Environmental and Economic Comparison of ICEV and EV in Car Sharing

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Abstract*— Transport electrification is increasingly seen as a necessary action to curb climate change. Free floating car sharing (FFCS) is a transport mode whose real benefits and disadvantages are still largely discussed. Here we compare possible FFCS which adopt either internal combustion engine vehicles (ICEV) or electric vehicles (EV). We focus on three main aspects: satisfied demand, emission, and system profitability. We use a realistic simulator to thoroughly compare the different dynamics of ICEV and EV based FFCS systems. Our simulator models mobility demand, fleet status, refueling operations, and estimates the satisfied demand, determines the equivalent CO_2 emission from the fuel production up to the fuel consumption, and computes operational profit. As case study we consider the city of Turin, where we compare 4 FFCS systems based on a fleet of Fiat 500 with different engines, i.e., gasoline, diesel, LPG, and electric. We run simulations using the demand as derived from trips recorded by the currently operational FFCS, and using the fueling infrastructures today present in the city. Results show that the EV FFCS system can satisfy the same demand as the ICEV based solutions. As expected, the EV fleet reduces emission. However, the current higher cost of EVs makes the FFCS system less profitable than ICEV solutions - questioning its adoption. Interestingly, cheap low-power chargers result the best solution for the EV FFCS, reducing also maintenance costs. We believe our approach and our simulator, which we make available for the community, is a first step to thoroughly compare the implications of different engines in shared mobility.

I. INTRODUCTION

In the last decades, cities are facing severe challenges to manage mobility, make it sustainable, and reduce air pollution [1]. Sharing mobility is seen as one of the transportation paradigms that helps mitigating this problem. Focusing on car sharing, the possibility to reuse the same vehicle by multiple users improves sustainability by increasing parking availability and by reducing pollutant emissions [2]. The Free Floating Car Sharing (FFCS) providers offer a fleet of vehicles that customers rent and return using their smartphones. Fleets can be based on internal combustion engine vehicles (ICEV) or electric vehicles (EV). Given the absence of local greenhouse emissions, the latter promise to be a more sustainable solution [3]. However, EVs are more expensive than ICEVs; they need proper charging infrastructure specifically optimized for car sharing [4], [5], and thus may result less profitable.

In this work, we present a thorough comparison of ICEV and EV FFCS solutions. We compare four systems: the first three adopt ICEVs using regular gasoline, diesel or Liquid Petroleum Gas (LPG) engines; the fourth, instead, is based on EVs. In our comparison, we consider three main research questions: (i) Do the different fueling options impact the ability to satisfy customers' demand? (ii) Which are the environmental benefits of using more eco-friendly fleets? (iii) What are the economic impacts of such a shift?

As a case study, we focus on the city of Turin, for which we collected hundreds of thousands of real trips from an operational FFCS provider [6]. Leveraging these data, we create a realistic mobility demand model that generalizes the temporal and spatial characteristics of the observed trips [7]. We then use this generalized demand model to run accurate trace-driven simulations to thoroughly study how the different fleet options impact performance, sustainability, and costs. In detail, we compare the simulation of the same traffic demand – changing the fleet vehicles and the refuelling infrastructure. We assume that to refuel vehicles, the FFCS provider relies on workers that access the actual fueling infrastructures as currently present in Turin. For the EV case, we further compare three charger technologies, namely Level-2, Level-3 and supercharger solutions.

Our simulator measures the fraction of satisfied trips the system could sustain – our main index to gauge the customer service level. It also measures the distance and duration of each trip, the number of refuelling operations and the time workers spend on each. With this data, we compute the greenhouse emission (GHG) according to the Well-to-Wheel emission cycle [8], i.e., from the fuel production up to the fuel consumption. At last, we project the profits of the FFCS system, considering the costs of vehicles, fuel, and workers, while revenues come from customers' cost-per-minute fares. Our results show that:

- Despite the more frequent and longer refuelling operations, an EV fleet has very similar performance to ICEV fleets in terms of ability to satisfy customer demand. Faster electric chargers give minimal benefit but increase sizeably the costs.
- The EV fleet has the smallest environmental impact due to the absence of local emission, with gasoline cars having 50% more emissions than EVs.
- Yet, from an economic point of view, EVs fleets are the least profitable. This is mostly due to the costs of the fleet, which, if not accurately sized, would quickly erode revenues.

