally clean in terms of production. Furthermore, an increase in EV penetration can lead to a rise in peak load demand due to unexpected individual EV charging times, which implies that more power plants must be constructed to maintain grid stability. There are several factors that influence consumer perception, such as the limited drive range [14] and extended charging time of EVs [9,16]. International standards have been defined to regulate the charging process of EVs, such as SAE J1772 and IEC 61851-1 [17]. For example, the IEC 61851-1 standard classifies charging systems in Europe and some other countries into four modes. Each mode defines the charging power, protection installation, and socket type.

Sanguesa et al. [2] reviewed batteries and their technology in EVs. These authors highlighted several battery characteristics, such as their capacity, energy density, specific power, life span, internal resistance, and efficacy. These characteristics depend on the battery technology. One of oldest and most widely used types of batteries is the lead-acid battery [2,18]. Because of the low energy density of lead-acid batteries [19], the battery industry faced developments in battery technology, and new types of batteries were developed, such as lithium-ion batteries [2,5] and zinc-nickel batteries [19]. Researchers have compared between the developed battery types and investigated possible improvements in their characteristics [2,19,20].

In recent times, various models for analyzing energy consumption of EVs have been established in the scientific literature. These models generally involve the examination of real-world data and investigating the impact of various factors on the energy consumption of EVs. Li et al. [21] employ a design of experiments to analyze the statistical significance of various factors that affect the energy consumption of EVs. Despite the large number of potential factors, their study focuses on four factors and their interactions, utilizing an empirical approach that has been tested with a real-world case. The results indicate that the use of heating, ventilation, as well as air conditioning and topography has the greatest impact on energy consumption compared to other factors. Yang et al. [22] investigate the impact of the road tilt angle on the energy consumption of EVs. Their study quantifies how the energy consumption increases as the tilt angle of the road increases on uphill sections and decreases on downhill sections. In another work, Mediouni et al. [23] propose a machine learning model for the prediction of the energy consumption based on vehicle speed and acceleration, road tilt angel, road coefficient of rolling resistance, wind speed, and extra weight carried in vehicles. Fiori et al. [14] present the Virginia Tech comprehensive power-based EV energy consumption model (VT-CPEM) as a solution to enhance the limited driving range and harness the energy obtained during braking. The proposed model is an EV energy model that utilizes instantaneous data—such as vehicle speed, acceleration, and roadway grade—to calculate the energy consumption of the vehicle for a specific driving cycle. Chen et al. [24] emphasize the significance of predicting future driving conditions such as vehicle speed, recognizing driving styles and patterns, or anticipating terrain information. They use this information to optimize energy consumption. Neural networks, which are primarily utilized for route and driving pattern recognition, are presented as the most promising equivalent factor adaptation methods for energy consumption management systems in EVs. Moreover, machine learning techniques are shown to have the capability to enhance control decisions through the use of historical and real-time driving data. Wu et al. [25] propose a system for collecting in-use EV data. The system collected and analyzed approximately 5 months of data. It was found that providing the driver with timely information on energy usage could lead to conscious adjustments in driving behavior, which in turn results in a reduction in energy consumption. An analytical model is also presented to estimate the instantaneous power and trip energy consumption in real time. It is based on the principles of vehicle dynamics and the correlation among various essential variables. The authors concluded that driving on urban city streets requires less power compared to driving on freeways—notice that this differs from the typical behavior of internal combustion vehicles. Wager et al. [26] studied energy consumption and driving range of EVs under the influence of various parameters using mathematical modeling. They found that the driving range is significantly reduced under high speed, as well as under scenarios where the overall weight increases. This is particularly true when the vehicle has also to face headwinds (20 km/h or more) and a roof rack. Their study also highlights that the combination of the 80% charge level limit of fast DC charging, battery aging, and battery safety margins result in not utilizing the full battery capacity. In other words, the battery weight is not being used but it significantly contributes to the vehicle's weight. Chang et al. [27] introduce an instantaneous power modeling of EVs to study the effect of velocity, acceleration, road slope, and EV weight on the battery power consumption. In addition, they consider the effect of an onboard charger and regenerative braking on the battery charging power. All the mentioned models found in the literature could potentially be used as an online energy management strategy for on-board control logic [28].

