Data Driven Scalability and Profitability Analysis in Free Floating Electric Car Sharing Systems

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Abstract

In this paper, we analyse the impact of system design options with different demand intensities for electric vehicle free-floating car sharing systems (EV-FFCS). We consider three different cities for which we collected rental data from a car sharing system. Using these data, we build demand and supply models of an EV-FFCS. We evaluate the performance of different design options from both the customers' and the operators' perspectives, i.e., quality of service and profitability. We study the number of chargers, their placement and the size of the fleet. We observe the impact on the system when demand is constant and then when demand increases. The results show that it is critical to scale the capacity of the charging infrastructure proportionally to the mobility demand. Conversely, the same fleet size can accommodate a 300% increase in demand, not satisfying less than 15% of it. Moreover, the observed demand and supply would likely not generate profits for the EV system. This is due to the high cost of electric vehicles and the need to manage the fleet for charging operations. The figure changes with at least a 5-fold increase in demand, with the current fleet size becoming profitable.

Keywords: data-driven analytics; car sharing; scalability; charging infrastructure; profitability; electric vehicles.

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1. Introduction

Today, about 55% of the world's population lives in urban areas, a proportion that will increase to 68% by 2050. [1] In this context, cities face major challenges to cope with the increasing demand for mobility and car sharing systems are seen as alternatives to private cars for mobility. By sharing the same car with others, they increase parking availability and reduce overall pollutant emissions [29, 32].

Among car sharing solutions, free floating car sharing systems (FFCS) allow customers to rent a car for a short period of time at any location within an operative area, paying only for the time of the trip. To take another step toward sustainable mobility, FFCS providers are converting their fleets from internal combustion engine vehicles (ICEVs) to electric vehicles (EVs). This switch can further reduce noise and pollutant emissions in metropolitan areas [31]. However, this transition poses some important challenges, such as creating and sizing appropriate charging infrastructure, managing charging operations, and assessing their scalability and economic sustainability.

Thanks to the development of the Internet of Things and mobile Internet technology, FFCS vehicles continuously collect and share information such as GPS location, battery status, energy consumption, etc. This data offers researchers new opportunities to provide useful information to operators and urban planners. For example, through spatial and temporal analysis, researchers have studied customer habits and the evolution of FFCS systems [15, 32, 36, 37], evaluated the optimization of FFCS systems [7, 9, 13, 42], proposed different pricing policies [16, 20, 34], and evaluated the scalability of shared mobility in different contexts, including urban ride-sharing [38] and station-based car-sharing systems [3, 12].

Despite the extensive literature on FFCS, most studies focus on examining the past or current state of FFCS systems. Here, the goal is to assess the

[1] Revision of World Urbanization Prospects: `https://www.un.org/development/desa/publications/2018-revision-of-world-urbanization-prospects.html`, last accessed 2022-08-26

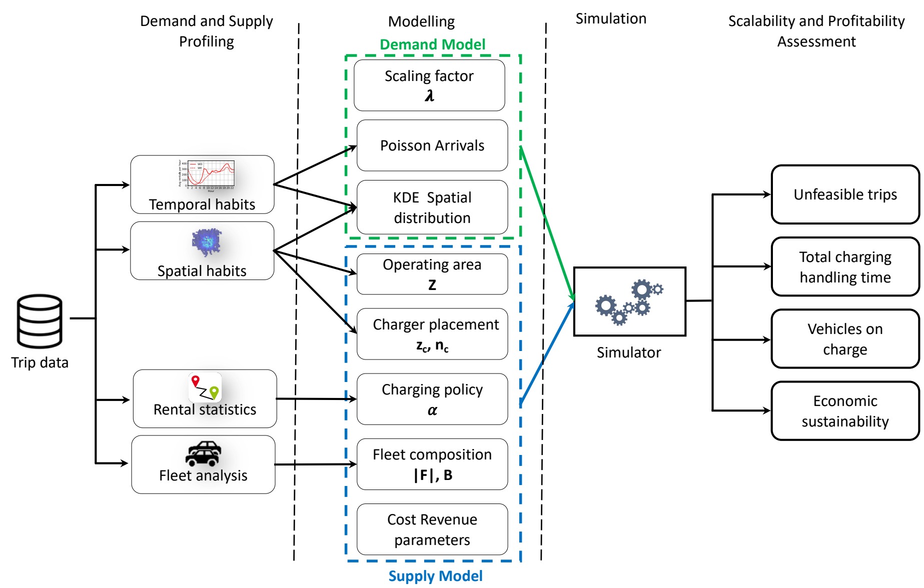


Figure 1: The data driven analytics pipeline.

impact of future system growth. First, we examine the tradeoffs that benefit both citizens (i.e., high car availability) and operators (i.e., low charging and maintenance costs) in a currently functioning FFCS mobility system. Second, we examine the scalability of the system, i.e., the impact that increasing mobility demand would have on the system. Third, we evaluate the expected profit that an FFCS operator would make. We determine which factors have the greatest impact and observe which system configurations would make the system profitable. In doing so, we contribute to the discussion of the economic viability of FFCS, which is questioned or supported in the literature [26, 44].

Figure 1 depict the data-driven pipeline we use to study the effects of a given demand and supply in a FFCS. The model has several parameters (highlighted in bold) that allow us to observe system behavior under different conditions. We consider three cities: Turin, Milan and Vancouver, in order to consider different scenarios. Starting from the raw data describing the real rentals observed in each city [6], we extract the temporal and spatial characteristics of the customers' mobility demand. Based on this, we build a generic demand model that we parameterize for scaling intensity. Similarly, we model the FFCS supply based on the actual fleet properties (number of vehicles, EV characteristics, etc.). We then define the charging management policies that the EV-based FFCS operator adopts.

To observe how the system scales and performs, we run accurate data-driven simulations to compare different what-if scenarios and observe the impact of the system configurations. Such a solution is widely used in the literature to evaluate different fleet deployment strategies [4, 19, 23], vehicle relocation deployment [35], and even overall system economic sustainability [21, 34]. In short, our simulator models each vehicle in a fleet and simulates rental requests from customers. For each request, the simulator looks for a suitable vehicle nearby. When available, the simulator moves the vehicle, updates the vehicle's State of Charge (SoC) and location, and manages any battery charging operation. At the end of the trip or charging time, the car is made available at its new position for other customers to use. The simulator collects several metrics. We focus on the satisfied demand (i.e., the percentage of trips that users can make) and the profitability of the system (i.e., the revenue that the operator earns from the rental minus the initial cost of the fleet and charging infrastructure and the cost of handling the charging operations).

To allow researchers to validate and extend our results,we provide in [5] the analytics we developed to reproduce all available graphs.

The paper is organized as follows: We introduce the demand and supply models in Section 2. In Section 3 we report the details of the simulation. In section 4 we present the results of our scalability and profitability assessment. In Section 5, we discuss our work in light of previous literature on FFCS and its economics. Finally, in Section 6 we discuss the limitations of the work and outline the main results.

2. Demand and Supply profiling and modelling

Our raw data consists of millions of rentals by car2go customers in Turin, Milan, and Vancouver, collected using the UMAP [6] tool. Each observed rental has geographic coordinates for the start and destination of the trip and timestamps with a granularity of one minute. Here we consider rentals for three months, from October 1 to December 31, 2017. Table 1 describes the main characteristics of these data. In Appendix A we report the characteristics of demand and supply observed in the three cities.

2.1. Demand model

We derive a generalized demand model from the observed trips in the dataset. We follow the approach proposed in [7], fine-tuning the parameters of the model to capture the current demand characteristics in each city. Note that we use the observed trips to derive an estimate of demand: we discuss this approximation and its implications in Section 6.