We believe the methodology we present is generic enough to offer researchers and providers interesting insights. We

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make the models and software available to perform further analysis of what-if scenarios to compare FFCS system optimization and design options.[1]

II. Related work

To the best of our knowledge, we are the first to use realistic simulations to compare ICEV and EV FFCS along with three main directions, namely customer service level, GHG emissions, and overall system profitability. We use actual demand, refuelling infrastructure, and vehicles characteristics to obtain credible figures in the specific use case. Rather than data-driven approaches, most previous works compare ICEV and EV with analytical models. Authors in [9] examined the life-cycle impacts on energy use (also called life-cycle inventory) and GHG emissions as a result of candidate travellers adopting car sharing in the US. Authors in [10] examined the GHG emission impacts resulting from shifts in transportation mode to car sharing. Using a mixed and a binary logit model, consumer's preferences and the probability of choosing car sharing or forfeiting ownership when using car sharing services were analyzed. Authors in [11] presented an approach to assess various types of EVs and ICEVs over several criteria from different sustainability dimensions. Authors of [12] examined key areas of interest such as EV and charging infrastructure deployment, ownership cost, energy use, carbon emissions and battery material demand. Authors of [13] investigated the impacts of an EV sharing scheme in carbon emissions and EV adoption using a system dynamics modelling approach. The results show that with the right incentive policies, EV adoption can increase up to 36% with a reduction of 29% of carbon emissions. Instead, authors of [14] presented a long-term forecast of the EV adoption in 26 countries predicting that 30% of the passengers will use EVs in 2032. Authors of [15] proposed a methodology to assess the impact of EVs in urban areas showing that the travel time of L-category (small vehicles with 3 or 4 wheels) EVs might be longer compared to cars. Furthermore, by replacing car trips with L-category EVs, carbon emissions could decrease more than 70% in a year.

III. Methodology

A. Simulator and parameters

Here we describe the principles and the assumptions of the demand model and the simulator we design to compare the performance of FFCS systems based on ICEVs or EVs.

Demand model

Given actual trips observed in a real system, we create a demand model that generalizes them into the probability distributions representing the demand dynamics in both time and space. To this end, we use the methodology presented in [7]. We create our demand model with data collected from the car sharing operator car2go [6]. In a nutshell, we collected a longitudinal trace describing all the trips performed by users during 2017 in 23 cities.

Given a trace in a city, we consider 48 independent one-hour-long time slots, 24 for each weekly workday (Monday-Friday), and 24 for the weekends (Saturday-Sunday). In each time slot, we model the demand in time by using inhomogeneous Poisson processes [16]. In detail, we assume that customers requests arrive as a Poisson process, with inter-arrival time distributed as a negative exponential random variable with mean that depends on the day and hour. We fit the arrival rate to match the average intensity of bookings occurring at the corresponding temporal slot in the trace.

To model the spatial demand, we rely on a Kernel Density Estimation (KDE) methodology [17]. The KDE estimates the probability distributions of a request to be originated in a zone and destined in another zone. We divide the city into a grid composed of squares having 500 m sides. We map the origin and the destination (OD) of each trip with the correspondingly 4-dimensional coordinates. We then fit the 4-dimensional KDE for each time slot according to the requests observed in the collected data. We use a Gaussian kernel [18] and set the bandwidth matrix of KDE to the 2 x 2 identity matrix. This gives us 48 probability matrices that we use to generate the OD of each request randomly.

Simulator

Armed with the generalized demand model, we employ our event-driven simulator to study the dynamics of different FFCS systems. The simulator models a homogeneous fleet of F vehicles composed of ICEVs or EVs. Cars move in the city areas over a grid of squared zones Z of 500 m side. All cars have a fuel capacity B - which depends on the model.[2] Customers look for a nearby car in an origin zone, and if it exists, drive it to the destination zone. The simulator tracks each car location, status (i.e., available, rented, under charge) and updates its State of Fuel (SoF) accordingly. To simulate different charging infrastructures, we consider fueling stations replicating the infrastructure currently present in Turin as described by OpenStreetMap for gasoline, LPG and diesel stations. [3] We consider the bluetorino and Enel X charging stations for the EV case.[4] We have 712 gasoline and diesel stations, 16 LPG stations, and 535 EV chargers. Notice that LPG stations are present only in the periphery.