The research directed to batteries is not limited to the estimation of energy consumption and affecting factors, but researchers also considered applying a circular economy regarding the manufacturing of batteries [29,30]. This research trend studies the handling of battery waste and re-manufacturing of batteries, as well as the collection of used batteries. Another research trend is focused on operational decisions concerning the utilization of the EVs that used these batteries. Thus, researchers planned routes that minimize traveled time and distance [31,32], resulting in the green vehicle routing problem [33]. Reducing the travel time and distance could reduce the energy consumption of vehicles and, hence, have a positive impact on the environment. In this context, approaches introducing battery sharing (battery swapping) were introduced [34]. For example, Li et al. [35] studied energy consumption in a vehicle routing problem of EVs where battery swapping is allowed. They aimed to support logistics enterprises so they can reduce energy consumption and gas emissions while delivering goods. This solution is an alternative to battery charging and affects the planning of EVs routes. Utilizing battery sharing might help to overcome one of the EV constraints presented as limiting driving range and long charging times. Thus, this paper investigates this approach using a simulation model.

3. Simulation Components and Architecture

In this paper, the simulation model consists of several components, as illustrated in Figure 1 and described in the following subsections. In addition, our simulation architecture includes algorithmic modules that are described in Section 4.

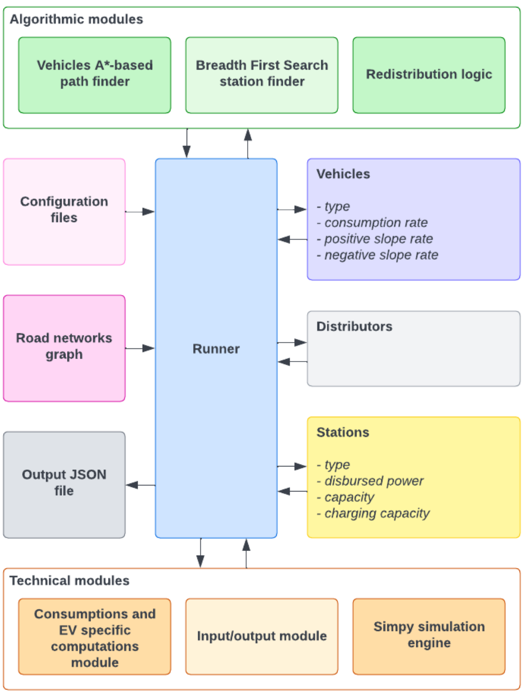


Figure 1. General architecture of the developed simulation library.

3.1. Batteries

Batteries are the lowest-level elements of the simulation. The proposed simulation library offers the possibility of introducing new battery types. Each type is characterized by a certain capacity (expressed in kWh) and can be limited to a specific vehicle, i.e., each vehicle may require a specific type of battery. Each battery instance is characterized by level attributes that describe the remaining energy level. Batteries move around the network carried by vehicles and can be left at charging stations or redistributed among charging stations.

3.2. Vehicles

Vehicles are powered by batteries and move around the road network during a simulation run. Even for vehicles, it is possible to define a set of vehicle types, and each vehicle type will mount a certain number of batteries, all of them belonging to a specific type. It is possible to associate a consumption rate (expressed in kWh per kilometer) with any vehicle type, as well as a positive and negative slope rate, i.e., a percentage that quantifies the effect of street slopes on vehicle consumption. Vehicle consumption is computed as follows:

$$consumption = L \cdot c \cdot (1 + s \cdot \theta)$$

where L is the road length, c is the vehicle consumption rate, θ is the slope of the road, and s refers to the vehicle slope rate, which is positive in the case of positive slope and vice versa. This relationship between road slope and EV consumption is based on the work by Yang et al. [22] and Anselma et al. [28].