2.1.1. Modeling the demand over time

First, we generalize demand over time using the results of the demand in time. We assume that customers behave independently, so the request process follows a Poisson model [30] in which the inter-arrival time between requests follows an exponential distribution, with the rate depending on the type (weekdays or weekends) and hour of the day. We separate work days from weekend days. Moreover, we choose a granularity of 1 hour as it represents well the daily traffic patterns (see Appendix A).

Table 1: Main characteristics of our dataset from October to December 2017. Both average (Avg) and median (Med) values are reported for rental duration and rental distance.

City	Rentals	Fleet Size	Rental Time [min]		Rental Dist. [km]			Zones
			Avg	Med	Avg	Med	Max	
Turin	180k	414	21.4	19.2	4.0	3.4	28.6	268
Milan	450k	863	26.1	23.1	4.2	3.7	29.7	534
Vancouver	480k	1066	29.3	26.1	4.8	4.0	48.4	520

To observe the error caused by the model, we compute the mean relative deviation ϵ_t for each time unit t:

$$\epsilon_t = \frac{1}{|\mathcal{I}_t|} \sum_{i \in \mathcal{I}_t} \left| \frac{\hat{N}_i - N_i}{N_i} \right| \tag{1}$$

where $\mathcal{I}_t$ is the set of all hours in the trace that maps to the temporal slot t, and N_i and $\hat{N}_i$ are the measured and expected number of requests at hour i, respectively. The mean arrival rate for the modulated Poisson process is simply $r_0(t) = \hat{N}_t / \Delta T$, with $\Delta T = 1$ hour in our case.

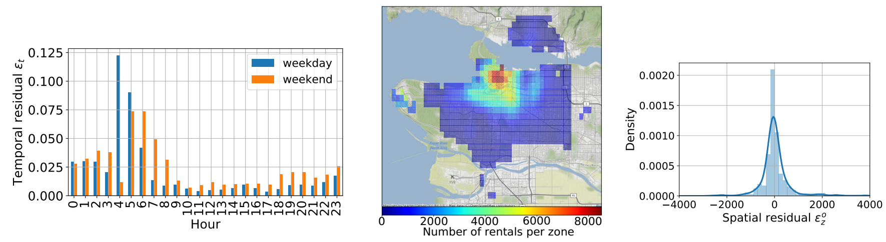
To estimate how accurate the Poisson assumption is, we calculate the average relative absolute error ϵ_t over the 48-time periods for the cities analyzed. We observe an average error of 0.016, 0.013, and 0.023 for Turin, Milan, and Vancouver, respectively. Figure 2a shows the ϵ_t value for each temporal slot for Vancouver. Note that the model has smaller residuals during the temporal slots with the highest demand, which determine the performance of the system. Instead, we find large residuals during nighttime hours and weekends when demand is significantly lower (see Figure A.14), so the relative error grows due to the small values of N_t. The same considerations, not reproduced here for brevity, also apply to Turin [7] and Milan, which we describe in detail in [5]

To investigate the scalability of the system, we introduce the demand scaling factor λ, which modulates the inter-arrival time between requests to scale the actual demand intensity. For example, at $\lambda = 2$, we have $r(t) = \lambda r_0(t)$, i.e., the average number of requests per unit time doubles compared to the original data.

2.1.2. Modeling the demand over space

To generalize the demand in space, we use a Kernel Density Estimation (KDE) [14]. We use the KDE as a spatial data smoothing tool to capture mobility patterns from rentals in the original trace while reducing the effects of noise or secondary phenomena at a finer scale.

To estimate the O/D matrix, we divide the city into a grid of 500 m x 500 m zones Z (the number of zones in each city is given in Table 1). We assign each



(a) Temporal mean relative absolute deviation ϵ_t

(b) Spatial data smoothing after KDE

(c) Spatial residual distribution ϵ_z^o

Figure 2: Model validation in Vancouver.

pair of spatial coordinates (x, y) to a zone. We compute the O/D matrix for each time slot by counting how many trips originate from a given zone O and travel to a given zone D. Next, we compute a KDE model for each time slot using a Gaussian kernel [14]. We manually set the bandwidth parameter to 1. We find that a bandwidth smaller than 1 does not significantly improve the estimation, while a higher value compromises the granularity of the city binning and reduces the ability of the model to describe spatial patterns.

To estimate this smoothing effect, Figure 2b shows the total number of rentals departing from each zone as generated by the model We can see that the zones with the most departures remain the same as in the original data (see Figure A.15c). As expected, the model shows smoothed behavior in the central zones, with rentals spread across more zones than in the real trace.

To quantify the smoothing effect, we calculate the difference between the total number of requests in the model and that in the original trace, for each zone. We define the spatial residuals ϵ_z^o for the origin o of the trips in a zone z as:

$$\epsilon_z^o = \hat{N}_z^o - N_z^o \tag{2}$$

where N_z^o and $\hat{N}_z^o$ are the total number of requests in zone z in the trace and model, respectively. Figure 2c shows the distribution of ϵ_z^o. The vast majority of zones have limited residuals that are around 0. Nevertheless, some zones have more (less) deviations in the model than in the trace, i.e., positive (negative) residuals. For example, we observe few zones with a sharp increase in departures, e.g., +2000. These values refer to a single 500 m x 500 m zone where there are no trips in the trace (e.g., in the middle of a park), while some trips appear in the model due to the smoothing effect of the KDE, which distributes trips to neighboring zones. Similar considerations also apply to Turin and Milan, which we report for completeness in [5].

2.2. Supply model

We consider a fleet F of electric cars, where F_0 is equal to the number of cars seen in the original data in each city Since the fleets consist of Smart ForTwo, we map the vehicle characteristics of an equivalent electric car, namely the MY2018 Smart EQ ForTwo, namely $B = 17.6$ kWh battery capacity and 15.9 kWh/100 km energy efficiency.[2]

We divide the city into a set Z of zones, each 500 m x 500 m, identifying the operating area where cars can be *parked, rented, charged, or returned.*

We consider n_c Level-2 chargers for the charging infrastructure, with 3.7 kW nominal power and 92% charging efficiency. To distribute the charging stations across the city area, we again rely on spatial analytics. Specifically, we place them in the zones with the highest probability of being origin zones with the most rentals starting from them (see Figure A.15). We proved that this is beneficial for performance [7, 8]. Specifically, we sort the zones $z \in Z$ by the total number of parkings $tot\_park(z)$ observed in the original trace. We then consider the top z_c fraction of zones and place in each zone a number of chargers proportional to $tot\_park(z)/\sum_z tot\_park(z)$.

Finally, we determine the threshold α as the minimum fraction of the battery below which the car battery must be charged. We set α to ensure that the longest possible trips within the city are feasible. To do this, we rely on the distance statistics calculated by the data analytics: we obtain $\alpha = 26\%$ for Turin, $\alpha = 27\%$ for Milan, and $\alpha = 44\%$ for Vancouver.

[2] `https://ev-database.org/car/1132/Smart-EQ-fortwo-coupe`, worst case of real city energy consumption.

3. Simulation and metrics

Equipped with the demand and supply models, we run simulations to evaluate the performance of different demand and design options. Written in Python 3.7, the simulation is based on Simpy 4.0.1, a discrete-event simulator.[3] Each event is an action that the simulator processes. Specifically, the simulator manages a fleet of cars and simulates rental requests from customers.

