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Time-Based Utilization Rate of the Fleet: Measuring Deep Inefficiencies in E-Scooter Services in Atlanta and Rome

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***Abstract*— E-scooter services have been deployed in cities worldwide, as a clean, flexible, and enjoyable mobility mode that contribute to reaching sustainable objectives. Given its recent advent, we still need to understand its actual operation and efficiency, and the corresponding result from users. This work contributes to this aim, providing a novel metric, the time-based utilization rate of the fleet, to measure the performance of e-scooter services. Its time-based nature implies a novel approach in the field, separating from traditional approaches that use the number of trips as the basic variable. We will mathematically demonstrate that these metrics are approximations of the exact value we provide as they intrinsically depend on the time interval they select for the calculation. In order to feed our method, we have retrieved e-scooter data from an operator (Helbiz) in Atlanta (USA) and Rome (Italy), corresponding to February 2021. These data include the state of each e-scooter in time, which allows us to precisely know whether they were used, out of service, or parked. Results show utilization rates of the fleet of 0.2021 % and 0.3310 %, respectively and high percentages of out of service vehicles that exceed 25 %. However, this inefficiency was not reflected in the profitability of the business. The economic analysis we conducted shows revenues close to 1 million euros in Rome, which may detach profitability from efficiency.**

***Index Terms*— Shared mobility, electric scooter sharing services, utilization rate of the fleet, economic analysis, efficiency.**

I. Introduction

BOOSTED by the disruptive appearance of shared economy, e-scooter services have been widely deployed worldwide [1], providing undoubted benefits for the three fundamental components of the mobility market: cities, users, and operators. This micromobility service supports cities' strategic plans to move travelers away from roads in order to reduce congestion and emissions. In addition, it allows municipal public transportation services to avoid crowding, which has become a key factor in the travelers' preferences as a direct consequence of the COVID pandemic [2]. Furthermore, e-scooter services provide a cost-effective mobility solution for districts with a low penetration of the public transport network and allow cities to easily integrate new metropolitan expansions into the existing urban environment [3]. Apart from these functionalities that specifically enhance urban transportation, micromobility also offers a modern and innovative way of visiting cities for both tourists and locals [4].

Some of these benefits, such as avoiding road congestion and crowded public transport scenarios, have a direct and positive impact on users. Moreover, e-scooter services provide them with a door-to-door transport mode that also prevents from time consuming issues related with parking their private vehicles and waiting times in public transport. And, from a different perspective, e-scooters are also perceived by citizens as a new way of wandering around the city for leisure purposes [5]. Finally, micromobility services have opened a new niche in the mobility market, in which operators can expand their economic activity, targeting novel services to new user segments that have recently emerged specifically attached to these novel transport modes [6]. Nevertheless, e-scooters must face some objections related to safety [7], comfort [8], obstacles for pedestrians [9], and low availability in peripheral areas [10].

In order to exploit e-scooter benefits and avoid their potential drawbacks, we must find an optimal implementation in practical terms. Unfortunately, this is not the case in current experiences across the world. The optimal design and management of e-scooter services takes the form of a high complexity problem as it has to meet two opposite objectives [11]. On one hand, operators must guarantee the spatial availability of e-scooters throughout the city in order to meet quality of service requirements [12]. On the other hand, they must avoid designing an oversize fleet, which will cause problems on both the city (obstacles on sidewalks, visual pollution, rebalancing operations using polluting vehicles, etc.) and themselves (extra costs) [13].

Adding complexity to the problem, these opposite forces impact on all three dimensions of the service in an interconnected way. Reducing the number of vehicles will decrease the quality of service received by the users, which will lower their use, which will diminish the economic turnover of operators. On the contrary, multiplying the number of vehicles will increase both initial and operating costs of the service and will aggravate the corresponding issues on the urban environment.

In order to address the problem, we need to quantitatively measure the performance of e-scooter services and work out effective solutions that maximize it. The subsequent metrics will also have to reflect the distinct users' behaviors, intrinsic to each city due to cultural, social, and geographical factors, so that we can perform comparative analyses of the actual efficiency of the e-scooter services deployed. However, the data we require to feed the proposed methodologies are often limited, which results in rough approximations to the actual performance of e-scooter services. As we aim to demonstrate in this paper, the current scientific state-of-the-art in the field is significantly floored by this lack of complete and rigorous data, which leads to questionable conclusions that could eventually result in erroneous decisions on the design of micromobility services.

Thus, the objective of this paper is to propose a methodology and associated metrics to quantify the actual performance of e-scooter services according to their operative and economic efficiency. To this end, we have constructed an enhanced *utilization rate of the fleet* based on time in use rather than on the number of trips. We will prove that the time-based utilization rate of the fleet provides the upper limit of accuracy for metrics that are based on the number of trips, thus correcting errors inherent to the latter. Furthermore, we will analyze the profitability of e-scooter systems considering the current fares and the actual utilization of the system.