Each vehicle type may represent a different class of vehicle characterized by the number of batteries and a specific consumption rate (which is associated with its weight). For instance, we may define three types of vehicles representing trucks, sport utility vehicles (SUVs), and city cars. Each of these vehicle types will have a different consumption rate and will require a different number and type of batteries.

3.3. Distributors

Distributors are particular vehicles in charge of taking unused batteries in a charging station and moving them to another station which is supposed to have a higher demand. For the sake of simplicity, in this work we have assumed that the fleet of distributors is large enough, so we do not need to worry about capacity limitations or recharging operations in vehicles belonging to this fleet.

3.4. Stations

Stations are the network nodes where vehicles can stop to charge or swap batteries. Charging takes place if no sharing is carried out, while swapping takes place only in case of battery sharing. Stations are split into types, and each type is characterized by a certain disbursed power (expressed in kW), a capacity, i.e., the number of vehicles that can be processed at the same time, and a charging capacity, representing the maximum number of batteries of each type the station can charge at the same time; if a station does not handle any battery type, this number can be simply set to 0.

In our experiments, battery charge is assumed to be linear with time, as discussed in Zeng et al. [36] and Cataldo-Díaz et al. [37]. In addition Cataldo-Díaz et al. [37] assumed linear recharge at stations, despite the fact that this assumption might not be fully accurate when using high recharging speeds. Hence, given a battery capacity C, a starting battery power level, and the station disbursed power p, the charging time is computed as follows:

$$time = (C - level)/p$$

3.5. Road Network

The road network is a directed graph including additional details that concern road slope, charging stations, real-time vehicle positions, and distribution of batteries among charging stations.

3.6. Runner

The runner is the main element of the simulation and is in charge of coordinating and running all the simulation processes. Given the number of travelling vehicles in the simulation N, the main process is designed to keep this number constant. Hence, it initially instantiates and executes N processes (one per vehicle). Then, as soon as a process is concluded, a new one is started. It may be represented as in Algorithm 1.

Algorithm 1 Main simulation process

```
Instantiate N vehicle trip processes
while Simulation is not concluded do
    Get the concluded vehicle trip processes
    for each process concluded do
        Instantiate a new vehicle trip process
    end for
end while
```

In the case of sharing, a parallel process is executed; this process is analogous to the one mentioned in Algorithm 1. However, while the main process is in charge of keeping constant the number of traveling EVs, i.e., the traffic intensity, this vehicle handles the redistributors, so that the redistribution of batteries never stops.

4. Incorporated Algorithms

In this section, a deeper description of the algorithmic modules represented in Figure 1 is provided. The algorithms herein described are essential for the simulation to function. Many alternative solutions can be designed and implemented in the simulation model, which allows us to analyze their performance. Notice, however, that the objective of this study is not to find an optimal solution, but rather to reproduce reasonable decisions a standard driver would make in his/her daily activity. The main decision-making processes to consider concern how drivers define the path and how battery redistribution is carried out.

4.1. Driver's Path Definition

The procedure for determining the path of a vehicle when traversing from point a to point b involves the following steps:

1. Using the A^* algorithm [38], find the shortest path from a to b.
2. If a path is not possible, we have a graph error and the trip is considered concluded as well as excluded from the final statistics.
3. If a path can be covered without stopping at the charging stations, the trip is simulated and the process concluded.
4. If b cannot be reached without stops, the algorithm iterates the nodes from a to b looking for a charging station s.
5. If s exists and is on the original path, we simulate a trip from a to s, set $a = s$, and go to step 1. Otherwise, if there are no stations on the path or the station s cannot be reached with residual battery, the algorithm moves to the next step.
6. For each node i from the last reachable node to a, consider i as the root and start a breadth-first search method [39], looking for a station outside the original path. If a station is found, then simulate a trip to s, set $a = s$, and go to step 1.