3.1. Simulation process

When we start the simulation, we configure both the demand and supply characteristics. For the supply characteristics, we set the size of the available fleet to $|F|$ cars and their respective characteristics, namely battery capacity B and battery consumption B_c. Then, we specify the city scenario and give as input the city grid having $|Z|$ zones to represent the operator's service area. We equip z_c of the zones with charging stations, where we place a total of n_c chargers according to the algorithm described in Section 2.2. At the beginning of the simulation, we randomly place cars in the service area, each with an initial State of Charge (SoC) uniformly distributed in $[0.5B, B]$. All cars are available for rental. Finally, for the demand characteristics, we scale the demand to the desired λ. Table 2 shows the simulation parameters with the values that we use for the analysis.

Each car is characterized by location, status (i.e., available, rented, on charge), and SoC. *Rental requests* are generated according to the modulated Poisson process with rate $r_t = \lambda r_0$. Each rental request event has origin and destination coordinates according to the demand characteristics and the KDE model of the current hour/day.

The simulator processes the following events:

Car request event. When a customer *rental requests* is triggered at time t, the simulator searches for a car within the origin zone and in the 1-hop neighbor zones (this according to the maximum walking distance to reach a car [18]). If

[3] `https://simpy.readthedocs.io/en/latest/`

at least one car with enough SoC is available to reach the desired destination, the customer rents the closest car with the highest SoC Then, the simulator schedules a *car return* event at time $t + t_{trip}$, the time to reach the destination. t_{trip} is proportional to the distance between O and D, with a factor that takes into account both the orography and the shape of the road network, and is different in each city [8]. If no car is available, the trip does not take place and the request is marked as *unsatisfied*.

Car return. When a *car return* event is triggered, the simulator updates the car SoC by decreasing it in proportion to the distance traveled, and the car is moved to destination D. If the SoC is above the threshold α, the car is marked as available. On the other hand, if the SoC value is below α, the simulator performs the charging process by moving the car to the nearest available charger and then scheduling an event *charge complete* at time $t+t_{charging}$. $t_{charging}$ includes both the time to reach the charger and the time to bring the SoC to 100%[4].

Charge complete. When a *charge complete* event is triggered, the car is marked as available and customers can rent it again. The charger is also released. Note that we return the car in the same zone where it was brought for charging, i.e., the system does not perform any relocation strategy after charging.

3.2. Scalability assessment

By increasing the scaling factor for the demand rate, we examine the impact of increasing demand on the FFCS system. To compare different design options, we focus here on the following performance metrics:

Unsatisfied demand: it is the percentage of rental requests that cannot be satisfied because there is no car with sufficient SoC at the desired origin or in the neighboring zones. It is an indicator of the quality of the system's service to customers, i.e., how easy it is to rent a car when desired. It should

[4]For simplicity, we assume that there are an infinite number of workers processing battery charging events, so that a car is serviced immediately. If all chargers are busy, the car is queued at the nearest charging station and serviced as soon as a charger becomes free.

Table 2: Summary of parameters used for the simulations.

Param	Description	Range in Turin	Range in Milan	Range in Vancouver
$\|F_0\|$	Fleet size	414	863	1066
$\|F\|$	Fleet size	[20, 600]	[42, 1250]	[52, 1550]
B	Battery capacity, Smart EQ ForTwo		17.6 kWh	
B_c	Battery consumption, Smart EQ ForTwo		15.9 kWh/100 km	
α	SoC charging threshold	0.26	0.27	0.44
$\|Z\|$	Number of 500 m x 500 m zones	268	534	520
z_c	Fraction of zones with chargers		$[0.002, 0.20]$	
n_c	Number of chargers 3.7 kW each	$[2, 290]$	$[5, 290]$	$[5, 290]$
λ	Rental demand rate scaling factor		$[1, 10]$	

be minimized.

Total charging handling time: it measures the monthly time spent by the system to process the charging operations, i.e., to bring the cars to the charging stations. It is the sum of the time spent by the employees to drive the cars to the next available charging station. It indicates how good the charging infrastructure is. Since it is a cost, it should be minimized.

Vehicle on charge: it is the percentage of the fleet that is charged at any one time. It provides information on whether charging is synchronized at certain moments. It should be minimized, especially at times of high demand, such as during commuting hours.

3.3. Profitability assessment

While performance analytics are useful to explore design options, the FFCS operator is ultimately interested in economic sustainability. To this end, we derive a cost model based on annual projections and a revenue model based on projections of each rental and its duration using a common rental pricing model. Armed with both, we estimate monthly profit. Given the confidentiality of economic agreements between the FFCS operator and third parties (e.g., discounts on parking fees or placement of charging stations), it is a complex task for each city to obtain reliable and accurate financial information. Therefore, we use the same cost and revenue values here for all cities. This setting allows us to compare cities and highlight the differences that arise from differences in rental

Table 3: Summary of cost and revenue parameters for the economic analysis analytics. These parameters can be easily customized by using the code in [5].

Param	Description	Value
C_{lease}	Yearly electric Smart ForTwo vehicle lease cost	4000 €/yr/vehicle [a]
$C_{charger}$	Material cost of a Level-2 charger	1700 €/charger [b]
C_{labor}	Labor cost to install a charger	2200 €/charger [b]
C_{setup}	Make-ready infrastructure cost per charging station	1500 €/station [b]
c_{life}	Charging station and charger lifetime - amortisation period for $C_{charger}$, C_{labor} and C_{setup}	10 yr [40]
C_{maint}	Yearly charger maintenance cost	500 €/yr/charger [b]
C_{ground}	Yearly ground occupation tax	355 €/yr/charger [c]
C_{energy}	Energy cost for kWh	0.19 €/kWh [d]
$C_{drivers}$	Hourly labor cost to bring the cars to charge	23 €/h [e]
C_{disinf}	Disinfection and interior cleaning cost	5 €/20 rentals
C_{wash}	Cost to wash the car	8 €/100 rentals
R_{rental}	Average revenue per rental minute (exl. VAT)	0.20 €/min [f]

[a] https://mymobilitypass.mercedes-benz.it/offerte-noleggio-lungo-termine/smart-fortwo-eq-passion

[b] https://rmi.org/ev-charging-costs

[c] http://www.comune.torino.it/cosap/

[d] https://ec.europa.eu/eurostat/statistics-explained/index.php/Electricity_price_statistics

[e] https://www.infodata.ilsole24ore.com/2019/08/19/39139/

[f] https://www.share-now.com/it/en/turin/

demand and city characteristics. However, we designed this analytics module to be easily customized so that anyone can observe the impact of different cost or revenue components. Table 3 summarizes the cost and revenue parameters with the values chosen for this paper. Readers interested in exploring different pricing and revenue models can access the software we used, provided in [5], and observe what happens when changing these numbers.

Specifically, we consider:

Vehicle cost: we assume that the cars are leased. All costs are included in the lease: Registration, tax, insurance, ordinary and extraordinary maintenance, and roadside assistance. We assume that electric cars do not incur fees for on-street parking and access to congested areas. Based on the annual lease rate C_{lease} and the number of vehicles, the total annual cost of the fleet can be derived.

Charging infrastructure cost: here we refer to actual use cases as defined in [33]. The cost of installing the charger is composed of material and labor costs.

The material cost $C_{charger}$ includes the hardware cost for Level- 2 chargers. The labor cost C_{labor} is highly dependent on the city and country. We also consider the infrastructure setup cost C_{setup}, i.e., the cost of setting up a charging station. They do not depend on the number of chargers per station, but only on the number of charging zones $z_c \cdot |Z|$. They are highly variable costs, as they depend on the location and the power distribution infrastructure already in place. In fact, the cost of digging trenches and laying conduits can add thousands of euros to the cost. All these costs are one-time costs, and we assume that their payback period is equal to the average lifetime of the charging stations and chargers c_{life}.