This type of metrics and subsequent studies require accurate and complete data of e-scooter trips. Thus, we have retrieved a detailed database of e-scooter trips in two cities, Rome (Italy) and Atlanta (USA), with dissimilar cultural, social, and topological characteristics. To the best of our knowledge, this is the first database to provide the state (in use, out of service, or parked) of every e-scooter throughout time, and the trajectory of each trip, thus allowing a solid analysis of the actual utilization of the fleet. We will apply the proposed metrics to these cities, and compare the obtained results. Our findings drift apart from other precedent works, and show extremely low utilization rates (below 0.35 %), which demonstrate that we are failing to obtain the most from e-scooter services, and eventually missing their capability of providing a novel solution to modern urban mobility that could generate evident benefits to cities, users, and operators worldwide.

II. Related Work

A. Shared Mobility Data

Every disruption in a market sector causes a new set of questions to be addressed regarding key issues such as user acceptance, economic viability and profitability, and operative implementation, among others. These insights are crucial specially for both companies and public administrations, in order to, on the one hand, optimize their services, fares, costs, and revenues, and, on the other hand, to build a suitable regulatory framework to guarantee its integration into the existing related sectors.

At the first stages of these disruptive services, information can only be collected through surveys given that there is still little data generated from their actual operation. This is the case of e-scooter services, where we can find recent surveys carried out in different cities and focused on several aspects such as user segments [14] (Vienna, Austria), [15] (Thessaloniki, Greece), perceptions [16] (Tempe, USA), [17] (Riyadh, Saudi Arabia), preferences [18] (Baltimore, USA), [19] (Portland, USA), and safety issues [7] (Paris, France) among others. This initial information is rather important for assessing the early stages of the e-scooter services and their potential viability and benefits.

Furthermore, data generated from their actual operation open up additional possibilities to extract knowledge about this preliminary observations. In this regard, e-scooter services are mainly operated by private companies that seldom provide an easy access to their internal operation. As a consequence, the scientific community has been forced to rely on an indirect way of collecting the data required to perform profound studies on the representative features of this novel service: scraping user APIs [20]. E-scooter service providers offer trips through an app that depicts all the available vehicles in a city for potential riders to select the one that best meets their needs. Obviously, this information is publicly accessible, which allows developing software tools to collect it in a systematic way. Doing so, scientists are capable of taking periodic “snapshots” of the available e-scooters of a specific operator in the city, including their unique identifier and location. Observing the temporal sequence of these samples, we can derive the e-scooters that have been rented (those that disappeared from the previous sample) and the origin and destination of their trip (once they reappear as available on the app).

Scraping the user APIs of e-scooters services in real operation, researchers have analyzed different significant factors such as mobility descriptors like trip duration and distance [21], [22], spatial [23] and temporal [24], [25] patterns, purposes [26], economic performance [27], and how this micromobility mode interrelates with the urban environment [28] and the transport network [3], just to mention a few. Given the inherent restrictions to access complete data, work in this research field is almost exclusively based on these user APIs. Nevertheless, the information retrieved is significantly limited. First, e-scooters may disappear from the app because they have been rented, but also because they are been reallocated, recharged or repaired. Second, reducing the trip information to origin and destination hinders further analyses about detailed trajectories, which ultimately result in inaccurate distance measurements and even discarding specific types of trips such as those describing circular paths. As a consequence, these incomplete and imprecise data may eventually lead to unreliable conclusions that could misdirect operators' and policymakers' strategical decisions. To overcome these issues, what we really require is information coming from some kind of “operator API” that include the exact state of each e-scooter and their real trajectories.

B. Performance Analysis of Shared Mobility Services

Despite the origin of the data, the performance evaluation of e-scooter services is critical, first, to guarantee their operational and economic viability, and second, to optimize the functionality they provide and the subsequent revenue. The current scientific literature has proposed several metrics to assess the performance of shared mobility services. These performance metrics are applied to the complete range of shared mobility systems, which encompasses cars, bicycles, motorbikes, and e-scooters.

The most basic performance metric is the number of trips per day and vehicle, which has been employed in controlled experiments with volunteers using e-scooters [5], and real shared cars [29], bicycles and e-scooter services [30]. This metric shows the volume of rentals the shared mobility system provides, as an absolute value. In order to extend the capability of this metric to compare systems with different characteristics, we must normalize these values to the overall size of the fleet as in [31]. Even these normalized values cannot accurately express the *efficiency* of the system given that they do not consider its temporal component. A shared mobility system shows two basic variables: number of vehicles and time. Thus, its efficiency does not exclusively depend on the percentage of vehicles that have been used by customers, but more importantly, the percentage of time that the fleet has been utilized. This approach was adopted in [32], where the authors were interested in optimizing rebalancing operations in shared car systems on the grounds of maximizing the time travelers use a vehicle within a day. Similarly, the authors in [24] study what they refer as the *scooter in-use duration*; however, this metric is only employed to construct the statistical distribution of trip duration among the e-scooter fleet, which does not reflect its actual utilization rate. Consequently, to the best of our knowledge, this is the first work that proposes a time-based efficiency metric for micromobility services, and mathematically proves its benefits.