4.2. Battery Redistribution

The process of redistributing batteries among charging stations is extremely important in periods when most of the vehicles are moving. In these periods, some stations could end up without batteries. As mentioned above, each station has a charging capacity describing the maximum number of batteries that it can charge at the same time. However, vehicles are allowed to leave exhausted batteries in a station even if the station charging capacity is saturated. These batteries will take the name of batteries on-the-side and will remain unused until the station has the opportunity to charge them. Distributors are responsible for identifying the nearest station with a critical number of batteries on-the-side and shipping them to the station with the greatest need for additional batteries. The path traversed by distributors is again determined using the A^* algorithm. As mentioned previously, distributors do not have loading capacity limitations and do not require recharging or refueling operations.

5. Validation and Results

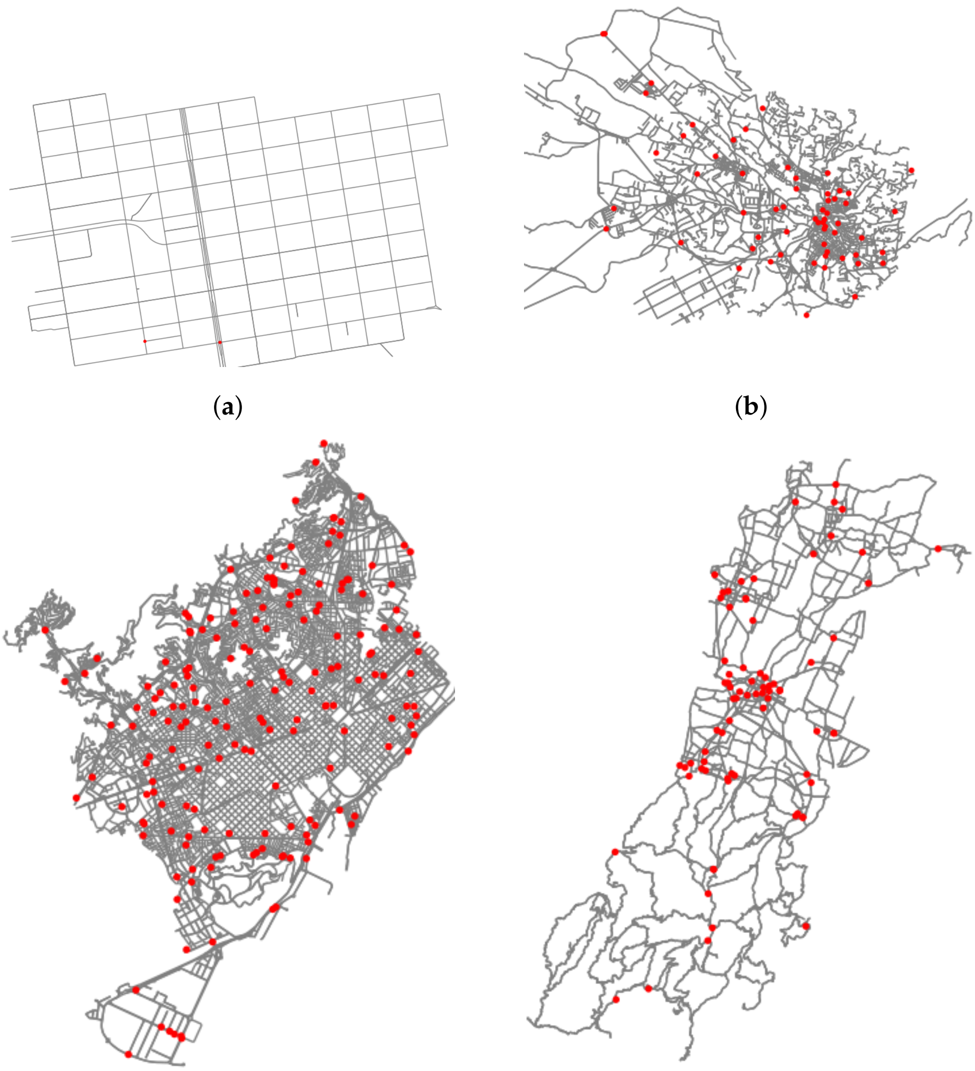
In order to validate the proposed concepts and show the benefits that battery sharing can provide, our simulation model was used to analyze several scenarios. First of all, four different road networks were used (Figure 2): (i) a small section of the Chicago (IL) downtown area, representing a small test network; (ii) the urban area of Modena, a typical Italian medium-sized city; (iii) the urban area of Sassari, an Italian city representing an ancient road network; and (iv) the urban area of Barcelona, representing a modern and large European city. As mentioned, each selected network has some peculiarities that make it a good representative for a specific scenario. The details that concern the road networks were extracted from Open Street Maps (OSM) by using the standard API. Concerning the elevation and altitude, since OSM does not provide this information, the possibility of querying the Open Elevation (https://open-elevation.com/, accessed on 8 April 2023) and National Map (https://www.usgs.gov/the-national-map-data-delivery, accessed on 8 April 2023) services was implemented. For this study, elevation data were taken from Open Elevation. For each road network, we simulated three different situations: (i) a scenario in which no sharing is carried out (i.e., when a vehicle arrives to a charging station, it simply waits to be charged); (ii) a scenario with battery sharing where drivers are allowed to take only fully charged batteries; and (iii) a scenario with battery sharing where even partially charged batteries can be picked up.