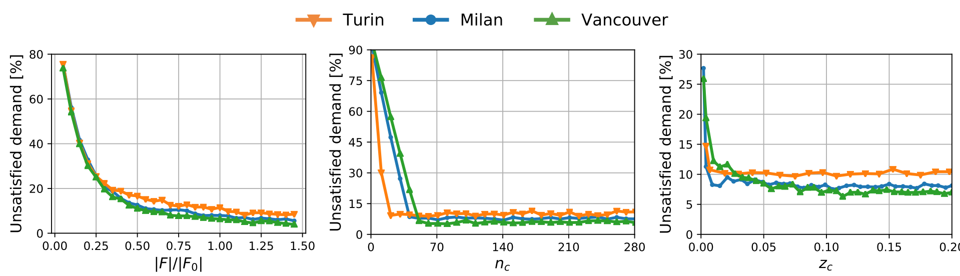
Next, we consider the maintenance cost for the charging stations C_{maint}, which we derive from variable site-specific parameters. In some cities, we also need to consider the per vehicle ground occupation tax C_{ground}, which usually depends on the surface for a specific charging station. Given the small size of the Smart ForTwo, we assume that the charging points for each charger are 4.50 m x 2.30 m in size.

Operating costs: for this, we consider the cost C_{energy} for the energy to charge the cars, the hourly cost for the workers $C_{drivers}$ to handle the charging, and the cost C_{disinf} to clean and disinfect the car each time the worker brings it to charge. Finally, we assume that the car is washed every 100 rentals, which costs C_{wash} each time.

Comparing these costs, notice that the annual cost of a single car is about an order of magnitude higher than the cost of a charging pole. Considering that the ratio between the number of vehicles and charging poles is about ten, you find that the annual cost of the fleet is one to two orders of magnitude higher than the annual cost of the charging infrastructure. The operating costs grow proportionally with the satisfied demand and turn out to be lower than the vehicle costs.

Rental revenue: we consider a simple average price per minute R_{rental}. This allows us to convert total rental minutes to total revenue.

Finally, as a metric to estimate the profitability of the design options, we consider **Profit**: this is the difference between the rental revenue generated



(a) Unsatisfied demand VS Fleet size

(b) Unsatisfied demand VS Number of chargers

(c) Unsatisfied demand VS Chargers spread factor

Figure 3: Unsatisfied demand with respect to fleet size, charging capacity, and infrastructure spreading factor. Curves show performance for Turin, Milan and Vancouver.

by satisfied demand and the cost of the vehicles, charging infrastructure, and operating costs.

4. Scalability and Profitability Assessment

We perform a set of simulations according to the demand and supply model described in Section 2. We simulate each system given three months of virtual time. Table 2 summarizes the parameters and the ranges considered that define the scenarios used in our simulations.

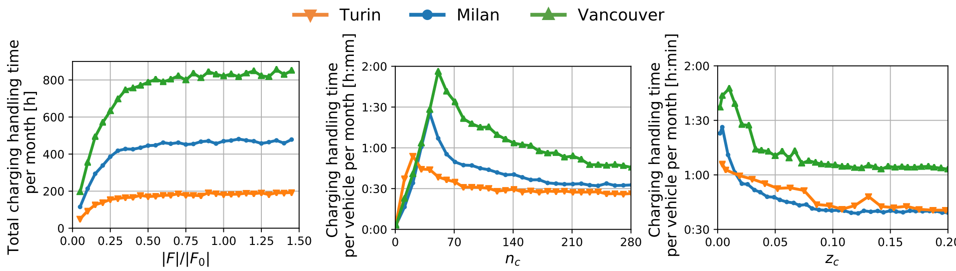
4.1. System parameters with current demand

First, we consider the effects of the design parameters given the current intensity of demand, i.e., $\lambda = 1$ and the current number of cars in our data (cfr Tab. 1)

In Figure 3, we consider the unsatisfied demand when varying the different design options. Figure 3a shows the impact of fleet size, which we normalize to the current size, i.e., $|F|/|F_0|$. We analyze a range from $|F|/|F_0| = 0.05$ to $|F|/|F_0| = 1.50$, which corresponds to the values given in Table 2. Here $z_c = 0.2$ and $n_c = |F|$ (which corresponds to a one pole per car system that guarantees that a free pole is always found when needed). Each curve represents a different city. The behavior of each city is very similar and shows that we can satisfy about 80% of customer demand with only 30-45% of current cars. Reducing the fleet size to less than 25% of the current number of vehicles would abruptly increase the unsatisfied demand because there are too few vehicles to meet customer demand. Interestingly, even with an increase in fleet size, we still observe a small percentage of unsatisfied demand. This is due to the mismatch between the locations of available vehicles and demand. Specifically, we observe an unsatisfied demand between 5% and 10% for Turin, 4% to 9% for Milan, and 3% to 6% for Vancouver

Next, in Figure 3b, we focus on the impact of the number of chargers n_c. Here we set $z_c = 0.2$ and $|F|/|F_0| = 1$ (the same fleet as now). Interestingly, we observe two working regions for all cities: in the left part of the graph, the charging capacity is insufficient and the system cannot supply enough energy to meet the mobility demand. In the right part of the graph, the charging infrastructure has enough capacity to supply the energy for customers' trips - resulting in constant unsatisfied demand. In short, once the system has enough charging capacity, the impact on satisfied demand is zero. The minimum number of chargers to reach this point is 13 for Turin, 48 for Milan, and 51 for Vancouver, respectively. When we calculate the number of chargers per vehicle, we find that in the three cities only 3 to 5 charges per 100 vehicles would be sufficient to support the current mobility demand.

Finally, in Figures 3c, we examine the impact of infrastructure extensiveness z_c on the unsatisfied demand. Recall that z_c represents the percentage of the zone equipped with a charging station. Here we consider an oversized charging infrastructure, i.e., $n_c = |F|$, and we set the fleet to $|F| = |F_0|$. The configurations on the far left correspond to one or very few zones where all stations are located, i.e., the so-called "charging hub" scenarios. Since we do not consider a post-charging relocation policy, the hub scenarios lead to a surplus of cars in the hub zone and a shortage of cars in other zones. This shortage of cars leads to high unsatisfied demand. The larger the operative area, the greater the impact, with Milan and Vancouver ending up with 30% or more unsatisfied demand when only a single hub is considered. Conversely, increasing z_c has the benefit of spreading charging stations, and therefore cars, across the city. If you



(a) Charging handling time vs Fleet size

(b) Charging handling time vs Number of chargers

(c) Charging handling time vs Chargers spread factor

Figure 4: Monthly management time for the average vehicle w.r.t. fleet size, charging capacity, and infrastructure spreading factor. Curves show performance for Turin, Milan and Vancouver.

choose to place charging stations in *top_park* zones, cars will naturally be placed in high demand areas where customers are looking for cars. This significantly reduces the unsatisfied demand and challenges the need for costly relocation efforts.

Let us now turn to the system cost of managing cars. In Figure 4 we report the total time required to bring cars to the nearest charging station. This gives the cost that the provider must pay to the workers. Figure 4a shows the results as a function of fleet size $|F|/|F_0|$. We set $n_c = |F|$ and $z_c = 0.2$. As expected, the total charging handling time grows along with the satisfied demand (cfr. Figure 3a) until near saturation for $|F|/|F_0| > 0.5$, i.e., when the unsatisfied demand reaches the minimum values. This reflects the intuition that the charging handling time is proportional to the satisfied mobility demand. Thus, the different absolute values observed across cities reflect differences in overall demand. This result confirms that in the current situation, the car sharing provider can halve the fleet size to achieve similar satisfied demand and charging handling time.