Finally, in our previous work [33], we formalized the definition and calculation of the utilization rate of the fleet, as a performance metric capable of representing the actual efficiency of the provided service. However, on one hand, this metric was based on the number of trips, which we will mathematically demonstrate that inevitably inserts errors in its practical calculation that we avoid using a time-based metric. In addition, the information about the state of each e-scooter included in the new database that we have collected, allows us to precisely separate actual user trips from others performed for maintenance purposes, thus extending the accuracy of the results and provide an exact performance metric for shared mobility systems.

III. Data and Methods

A. Time-Based Utilization Rate of the Fleet

Let's consider a fleet of N e-scooters ($n = 1, 2, \dots, N$). At each moment, an e-scooter can be in one of 3 different states: in use, out of service, or parked on the street. Let the tuple $u(n, t, \delta t) \in \mathcal{V}_u$ denote a trip done by e-scooter n, starting at time t, and with duration δt, included in the set of user trips $\mathcal{V}_u$. Similarly, let tuple $o(n, t, \delta t) \in \mathcal{V}_o$ denote *out of service* periods of time $[t, t + \delta t]$ in which e-scooter n was unavailable due to charging, reallocation, or repair tasks.

In addition, let $W = [w_i, w_f]$ be the time interval of study, for which we have available data, and $|W| = w_f - w_i$ its longitude. We can then restrict the original sets of trips and out of service periods to this interval, considering the tuples $u(n, t, \delta t)$ and $o(n, t, \delta t)$ that start before w_f and end after w_i, which results in

$$\mathcal{V}_u(W) = \{u(n, t, \delta t) \in \mathcal{V}_u \mid t < w_f \ \wedge \ t + \delta t > w_i\}$$

and

$$\mathcal{V}_o(W) = \{o(n, t, \delta t) \in \mathcal{V}_o \mid t < w_f \ \wedge \ t + \delta t > w_i\}.$$

Note that a trip cannot end just at the start of the window ($t + \delta t = w_i$) or begin just at the end of it ($t = w_f$), given that its duration would equal to 0.

For this time window W, we calculate the total time that the fleet has been in use ($\mathcal{T}_u(W)$) or out of service ($\mathcal{T}_o(W)$), and derive the total parking time ($\mathcal{T}_p(W)$) from the former:

- Time in use:
$$\mathcal{T}_u(W) = \sum_{u \in \mathcal{V}_u(W)} \delta t^\star(u).$$
- Time out of service:
$$\mathcal{T}_o(W) = \sum_{o \in \mathcal{V}_o(W)} \delta t^\star(o).$$
- Time parked:
$$\mathcal{T}_p(W) = |W| - \mathcal{T}_u(W) - \mathcal{T}_o(W),$$

where $\delta t^\star(u)$ and $\delta t^\star(o)$ respectively represent the duration of the trip u or the out of service period o, restricted to time window W. Using a common nomenclature,

$$\delta t^\star(x) = \min\{t(x) + \delta t(x), w_f\} - \max\{t(x), w_i\},$$

for $x \in \mathcal{V}_u(W)$ and $x \in \mathcal{V}_o(W)$ respectively.

From these global times, we can easily calculate a time-based utilization rate of the fleet by simply normalizing by the total number of vehicles N and time $|W|$:

$$\begin{aligned} \tau_u(W) &= \frac{100}{N \cdot |W|} \mathcal{T}_u(W) \ (\%). \\ \tau_o(W) &= \frac{100}{N \cdot |W|} \mathcal{T}_o(W) \ (\%). \\ \tau_p(W) &= \frac{100}{N \cdot |W|} \mathcal{T}_p(W) \ (\%). \end{aligned} \tag{1}$$

These three metrics, $\tau_u(W)$, $\tau_o(W)$, and $\tau_p(W)$ represent the percentage of time that an average e-scooter in the fleet is in each of its three possible states, and obviously,

$$\tau_u(W) + \tau_o(W) + \tau_p(W) = 100\,\%.$$

B. Mathematical Relationship Between Metrics Based on Time and on Number of Trips

In [33] we proposed a utilization rate of the fleet based on the number of trips, which also considered their duration. This way, we improved the capability of previous metrics that restricted their calculation to the number of trips.