At simulation startup, cars are randomly placed among zones, with initial SoF uniformly distributed in $[0.5B, B]$. All vehicles are marked as available. The simulation starts, with the first **car request event** at $t_i = 0$, associated to a desired origin O_i and destination D_i zone. Since topically users are willing to walk up to 500 meters [19], the simulator seeks an available car in O_i or any 1-hop neighboring zones. If available, the simulator computes the time t_{trip} to reach D_i, and schedules a **car release** at a time $t_i + t_{trip}$ in O_i. If no car is available, it marks the request as *unsatisfied*.

[1] *https://smartdata.polito.it/odysseus-an-origin-destination-simulator-of-shared-e-mobility-in-urban-scenarios/*

[2] Here, we use the term *capacity* and the term *State of Fuel (SoF)* to refer to the energy/fuel level regardless of the type of engine.

[3] `https://wiki.openstreetmap.org/wiki/Tag:amenity%3Dfuel`

[4] `https://www.bluetorino.eu/la-mappa-delle-stazioni` `https://www.enelx.com/it/en/electric-mobility/charging-stations-map`

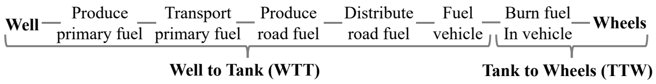


Fig. 1: Well-to-Wheel cycle

When a car release at time t_j is triggered, the simulator computes the consumed amount of fuel to update the SoF, marking the car back as available. If the SoF is below a threshold α, the simulator marks the cars as refuelling. It handles the refuelling event by moving the car to the nearest-free station and schedules a **refuel complete** event, which accounts for both the time t_{relo} to reach the station and to bring the car back to the original zone, and the time t_{fuel} to bring the SoF back to $100\%B$.[5] We compute the t_{fuel} assuming that the station delivers the fuel following a linear fueling time. When a **refuel complete** event fires, at time $t_j + (t_{relo} + t_{fuel})$, the car is marked again as available, and customers can rent it again. The pump/charger is freed as well.

Based on the described simulation, we compute the following system performance metrics:

Unsatisfied demand: it is the fraction of requests that are not satisfied because there is no car in the origin. It indicates the quality of the service in terms of car availability for customers, and it shall be minimized.

Total refuelling handling time: it measures the monthly time spent by the system to bring cars to the pump/charger. It is the sum of the driving time spent by workers to drive the cars to the nearest free pump/charger, refuel it, and bring it back to the original destination. It indicates the goodness of the charging infrastructure. Being it a cost, it shall be minimized.

B. Emissions and energy model

While both ICEVs and EVs may offer good system performance metrics, they may have different environmental impacts. To evaluate the environmental impact of the different FFCS system implementations, we rely on the *Well-to-Wheel* approach [8] depicted in Figure 1. With this, we compute the greenhouse gases emissions, in terms of Carbon dioxide equivalent CO_2e, considering two main components: the *Well-to-Tank*, and the *Tank-to-Wheels* emission.

Well-to-Tank: It considers the amount of greenhouse emissions from the production of the raw material up to the moment the fuel/energy is delivered to the vehicle. Thus, it accounts for the processes required to extract, produce, transport, and deliver it.

For ICEVs, it is complicated to find accurate Well-to-Tank data as this is very sensitive and may drastically change based on different factors, e.g., the presence of oil pipelines. A reliable source for data for the European context is provided by [20], with additional details for each process of the Well-to-Tank component. In detail, we rely on the Well-to-Tank (WTT) GHG emission data reported in the Oil and Gas section. This data reports, for each fuel f, the $WTT_{MJ}(f)$ as the grams of CO_2e emitted to produce a total energy of $1MJ$ of finished fuel, i.e., the energy that it can produce when burned, based on its lower heating value (LHV)[6]. By knowing the $WTT_{MJ}(f)$ of the fuel, the respective LHV, and the fuel density ρ, we compute the $WTT(f)$ per unit of fuel, i.e., l, as follows:

$$WTT(f) = WTT_{MJ}(f) \cdot LHV(f) \cdot \rho(f) \tag{1}$$

For electric cars, we compare the energy mix used to produce electricity in Europe as presented by authors in [21] and in Italy [22]. The energy mix is the overall contribution of the sources used to produce electricity. Starting from this data, we compute the average emission to produce the electricity GHG_{avg}, i.e., the primary fuel, as follows:

$$GHG_{avg} = \sum_{c \in C} GHG(c) \cdot w(c) \tag{2}$$

where c is one of the components of the country energy mix C, GHG is the greenhouse emission emitted to produce $1kWh$ of electricity, and w represents the share of the components. However, to properly consider Well-to-Tank impacts, we take into account other aspects. Thus, we consider the electricity losses for transmission and distribution with an average efficiency $\eta_{transport}$, and the charging efficiency $\eta_{charging}$ as suggested in [23]. As such, we compute the Well-to-Tank (WTT) greenhouse emission, per electricity unit, i.e., kWh, as follows:

$$WTT(f) = GHG_{avg} / (\eta_{transport} \cdot \eta_{charging}) \tag{3}$$

Armed with the Well-to-Tank emissions per unit of each fuel/energy f, by knowing the *car consumption* based on the fuel $CC(f)$, we compute the Well-to-Tank emission per *km* as follows:

$$WTT_{km}(f) = WTT(f) \cdot CC(f) \tag{4}$$

Finally, by knowing the fuel/energy f used during simulation, and the total traveled distance by the cars (Tot_{km}), we compute the total Well-to-Tank emissions as follows:

$$WTT_{tot} = WTT_{km}(f) \cdot Tot_{km} \tag{5}$$

Tank-to-Wheels: The Tank-to-Wheel refers to the amount of tailpipe GHG emissions emitted by the vehicle during its operation.

For ICEVs, we build our model upon the data published in [24]. The report analyzes the greenhouse gas emission considering the CO_2, the Methane (CH_4), and the Nitrogen Oxide (N_2O) exhaust emissions. We consider the CO_2e from the three gases, and we compute the Tank-to-Wheel emissions as follows:

$$TTW_{tot} = GHG(f) \cdot CC(f) \cdot Tot_{km} \tag{6}$$

[5]For simplicity, we assume there is always an available worker to handle the fueling event so that a car gets serviced immediately. If all stations are busy, the car gets queued to the closest station and gets serviced when a pump/charger is freed.

[6]The Lower Heating Value reports the amount of heat released by combusting a specified quantity of fuel.

TABLE I: Summary of fuel characteristics.

Fuel	WTT	LHV	ρ	$\eta_{Trans-port}$	$\eta_{Charg-ing}$	Emission WTT	Emission GHG
	g/MJ g/kWh	MJ/kg	g/l	$-$	$-$	g/l g/kWh	g/l g/kWh
Gasoline	17.0	42.3	745.8	-	-	536.3	2314.8
Diesel	18.9	42.7	836.1	-	-	674.7	2616.5
LPG	7.8	46.0	550.0	-	-	197.3	1660.7
EV-EU	424.9[a]	-	-	0.92	0.80	577.3	0
EV-IT	269.0[a]	-	-	0.92	0.80	365.5	0

[a] The WTT reports the GHG_{avg} based on the European or country energy mix.

where f represents the vehicle fuel, GHG represents greenhouse emitted per liter l of fuel, CC is the car energy consumption, and Tot_{km} reports the total traveled distance in the simulation. In the case of EVs, no direct local CO_2e emission is present. Thus, we assume $TTW_{tot} = 0$.

Table I reports the values used for the fuel variables and the resulting emissions. For electric vehicles, we report in the WTT column the GHG_{avg} in Europe and Italy, respectively. Notice that the Well-to-Wheel cycle does cover the entire Life Cycle of the vehicle since it does not consider energy and emissions involved in building facilities, manufacturing the vehicles, or end of life.

C. Cost model

While performance and emission indexes help exploring design options identifying the best one for the customer and the environmental point of view, the FFCS operator is ultimately interested in economic sustainability. For this, we derive a cost model based on vehicle costs, refuelling costs, operating costs, and revenues with a yearly projection.