To optimize the charging infrastructure, we next review the charging handling time per month. Here we normalize the total processing time with respect to the fleet size and obtain the number of hours per vehicle. Figure 4b shows this metric as a function of n_c, with $|F| = |F_0|$ and $z_c = 0.2$. If the system has too few chargers, the charging capacity is not sufficient to support the mobility demand. Cars are queued at a charging station and are not available. This leads to the paradox that the system saves handling time. That is, if you do not rent a car, you do not need time to charge it.

Instead, consider the region where the system has just enough charging capacity to support the mobility demand, i.e., $n_c = 25$ in Turin, $n_c = 52$ in Milan, and $n_c = 64$ in Vancouver. Chargers result utilized for most of the time and workers have to drive their cars further away to find a free charger. This lack of free chargers results in the highest charging handling time per vehicle, about 1 hour in Turin, 1 hour 25 minutes in Milan, and almost 2 hours in Vancouver. By increasing n_c, we increase the probability of finding a free charger nearby and can significantly reduce the driving time to get the car there to charge.

Last, we consider the charging handling time per vehicle per month as a function of z_c, with $n_c = |F|$ and $|F| = |F_0|$. In Figure 4c, we see how a centralized infrastructure leads to a higher handling time, since workers have to drive the hub. In Turin, the average monthly charging handling time per vehicle steadily decreases as z_c increases. In Milan and Vancouver, however, there is a sharp decrease in the range of $z_c \leq 0.05$, followed by a more uniform decrease. This is due to higher unsatisfied demand, which saves handling time. In summary, distributing the same number of chargers to more zones reduces unsatisfied demand and charging handling time when considering the demand scenario from the original data. However, the constraints and costs associated with installing and maintaining a distributed charging infrastructure must be considered. A detailed discussion of these costs is beyond the scope of this paper.

4.2. Demand growth with constant fleet size

In the previous section, we saw how the current demand could be satisfied with a smaller fleet. Now we examine how the current fleet can handle demand To this end, we scale the demand by λ and hold the fleet size constant at the values corresponding to $\lambda = 1$ ($|F| = |F_0|$). Note that for simplicity, we do not

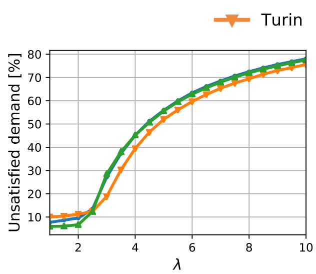


Figure 5: Unsatisfied demand for increasing λ and fixed number of vehicles with 1 charger every 10 vehicles ($n_c = |F_0|/10$).

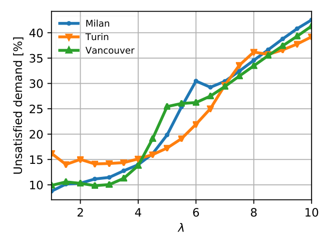


Figure 6: Unsatisfied demand for increasing λ and fixed number of vehicles with 1 charger for each vehicle ($n_c = |F_0|$).

consider the possible change in demand due to a change in customers' willingness to use the service. Indeed, in a demand scenario, we do not consider (i) the churn rate due to high unsatisfied demand; (ii) the surge in demand triggered by the increasing availability of the fleet; (iii) the inhomogeneous growth in different zones of the city. We assume that the same spatial and temporal patterns apply, just with a different intensity. Although this is simplified, it allows us to obtain comparable figures.

We consider a distributed charging infrastructure with $z_c = 0.20$, which we have shown gives the best results. We examine two scenarios: In the first, the infrastructure is large enough to satisfy the current demand. Here, we choose $n_c = |F|/10$. In the second scenario, the charging infrastructure is largely oversized. We set $n_c = |F|$ to guarantee that we can always find a free charging pole. Figures 5 and 6 show the unsatisfied demand for each scenario.

Beginning with the limited charging capacity scenario, Figure 5 shows that current fleets can easily handle mobility demand growth by a factor of $\lambda = 2.5$ with limited effects on the unsatisfied demand. After this point, the increase in demand begins to result in a significant increase in unsatisfied demand. This is due to the limited availability of chargers, so the system cannot cope with the energy demand and then enters the region where the unsatisfied demand grows linearly with the lack of chargers (cfr. Figure 3b).

In the case where the charging infrastructure is oversized, Figure 6 is even

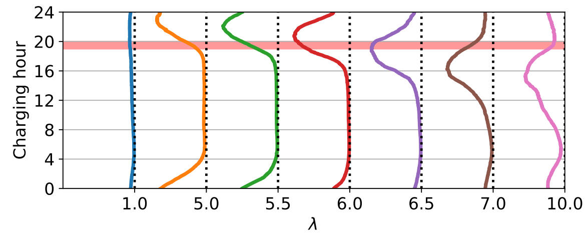


Figure 7: Median percentage of the vehicles on charge over time in Milan for increasing λ ($|F| = |F_0|$ and $n_c = |F_0|$).

more interesting. The exact number of vehicles $|F_0|$ can sustain a sizeable demand growth. In fact, the increase in unsatisfied demand in all three cities is negligible up to $\lambda = 3$, with a total of less than 15% of unsatisfied demand. Fleet usage increases proportionally to λ and so do charging operation cost. When demand increases above $\lambda = 3.5$, the initial fleet size is no longer sufficient to handle the demand growth, resulting in an increase in unsatisfied demand. Here, the demand loss is expected to be proportional to λ. Surprisingly, we observe some non-linear trends in this region with some short plateaus of unsatisfied demand occurring in all three cities (albeit at different values of λ).

To investigate this phenomenon, in Figure 7, we report the median percentage of vehicles on charge during each hour in Milan for different values of λ. The y- axis indicates the hour of the day with a granularity of one minute. Each curve gives the median percentage of vehicles on charge for each value of λ on the x-axis. Each curve varies in the range from 0%, meaning no car is on charge, to 100%, meaning the entire fleet is charging, and no car is available for rent. The red area highlights the commuting hour, i.e., 19:00 to 20:00, when we observe the highest demand (cfr. Figure A.14b). Focus on our baseline scenario with $\lambda = 1$. In this scenario, only a small percentage of the fleet is charging, with a maximum of 7% of cars charging at any one time. As we increase λ, we can see how most charging is synchronized after the peak in the commuting hour. This reflects that cars need to be charged after a period of high utilization to replenish the batteries. This phenomenon is particularly evident for λ

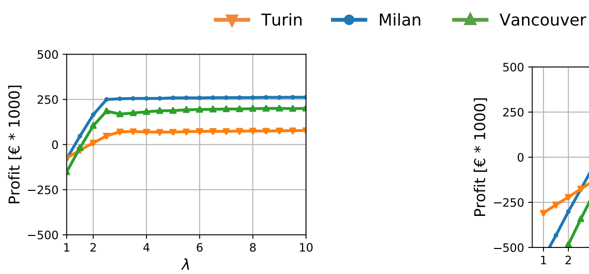


Figure 8: Monthly estimated profit for increasing λ and fixed number of vehicles with 1 charger every 10 vehicles ($n_c = |F_0|/10$).

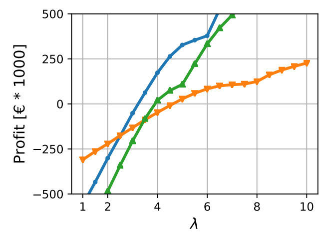


Figure 9: Monthly estimated profit for increasing λ and fixed number of vehicles with 1 charger for each vehicle ($n_c = |F_0|$).