The proposed simulation model described in Section 3 offers many possibilities to customize the system's behavior. However, in order to carry out a feasibility analysis and validate the BS approach, we will standardize it using the following configuration:

- The simulation handles three types of batteries—small, medium, and large—with respective capacities 10, 15, and 20 kWh. For experimental purposes, we have considered that the batteries do not reduce their performance with use. Thus, the simulator assumes that the capacity of the batteries does not decrease with the charge cycles.
- In each road network, exactly 2% of nodes are characterized by the presence of a charging station. This results in a different number of charging stations for each network: 4 charging stations in the test network, 69 in Sassari's network, 66 in Modena's network, and 196 in Barcelona's network.
- The simulation handles three types of vehicles. The first two types are more frequent and powered by two batteries each, while the latter is less frequent and powered by three batteries.
- All vehicles have the same consumption rate, 0.3 kWh/km, and their consumption is equally affected by the road slope.
- The simulation handles two types of equally spread charging station, small and large. The first one can process only one vehicle at a time and disburses a power of 10 kWh. The second one can process two vehicles together and disburses a power of 12 kWh. The charging time can be easily estimated using the following equation:

$$ChargingTime = \frac{BatteryCapacity \cdot CurrentBatteryLevel}{DisbursedPower}$$

- The number of traveling vehicles is constant, exactly 1, 100 vehicles, during the entire duration of the simulation.
- Battery swapping takes 60 s.
- There are 10 vehicles dedicated to battery redistribution, and a new redistribution is carried out every hour if the previous one is already concluded.
- The simulation runs for 8 h.



(**a**) (**b**) (**c**) (**d**)

Figure 2. Main streets of considered roads networks. (**a**) Test network (**b**) Sassari (**c**) Barcelona (**d**) Modena.

Notice that all technical and quantitative data we assumed herein are in line with the current technical solutions on the market, as well as well-justified by scientific publications [13,16,30].

Results are presented in terms of relative travel time (i.e., travel time/covered distance), average waiting time at charging stations (i.e., difference between the time at which the vehicle enters the charging station to be processed and the time at which it enters the queue), and average queue at the entrance of the charging station. Results are reported in Tables 1–4, which are also summarized in Figures 3–5.

Table 1. Results concerning the test network.

Scenario	Relative Travel Time [min/km]	Waiting Time [s]	Queue
Sharing of partially charged batteries	1.020	127	3.247
Sharing of fully charged batteries	1.091	3060	77.104
No sharing	1.200	5803	103.570

Table 2. Results concerning Sassari's city network.