Vehicles costs: We suppose that the operator leases the cars with a three-year-long contract. We assume that the contract includes all the costs for registration, tax, insurance, ordinary and extraordinary maintenance, and roadside assistance. Since precise information about C_{lease} is not available, we set a baseline price for the gasoline version of the Fiat 500. Then, we scale-up the price for the other vehicles according to the ratio between the MSRP price of the vehicle and the MSRP price of the gasoline version. Notice that given the lack of precise information, we do not consider any discount nor subsidies that may impact the vehicles' final price, especially while buying low emission ones. Finally, by knowing C_{lease} and the number of vehicles, we derive the total yearly fleet cost.

Refueling cost: For the refuelling cost, we consider that the car sharing operator relies on the public city infrastructure. Thus the operator has no infrastructure cost. Since workers bring to refuel the cars, we consider a C_{worker} hourly labour cost. For the fuel price, we consider a C_{fuel} cost depending on the fuel. For electric vehicles, we consider three scenarios based on the charger type, i.e., Level-2, Level-3, Supercharger.

Emission costs. For the emission, we consider that the car sharing provider pays a $c_{emission}$ fee for each metric ton (1000 kg) of CO_2e emitted by its customers and for the required refuelling operations. We assumed a value in line with the current level of carbon pricing [25].

TABLE II: Summary of cost and revenue parameters.

Param	Description	Range
C_{lease}	Yearly lease for gasoline ICEV	4000 €/yr/vehicle
	Yearly lease for diesel ICEV	4670 €/yr/vehicle
	Yearly lease for LPG ICEV	4610 €/yr/vehicle
	Yearly lease for EV	7140 €/yr/vehicle
C_{fuel}	Gasoline cost for l	1.58 €/l[a]
	LPG cost for l	0.65 €/l[a]
	Diesel cost for l	1.44,€/l[a]
	Level-2 charger, Energy cost for kWh	0.40 €/kWh[b]
	DC charger, Energy cost for kWh	0.50 €/kWh[b]
C_{worker}	Hourly labour cost to bring the cars to refuel	23 €/h[c]
C_{disinf}	Disinfection and interior cleaning cost	5 €/20 rentals
C_{wash}	Cost to wash the car	8 €/100 rentals
$C_{emission}$	Cost for 1 ton of CO_2e	50 €/t CO_2e [25]
R_{rental}	Average revenue per rental minute	0.26 €/min[d]

[a] https://www.mylpg.eu/stations/italy/prices/
[b] https://www.vaielettrico.it/nuove-tariffe-enel-x-per-la-ricarica-dal-1-giugno/
[c] https://www.infodata.ilsole24ore.com/2019/08/19/39139
[d] https://www.share-now.com/it/en/pricing/

Management costs. We also consider other management costs required to run a car sharing service. For instance, we consider the cost C_{disinf} to clean and disinfect the car any time the worker brings it to refuel. Furthermore, we assume exterior car washing every 100 rentals, each costing C_{wash}.

Rental Revenue We consider an average cost-per-minute R_{rental} based on current Share Now fares. This consideration allows us to transform the total rental time into the total revenues. Table II summarizes the cost and revenues parameters, with their chosen values for this work.

IV. RESULTS

As a case study, we focus on the city of Turin. The city is characterized by a fleet size $|F|$ of 400 vehicles. Despite being non-stationary, especially during periods like August and Christmas holidays, the service usage follows an hourly and weekly pattern, with more rentals during the commuting hours and in general in the weekdays [26]. Considering the characteristics of the trips, the average distance is less than 4 km with an average duration of 21 minutes. The longest observed trip is about 20 km (to reach the airport).

We consider 4 different fleets composed of homogeneous cars powered either by gasoline, diesel, liquefied petroleum gas (LPG), or electricity for our simulations. Table III summarizes the characteristics of each vehicle type. For each fleet type, we set α as the minimum fuel/energy required to perform the longest trip in Turin. For EVs, we investigate whether the charge speed impacts the satisfied trips due to the fleet reduction induced by the long charging operations. To this end, we consider slow Level-2 AC chargers at $3.7kW$, $11kW$, and fast Level-3 DC chargers at $50.4kW$. We consider the impact of the fleet size as the main parameter that the provider can choose to reduce the cost. To this end, we vary

TABLE III: Summary of vehicles and fuel characteristics.