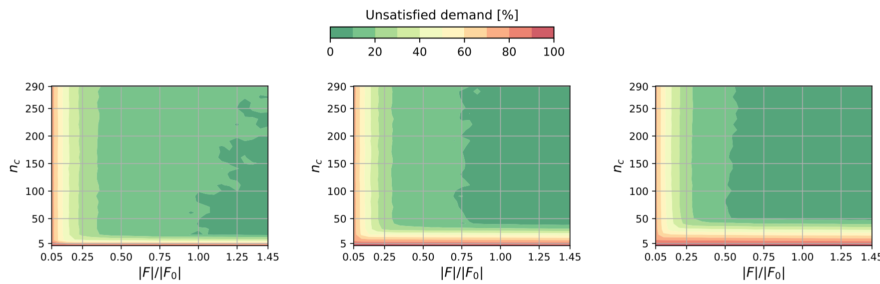
from 5 to 6, where we observe the highest peak at 78% at 20:41. For $\lambda = 6.5$ we observe a lower peak value of 70% at 18:44. Synchronization of charging operations leads to a drastic reduction in fleet size, reducing the possibility of satisfying customer demand, which peaks precisely at these times. This effect causes the nonlinear effects shown in Figure 6.

This result suggests that an innovative charging policy could help improve the scalability of the system. We leave this as future work.

Now we evaluate the economic impact of these decisions.

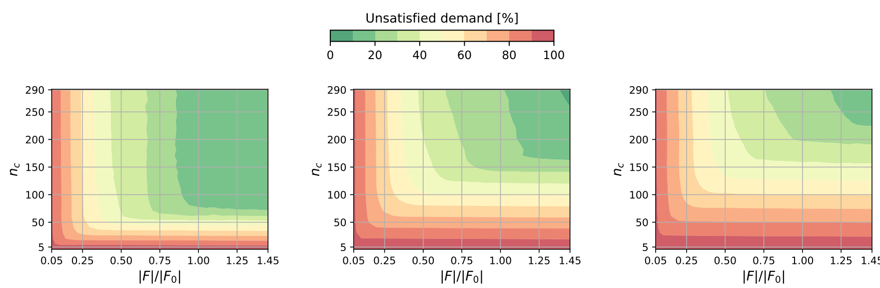
In Figure 8 we show the estimated profits when the system has limited charging capacity ($n_c = |F|/10$), and in Figure 9 we consider the case of one charger for each vehicle ($n_c = |F|$) When the charging capacity is limited, the increasing demand makes the profit increase. However, when the capacity of the charging infrastructure limits the ability of the system to satisfy mobility demand, profit can no longer grow. That is, unsatisfied demand grows at $\lambda > 2.5$ (Figure 5) and profit remains constant.

If we remove the charging capacity limitation, the system utilization can increase and we also observe monotonically increasing profits. Although the unsatisfied demand continues to increase in this case (Figure 6), the absolute number of satisfied trips increases and so does the revenue. The additional costs incurred by the additional charging stations pay for themselves after about $\lambda = 4.5$ for Turin, $\lambda = 3.0$ for Milan, and $\lambda = 4.0$ for Vancouver, respectively.



(a) Turin (b) Milan (c) Vancouver

Figure 10: Unsatisfied demand varying number of chargers n_c and fleet size $|F|$. $z_c = 0.20$, $\lambda = 1$.



(a) Turin (b) Milan (c) Vancouver

Figure 11: Unsatisfied demand varying number of chargers n_c and fleet size $|F|$. $z_c = 0.20$, $\lambda = 5$.

In summary, it is better to invest in preparing an oversized charging infrastructure that can provide enough energy to handle an increase in demand. Current systems will become unprofitable until demand increases fourfold.

4.3. Demand growth with different fleet size and charging capacity

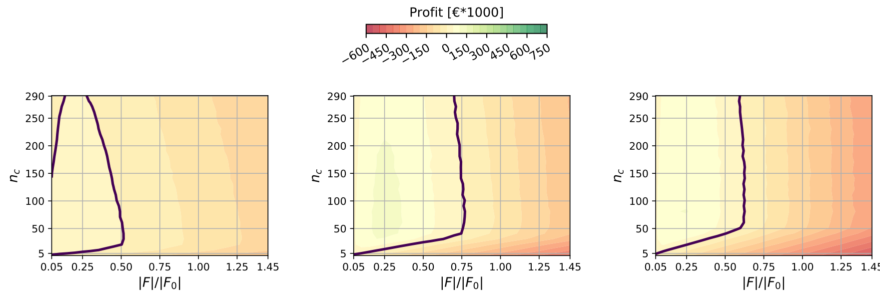
Here we observe the impact of scaling the demand varying $\lambda \in [1, 10]$, with different fleet size and charging infrastructure. To observe in more detail the impact of the combined effects of the fleet size $|F|$ and number of chargers n_c, we present contour maps of the unsatisfied demand. Figure 10 and Figure 11 report results for $\lambda = 1$ and $\lambda = 5$, respectively, for each city. In all cases, when a too small charging infrastructure or fleet size is present (left and bottom part of the figures), we observe a significant, unsatisfied demand. Conversely, as soon as the system has enough charging capacity to support the mobility demand ($n_c \geq 21$ for Turin, $n_c \geq 41$ for Milan, and $n_c \geq 53$ for Vancouver), just 30% of the original fleet size produces an unsatisfied demand below 20%.

Move to Figure 11. Here we consider the same chargers and fleet size ranges, but with a five-fold demand increase ($\lambda = 5$). As expected, the system has worse performance with the same resources, and fleet size and chargers have a larger impact. Interestingly, with a fleet comparable to the current configuration, the system can keep the unsatisfied demand below 20%, provided enough charging capacity. In detail, by having 290 chargers, we can satisfy 80% of the $\lambda = 5$ demand with 95%, 115%, and 125% of the current fleet in Turin, Milan, and Vancouver, respectively.

In general, we observe that the fleet size and the size of the charging infrastructure have almost independent effects on the unsatisfied demand. n_c is easier to set, having a minimum threshold above which increasing it brings no benefit (as seen in Figure 3b). The impact of $|F|$ is more complex, being affected by the demand's spatial and temporal diversity.

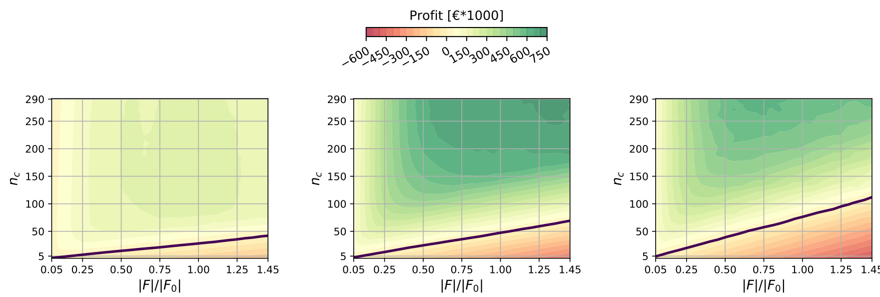
To better understand the interplay of charging infrastructure, fleet size, demand, and profit, we focus here on the monthly profit that an EVs FFCS provider would earn for various combinations of $|F|$ and $|n_c|$, i.e., its investment in fleet and charging infrastructure.

Figure 12 shows the results for $\lambda = 1$. Green shading indicates positive profit, yellow and red shading highlight loss-making configurations. The black lines indicate the boundaries between the two areas. Interestingly, the zones with the highest profits tend to be in the leftmost part of the figure, i.e., for a small number of vehicles and chargers. While this leads to higher unsatisfied demand - see Figure 10 - it looks like this is the only way to reduce the cost of the fleet, leading to the highest costs. Interestingly, the impact of charging infrastructure is fairly negligible unless n_c becomes too small (i.e., if there is not enough charging capacity available, resulting in lost revenue). This is due to the low cost of purchasing and installing a charger, which is amortized over $c_{life} = 10$



(a) Turin (b) Milan (c) Vancouver

Figure 12: Monthly estimated profits varying number of chargers n_c and fleet size $|F|$. $z_c = 0.20$, $\lambda = 1$.