Scenario	Relative Travel Time [min/km]	Waiting Time [s]	Queue
Sharing of partially charged batteries	1.020	62	0.154
Sharing of fully charged batteries	1.2	5517	30.004
No sharing	1.38	8917	31.692

Table 3. Results concerning Modena's city network.

Scenario	Relative Travel Time [min/km]	Waiting Time [s]	Queue
Sharing of partially charged batteries	1.020	62	0.126
Sharing of fully charged batteries	1.14	2020	6.679
No sharing	1.200	4091	15.641

Table 4. Results concerning Barcelona's city network.

Scenario	Relative Travel Time [min/km]	Waiting Time [s]	Queue
Sharing of partially charged batteries	1.020	31	0.037
Sharing of fully charged batteries	1.083	1074	2.012
No sharing	1.267	2933	5.553

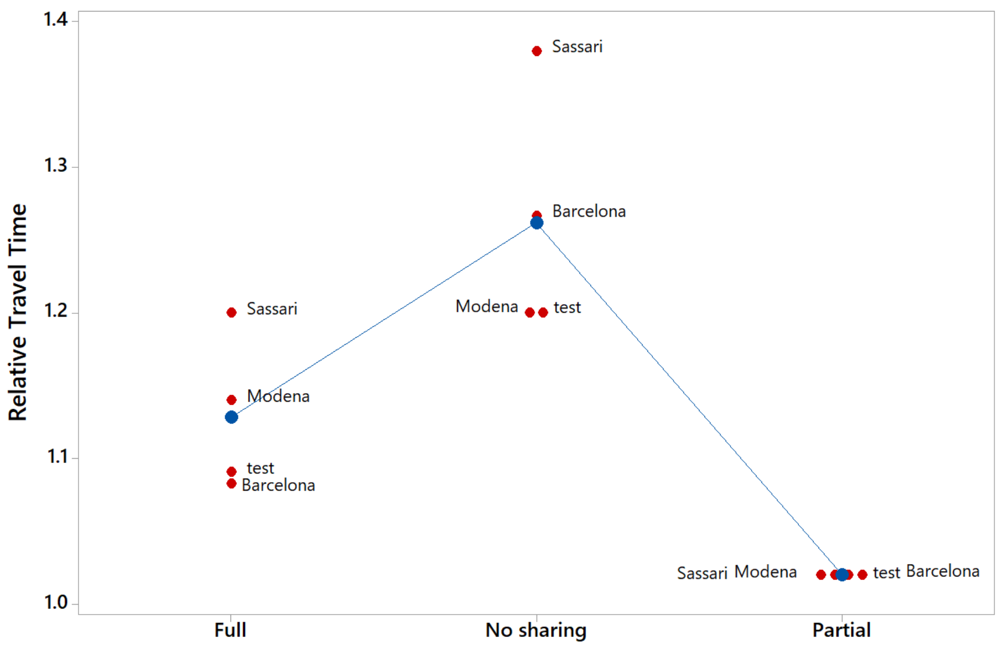


Figure 3. Comparison of relative travel time for each scenario.