Model	Fuel type	Capacity	CC	Range	α
	[-]	$[l, kWh]$	$[per\ km]$	$[km]$	[-]
Fiat 500 1.2	Gasoline	35	0.058	600	4.5%
Fiat 500 1.3	Diesel	35	0.042	827	3.3%
Fiat 500 1.2	LPG	30	0.071	425	6.4%
Fiat 500-e	EV	37	0.188	196	13.9%

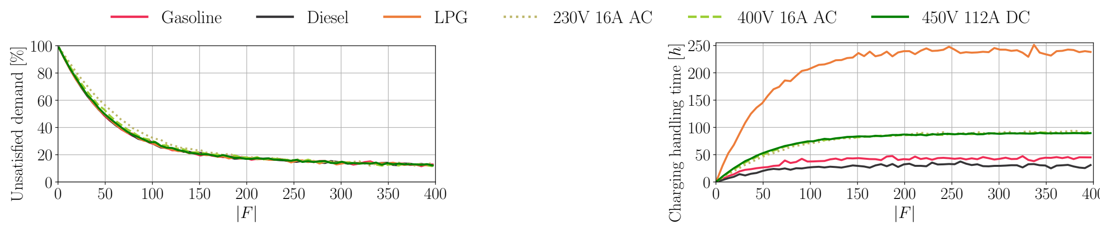
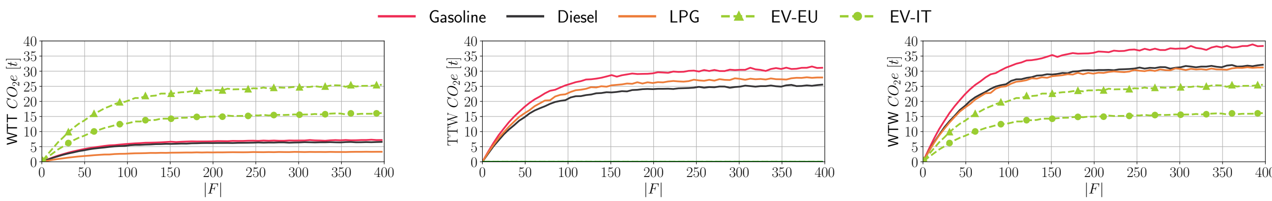


Fig. 2: Unsatisfied demand

Fig. 3: Monthly charging handling time



(a) Well to Tank (WTT)

(b) Tank to Wheels (TTW)

(c) Well to Wheels (WTW)

Fig. 4: Monthly emission for the customers' mobility and the charging operations

the fleet size from $|F| = 0$, up to $|F| = 400$, corresponding to the currently available fleet.

Firstly, we focus on the impact of the fleet size on the unsatisfied demand reported in Figure 2. All fuels/chargers show similar performance. For EV fleets, a faster charger gives only a minimal contribution, with an increase of 2.5% on the satisfied demand when 100 vehicles are employed. With more than 200 cars, all the curves overlap and decrease at very small rate, suggesting that the current fleet, composed of 400 vehicles, might be slightly oversized regarding this metric.

Next, in Figure 3 we study the impact of the fleet size on the charging handling time. Here we report the total time to handle the charging operations in 1 month. Consider the region $|F| \geq 200$. The diesel and the gasoline fleets show the lowest charging handling time due to their long *range* and the charging infrastructure ubiquity. Interestingly, despite the shortest range, the EV fleet asks only twice as much time as the gasoline fleet to handle the refuelling events. Considering LPG, the time required to handle the refuel events is much higher due to limited infrastructure, which is usually far from the city centre. As such, the workers have to drive for longer distances to refuel the vehicle and bring it back. In both the unsatisfied demand and the charging handling time the charger technology does not impact the performance. Hence, from now on we consider only the *400V 16A AC* charger.