(a) Turin (b) Milan (c) Vancouver

Figure 13: Monthly estimated profits varying number of chargers n_c and fleet size $|F|$. $z_c = 0.20$, $\lambda = 5$.

years. Therefore, the overall economic impact of charging infrastructure is less than that of fleet size. These considerations apply to all cities, with Vancouver experiencing the highest losses, which is also due to its large fleet $|F_0|$.

Figure 13 shows the results with $\lambda = 5$. Here we expect the system to be profitable when $|F| = |F_0|$, and therefore check which ranges of n_c and $|F|/|F_0|$ would yield the most profits. In Turin, n_c and $|F|$ have little impact on profits, provided the charging capacity sustains the mobility demand. In this case, a good trade-off would be to operate in the region with the highest satisfied demand and the lowest resources, i.e., $|F| = |F_0|$ and $n_c = 100$. In Milan, the influence of n_c and $|F|$ is more evident. To achieve the highest profit, at least 250 chargers and a 25% increase in fleet size are required. Interestingly, in Vancouver, the highest profit is obtained when the fleet size is reduced to about 75% of the current value. In summary, given the same satisfied demand, this further confirms that it is more profitable to increase the number of chargers and reduce the number of cars as much as possible.

In summary, we can conclude that the FFCS provider needs to carefully evaluate the fleet size in the system. The high cost of EV suggests that the number of vehicles should be limited to make the system profitable under both low and high demand scenarios. On the other hand, the limited cost of installing the charger and the long amortization time impact the cost marginally, suggesting that, if possible, it is better to make the infrastructure as large as possible.

5. Related work

Given the increasing popularity of shared mobility services, researchers strongly focused on these mobility solutions.

Much work has focused on understanding user habits and the growth of car sharing systems. Sprei et al. [37] used data from 12 cities to examine the customers' habits of FFCS customers based on EV fleets. Alencar et al. [1] compared FFCS systems with one-way and two-way carsharing systems in the same city. Recently, in [15], we used big data analytics to analyze data from 25 cities worldwide to characterize the current use of ICEVs and electric FFCS. In doing so, we found that EV fleets in similar cities actually have higher utilization rates than ICEV fleets.

Other works focused on the pole placement for car sharing systems based on EVs. In our previous works [8, 9], we used a trace-driven simulator to evaluate the placement for EVs FFCS systems: our results showed that placing charging stations in high-demand areas improved performance. Vazifeh et al. [41] leveraged mobile phone locations of one million customers in Boston to determine the best solution for charging station placement using a genetic algorithm.

Unlike these previous works, our primary goal here is not to explore different charging station placement strategies or optimise design options to optimize current demand. Instead, we are interested in evaluating the impact of an increase in mobility demand. Rather than using a trace-driven simulator that replicates current trips, we first create a demand model that generalises current demand and use it to feed an event-based simulator. Then, we explore how to scale up the charging infrastructure and/or fleet size while increasing the car sharing demand.

In the field of transportation research, one of the most important tasks for resource management In this direction, predicting the trajectories of moving resources is an important task to consider the possible effects in practice, such as avoiding collisions between autonomous driving vehicles. In this direction, Xiaofeng et al. [43] proposed a hybrid solution based on knowledge-based and data-driven methods for vehicle trajectory prediction. Yuhui et al. [24] proposed a mechanism based on dynamic modeling of social interaction that minimizes structural entropy. Another prediction problem considers mobility pattern to predict urban traffic. Wen et al. [46] propose a machine learning method that combines Graph Attention Networks and Embedding methods to predict traffic congestion. Similarly, Gaozhong et al. [39] propose a spatio-temporal Recurrent Neural Network to predict the future trends of crowds. FFCS systems use mobility prediction to satisfy more demand by predicting to customer spatial demand and scheduling the relocation of vehicles. Illgen et al. [22] provided a review of the current literature on the relocation problem in a one-way car sharing network. Several studies investigated the combined impact of charging and relocating vehicles in electric FFCS systems. Folkestad et al. [13], and Weikl and Bogenberger [42], in which the authors proposed an analytical formulation of the problem of charging and relocating vehicles in electric FFCS and used a genetic search to find optimal solutions. Di Febbraro et al. [11] explored how user-based vehicle relocation strategies can help manage a one-way car sharing system and maximise profits. Other works focused on relocation in other shared transportation systems. In particular, many recent works focused on bike sharing. For instance Ma et al. [27] proposed an integer programming model for rebalancing bike availability, Zhang et al. [45] proposed several policies for repositioning bikes, and Zhao et al. [47] improved fleet management by predicting bike availability with a deep learning method and similarly, Zi et al. [48] developed a deep learning method based on a graph convolutional network for predicting bicycle availability in a station-based system.

Here, we do not use any relocation. However, we show how our heuristic placement is also beneficial for relocation since cars are naturally moved to high demand zones.

Considering the methodologies, simulations are often used in research related to car sharing systems. They allow flexibility and let one study different what-if scenarios with different boundary conditions. Illgen and Höck [21] used an event-driven simulator similar to ours to compare the feasibility and economic sustainability of a station-based car sharing system based on EVs and ICEVs. More recently, Illgen and Höck [23] used a similar approach to study factors such as user demand, trip distance, and vehicle utilization that hinder the development of car sharing systems in rural areas. Brendel et al. [4] used an event-driven simulator to model the battery management system to optimize EVs in station-based car sharing systems. Similarly, Hu et al. [19] used an event-driven simulator to study the effects of battery capacity and charging speed on a station-based car sharing system.

A different simulation approach consist in agent-based simulation, in which the system is modeled as a collection of autonomous, decision-making entities called agents.In this direction, Pasqual et al. [28] proposed `SimFleet`, an agent-based simulation for FFCS. Santos et al. [35] explored a mixed integer programming (MIP) model and simulation approach for an ICEV-based FFCS to investigate the impact of relocation and relative costs, and discovered that the increase in revenue is unlikely to overcome the costs associated with hiring and staffing costs. Giorgione et al. [16] used `MATSim` an agent-based simulation approach to evaluate different dynamic pricing policies based on vehicle availability in a station-based car sharing system. The results show that dynamic pricing can reduce the number of bookings, as customers would prefer other modes of transportation. In a subsequent study, Giorgione et al. [17] used the same `MATSim` simulator to evaluate competition between one-way and two-way car sharing systems and showed that these systems do not compete with each other. Finally, Klöppel et al. [25] used simulations to study how the BeeZero car sharing system works with 50 hydrogen-powered vehicles in a two-way car sharing system. At last Yoon et al. [44] used a Monte Carlo simulation approach to study the configuration of a station-based car sharing system in Beijing and concluded that a mix of EVs and ICEVs is the best solution.

Differently to all these studies, we use an event-driven simulation approach, where both demand and supply are estimated from observed trips. Our objective differs as we study the impact of scalability as demand increases rather than the current usage of the system.

The problem of optimizing transportation resources while scaling demand is not new in the literature. For example, Tachet et al. [38] used data to predict the shareability of an urban ride based on urban growth and found that this is a city-invariant property. To the best of our knowledge, the only work for car sharing that is close to our work is by Fassi et al. [12] and by Boyacı et al. [3]. Fassi et al. [12] examined the growth of a two-way car sharing system using an event-based simulator that measures whether and how charging stations generate profits. Boyacı et al. [3] instead proposed a MILP formulation for optimizing one-way electric car sharing that accounts for charging and relocation and uses data on two-way ICEV car sharing. Unlike them, here we study a FFCS system that is more complex since the customer can freely park the car anywhere within a geo-fence. Moreover, unlike the works of Boyacı et al. [3] and Fassi et al. [12], here we use actual FFCS trips from three different cities to build a demand and supply model, and then scaling it linearly with the intensity of the overall demand.