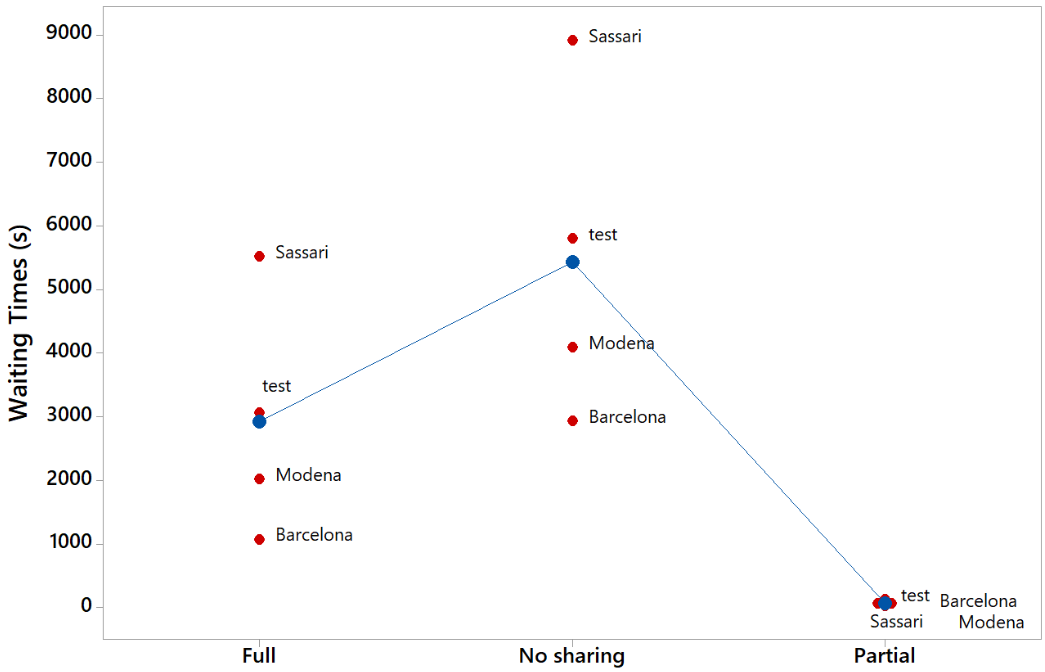


Figure 4. Comparison of waiting times for each scenario.

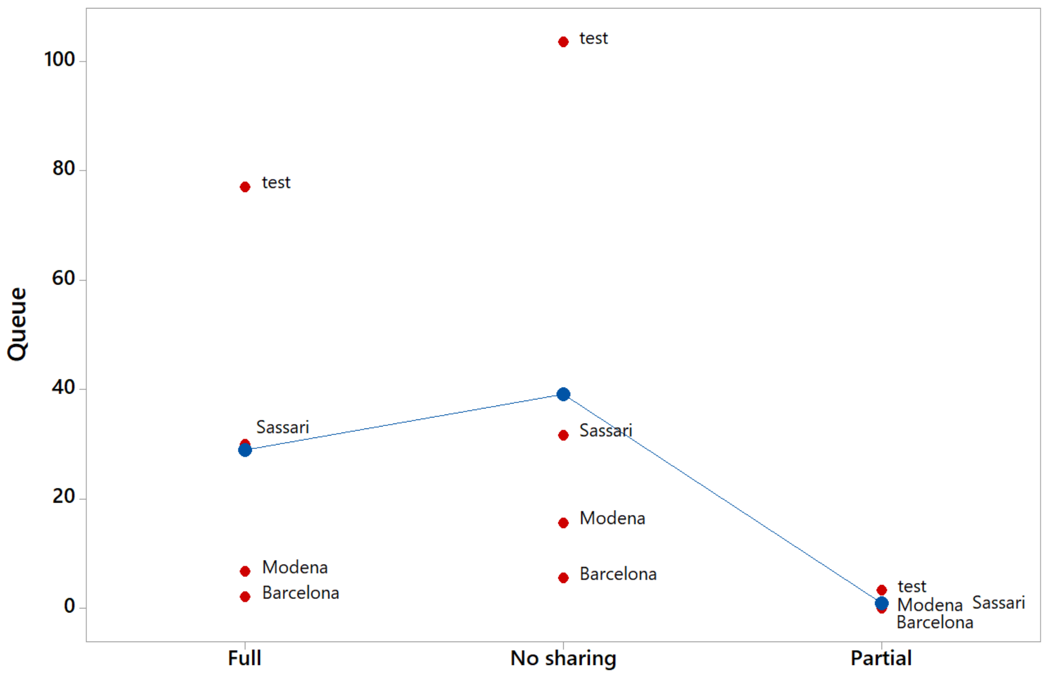


Figure 5. Comparison of queues for each scenario.