Considering the environmental impact, Figure 4 reports the monthly CO_2e the emission for the customers' mobility and the charging operations. Focus on the WTT first. The EV fleets show the highest CO_2e emission. With the European energy mix, it is almost up to 4-times than than gasoline or diesel fleets (2 times for the Italian energy mix). The LPG shows the lowest emission driven by the lowest WTT in Table I. Next, we consider TTW emission. Gasoline and diesel show different trends, with gasoline having the highest emission while diesel and LPG the lowest ones. The EV fleet, by definition, shows no emission. Finally, we consider the

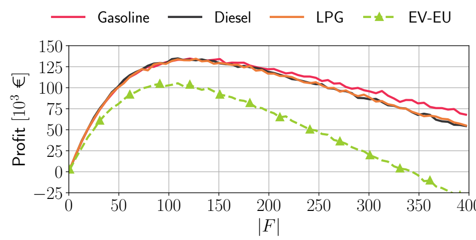


Fig. 5: Monthly estimated profit

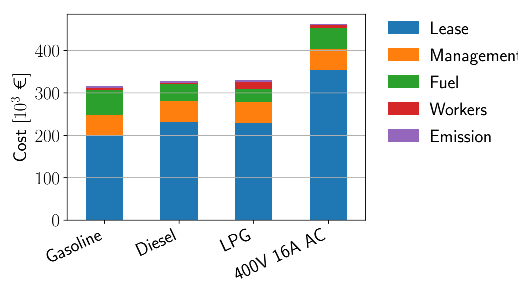


Fig. 6: Monthly breakdown of the costs when $|F| = 200$

global WTW emission. Given the higher contribution of the TTW emission, gasoline results in the highest emission level, with 50% more emission than EV charged with the European Energy mix. Finally, notice how, Diesel show similar WTW emission to LPG. This result is due to the better engine efficiency and autonomy, which counterbalance by the higher WTT emissions.

Finally, we project the results into costs and revenues to gauge the economic implications of the design choices. Figure 5 reports the estimated profit per month. We estimate the profit by computing the total revenues and subtracting the costs considered in Table II. For the emission cost of EV, we consider the EV-EU emission. We use this analysis to identify the impact of the different design choices rather than give precise cost-revenue information. When $|F| < 350$ vehicles, all fleets show a positive profit, while for bigger fleets, the EVs start having a loss due to the high leasing cost. Despite the high unsatisfied demand, i.e., more than 21%, the maximum profit is achieved using around 100 and 130 vehicles for EV and ICEV fleets, respectively. This result is driven by the highest leasing costs of EVs which do not increase the revenues. To investigate the differences in profit, in Figure 6 we break down the costs that the car sharing provider could face every month. We consider a fleet of 200 vehicles for this analysis as it guarantees almost an iso-satisfied demand ($\pm 1\%$). The leasing cost dominates, especially in the EV fleets. Given the iso-satisfied demand, also the operating cost is almost the same for all the fleets. Instead, the energy cost shows the highest variability, with the gasoline and the electric fleets showing the highest cost. The cost for the workers to handle the charging operations is limited in all fleets except for the LPG due to the limited existing infrastructure. Interestingly, if the operator pays a carbon fee for their WTW emission, this cost has a marginal impact and almost equal for all the fleets. Overall, ICEV fleets keep having lower costs.

V. Conclusion and future work

This paper presented a comparative analysis among different free floating car sharing fleets based on ICEVs or EVs. Our results show how EVs have similar system performance to ICEVs with almost equal satisfied demand when the same fleet size is used. Faster chargers give only a limited benefit; thus, a slower and cheaper charger can be employed. Moreover, the EV infrastructure's ubiquity helps in reducing the time to relocate the cars to a charger. The EV fleets have the smallest environmental impact WTW, with a reduction of more than 50% with respect to a gasoline-based fleet. The absence of local emissions drives the benefit of the electric fleet. From an economic point of view, EV FFCS currently results in the least profitable system, being also at a loss due to the high costs of the vehicles.

We are planning on widening our analysis by considering the fleets' entire life cycle for the emissions assessment, comparing the emission with full hybrids vehicles, and optimizing the charging infrastructure location. Furthermore, while considering the emission, we plan to extend our analysis to consider pollutants that may impact the quality of life in the city.

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