In this paper, we extend our work [2] in which we studied the impact of demand intensity on fleet size and charging infrastructure design, limited to the case study of the city of Turin. Here we improve and extend our simulation scenarios. First, we now use a generalized demand model by tuning the parameters of the KDE to closely match the original demand. Second, we extend the impact of system design options to understand their intertwining. Third, we consider two additional case studies (Milan and Vancouver) to observe the effects of city size and mobility demand distribution.

6. Conclusion and discussion

In this paper, we presented big data analytics and simulation approaches to assess scalability and profitability of free floating car sharing systems based on electric vehicles. We build demand and supply models to enable what-if studies and evaluate the impact on performance implications on EV car sharing systems. We focused on both customer and operator perspectives and consider unsatisfied demand, fleet management overhead and economic revenues and costs.

6.1. Take-away messages

Several conclusions can be drawn from our study. Even though each city has its own mobility demand, we observe common patterns among them:

- The capacity of the charging infrastructure must grow proportionally to the mobility demand. Interestingly, the number of chargers results to be very small in relation to the number of vehicles. In all cities studied, 4 to 5 chargers per 100 vehicles guarantee sufficient charging capacity to sustain the mobility demand.

- Chargers shall be placed in high-demand areas so that cars are naturally brought to where customers look for them. This placement allows the system to capture most of the customer demand and thus maximize revenue. It is important to have many such areas spread in the city covering about 10-20% of the city to save the cost of workers bringing the cars to charge.

- The same fleet size can sustain a significant increase in mobility demand, resulting in sublinear growth with demand. The current fleets observed in the data might sustain a 300% increase in demand (not satisfying in total less than 15% of it).

- The cost of EV and the need to manage frequent and lengthy charging operations are the main factors limiting profitability. Choosing the right number of vehicles is more fundamental than optimizing the cost of charging infrastructure.

- From an economic perspective, the demand currently observed would not benefit from a switch to EVs. To reach profitable regions, operators would either have to reduce fleet size by 50% to 75% or wait for demand to increase by 5-8 times.

In the current situation, large cities such as Vancouver and Milan with high and spatially spread demand have higher losses than small cities such as Turin with lower and more concentrated demand. However, large cities would benefit from a future increase in demand and reach the break-even point earlier than small cities. Milan, with high demand limited to a few areas, appears to be more profitable than Vancouver, where mobility demand is too widely dispersed to optimize costs.

6.2. Limitations and future work

In considering our results, it is important to remember the assumptions and simplifications we made in the modeling and mobility simulations

First, our demand model is obtained by generalizing observed trips in time and space using Poisson process and KDE. However, the data we start from only represent the trips corresponding to the satisfied demand in the current scenario in the observed cities. Therefore, we might underestimate the demand intensity. Possible future improvements include data-driven estimation of this difference, including adoption of classical modeling based on the four-stage trasportation model [10].

The O/D pairs simply describe the trip distribution we generate. In our simulator, we estimate the actual length and duration of the trip regardless of the specific route and time of day. This assumption might have a stronger impact during peak hours, when congestion is more likely to occur.

When considering our results, it is important to note that we assume that demand is not affected by supply availability. That is, we do not consider that customers' willingness to use the service may change depending on the probability to complete the trip. Namely, in a demand scenario, we do not consider: (i) possible churn rate due to unsatisfied demand; (ii) surge in demand triggered by the increasing availability of the fleet; (iii) inhomogeneous growth in different zones of the city, and (iv) use of multiple modes for the same trip. These four aspects should be considered to realistically simulate human behavior. We leave this as future work.

In the current formulation, we assume that a worker is always available to manage the charging process. This is an optimistic assumption, and the delay due to the absence of a staff member should be considered.

We also plan to quantify the impact of allowing customers to charge vehicles, e.g., by taking the car to a charging station at the end of a trip. Similarly, we plan to explore proactive smart charging strategies, such as charging cars during off-peak hours. We expect this to reduce administrative costs and increase the satisfied demand

As mentioned in Section 3, obtaining reliable and accurate financial information is a complex task for any city. While we have provided some examples of the economic parameters in our study, we provide our code [5] to explore different pricing and revenue models.

Acknowledgements

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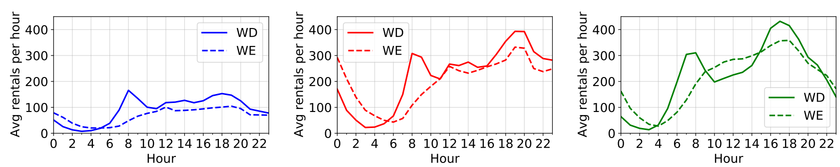
Appendix A.

Here we report the characteristics of demand and supply observed in the three cities studied, Turin, Milan, and Vancouver. We aggregate the raw data per trip into temporal and spatial bins.

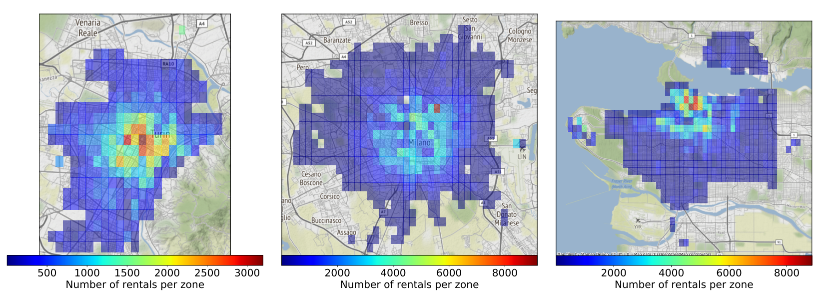
Regarding temporal patterns, Figure A.14 shows the average number of rentals per hour separately for weekdays (Monday to Friday) and for weekends. The hourly profile for weekdays reflects commuter flows, with two clear peaks in the morning and evening rush hours. Interestingly, the cities differ:

Turin and Milan have a similar morning peak at 8:00, but different afternoon peaks at 18:00 for Turin and 19:00 for Milan. In Vancouver, on the other hand, customers tend to travel early in the morning (before 8:00), and the afternoon peak is also earlier, at 17:00. Weekends have a higher number of night trips than weekdays, likely due to the busy nightlife, with Milan having the highest night usage of the three cities. Note also that the morning peak decreases dramatically in all cities.



(a) Turin (b) Milan (c) Vancouver

Figure A.14: Average number of rentals per hour during weekdays (WD) and weekends (WE).



(a) Turin (b) Milan (c) Vancouver

Figure A.15: Spatial rental distribution.

In Figure A.15 we illustrate the spatial habits of customers. For this purpose, we divide cities into square zones of 500 m x 500 m. Next, we compute the number of rentals departing from each zone in the trace As before, the cities show some similarities, with most rentals departing from a few zones. In Turin, these zones are concentrated around the city center, while in Milan and Vancouver they tend to be found in several zones of the city. As described in Section 4, this difference in mobility demand makes the infrastructure placement more challenging.

Next, we look at rental statistics in terms of duration and distance. Full details can be found in Table 1. Vancouver has the longest trips, both in terms of duration and distance. Finally, to consider the characteristics of the service, we evaluate the cars model and fleet size. Since the number of cars can fluctuate during the period, for example due to maintenance, we calculate the number of vehicles as the median number of vehicles per week. In the studied period, the fleet consisted of Smart ForTwo and with 414 vehicles in Turin, while Milan and Vancouver had larger fleets with 863 and 1066 vehicles, respectively.