As can be seen in these figures, the scenario without battery sharing shows visible traffic congestion that would require the installation of further charging stations. The waiting time at charging stations always exceeds 1 h (and sometimes exceeds 2 h). The relative travel time is higher (because of waiting time at charging stations), and queues exceed 103 vehicles in the test network, 30 vehicles in Sassari city, 15 vehicles in Modena city, and 5 vehicles in Barcelona (since the number of vehicles is constant, the queue length is higher in small networks characterized by fewer charging stations). All conditions being equal, the adoption of partially charged battery sharing leads to a perfectly feasible situation with no need of further charging stations. The relative travel time is reduced, while the waiting time and the queues are almost non-existent. Of course, one should notice that sharing of partially charged batteries generally requires drivers to take more stops during a single trip. Therefore, it may be convenient in terms of the overall network but inefficient from a drivers' perspective. The scenario in which battery sharing is allowed only for fully charged batteries lays in between the other two scenarios. The average waiting time at charging stations is between 30 min and 1 h. This can be considered as an amount of time reasonable according to current standards, even though it can be improved. The queue length at charging stations is often excessive, especially in small networks, and the relative travel time lays in between the results obtained in other scenarios.

As an example, in order to provide an intuitive and visual representation, we can compare in Figures 6 and 7 a representation of the Barcelona city network before and after implementing battery sharing. In the figures, we can see in red, orange, and green the streets with high, medium, and low traffic, respectively. The red points represents the charging stations, and it is easy to see how, in the case of no sharing, the most congested streets are the ones characterized by the presence of a charging station, where vehicles waste a considerable amount of time.

Additional results are obtained by increasing the number of redistributors, i.e., vehicles in charge of moving batteries from one charging station to another, from 10 to 100 vehicles. Table 5 shows how sharing of fully charged batteries may be easily improved with a relatively low budget if compared to the construction of new charging stations required by a scenario with no sharing.

Figure 6. A view of Barcelona city network with no battery sharing.

Figure 7. A view of Barcelona city network after implementing battery sharing.

Table 5. Results obtained increasing the number of redistributors in a scenario of fully charged battery sharing.

Scenario	Relative Travel Time [min/km]	Waiting Time [s]	Queue
Test network	1.158	3010	45.210
Sassari	1.28	2012	5.110
Modena	1.13	1920	3.029
Barcelona	1.083	433	1.512

6. Conclusions and Future Work

This paper has analyzed a novel concept: the impact of using a strategy of battery sharing in electric vehicles as an alternative to a full charging strategy, which is not handy and efficient at the moment mainly due to long charging times. Battery sharing strategies are based on the fact that drivers remove exhausted batteries and replace them with the charged batteries previously left by somebody else (after they have been partially recharged in the station). This allows for significantly reducing the waiting queue at the charging stations. To assess how this approach may affect traffic conditions and how it relates to a classic scenario where no sharing of batteries is used, we have developed a discrete-event simulation model, which validates our approach in four different real road networks and under several environmental conditions. Results show that battery sharing, if feasible from a technological point of view, may be beneficial for traffic networks and easily scalable in case of limited resources, such as the possibility or the budget to install several high-performance charging stations. The current study does not consider imposed costs associated with swapping those batteries and their handling, which are partially caused by the need to hire more staff at the stations. We are aware that research is moving fast in this area and parameters, technologies, and interests may be subject to rapid changes. The objective of this paper was to share a first starting point of a long research project that may also lead to several possible improvements and changes according to the evolution of the EV market. In addition, the simulation results we have obtained are based on some assumptions and data, which means that modifications in these inputs might generate slightly different results. As future work and research perspective, we plan to include into the simulation model more realistic and accurate aspects concerning battery changes and energy consumption starting from weather conditions, passengers, type of vehicle, road state, and many others. As future work, we also plan to combine optimization methods with the proposed simulation model, in order to optimize decisions about which battery has to be selected. Notice that this might depend upon different variables, including the travel time to reach the destination, the type of vehicle, or the number of passengers.

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