We calculate the utilization of the fleet, which expresses the number of trips that are performed within the time interval W, as

$$\Phi(W) = \mathrm{card}\,(\mathcal{V}_u(W))\,.$$

Normalizing this metric by the total size of the fleet N, we define the utilization rate of the fleet based on the number of trips as

$$\varphi(W) = 100 \cdot \frac{\Phi(W)}{N}. \tag{2}$$

In practical terms, the calculation of any performance metric will be fed with data generated by a set of snapshots of the operation of the e-scooter service. This means that the overall metric for a specified time window W will be constructed from the calculation of values corresponding to a subdivision of W into K equally sized sub-intervals $W^k = [w_i^k, w_j^k]$ such that

$$W = \bigcup_{k=1}^{K} W^k \quad \wedge \quad w_i = w_i^1; \quad \forall i, j, \ |W^i| = |W^j|. \tag{3}$$

This way, we calculate the utilization rates of the fleet by averaging their values corresponding to each sub-interval:

- Based on time:

$$\tau_u(W) = \frac{1}{K} \sum_{k=1}^{K} \tau_u(W^k).$$

- Based on number of trips:

$$\varphi(W) = \frac{1}{K} \sum_{k=1}^{K} \varphi(W^k).$$

Although these two sets of metrics may seem analogous, they present a key difference that impacts on the final capability of representing the performance of an e-scooter service. Let us develop the mathematical expression of $\tau_u(W)$ in Equation 1,

$$\tau_u(W) = \frac{100}{N \cdot |W|} \mathcal{T}_u(W) = \frac{100}{N \cdot |W|} \sum_{u \in \mathcal{V}_u(W)} \delta t^\star(u). \tag{4}$$

Note that $\delta t^\star$ represents the duration of trip $u(n, t, \delta t)$ restricted to the interval W. Dividing W in K sub-intervals means that

$$\sum_{u \in \mathcal{V}_u(W)} \delta t^\star(u) = \sum_{k=1}^{K} \sum_{u \in \mathcal{V}_u(W^k)} \delta t^\star(u),$$

thus, we can further develop Equation 4

$$\begin{aligned}
\tau_u(W) &= \frac{100}{N \cdot |W|} \sum_{u \in \mathcal{V}_u(W)} \delta t^\star(u) \\
&= \frac{100}{N \cdot |W|} \sum_{k=1}^{K} \sum_{u \in \mathcal{V}_u(W^k)} \delta t^\star(u) \\
&= \frac{100}{N \cdot |W|} \sum_{k=1}^{K} \mathcal{T}_u(W^k).
\end{aligned} \tag{5}$$

In addition, given that W is subdivided into K sub-intervals W^k with the same longitude, $|W| = K \cdot |W^k|$ and

$$\begin{aligned}
\tau_u(W) &= \frac{100}{N \cdot |W|} \sum_{k=1}^{K} \mathcal{T}_u(W^k) = \frac{1}{K} \sum_{k=1}^{K} \frac{\mathcal{T}_u(W^k)}{N \cdot |W^k|} \cdot 100 \\
&= \frac{1}{K} \sum_{k=1}^{K} \tau_u(W^k).
\end{aligned} \tag{6}$$

Consequently, the time-based utilization rate of the fleet does not depend on how we divide the time window W. However, this is not true for the utilization rate of the fleet based on the number of trips. Developing Equation 2 results in

$$\varphi(W) = 100 \cdot \frac{\Phi(W)}{N} = \frac{100}{N} \operatorname{card}(\mathcal{V}_u(W)).$$

Nevertheless, in this case, we cannot state that

$$\operatorname{card}(\mathcal{V}_u(W)) = \sum_{k=1}^{K} \operatorname{card}\left(\mathcal{V}_u(W^k)\right)$$

given that a trip that extends throughout a set of z consecutive sub-intervals would be considered as a separate trip on each sub-interval, thus being counted z times. This means that the utilization rate of the fleet based on the number of trips depends on the specific division of the window of study W we choose. Note that this effect is reduced as we decrease the longitude of the sub-intervals, which subsequently avoids considering the same trip more than once in the global time window W.

In fact, in the limit, $|W^k| \to 0$, $\varphi(W)$ coincides with $\tau_u(W)$. Let us prove this assertion. If $|W^k| \to 0$, then the number of trips in each sub-interval $\Phi(W^k)$ represents the number of simultaneous trips on each instant w. Given that no vehicle can be reused within an infinitesimal time lapse, the number of trips at time w, $\Phi(W^k)\big|_w$ coincides with the number of vehicles that are simultaneously in use at that instant. Let $v_n(w)$ be a function expressing whether vehicle n is in use, $v_n(w) = 1$, or not, $v_n(w) = 0$, at instant w. Consequently,

$$\Phi(W^k)\big|_w = \sum_{n=1}^{N} v_n(w).$$

Using these considerations, let us develop the expression of $\varphi(W)$ and analyze how it behaves as we reduce the longitude of the time sub-intervals, $|W^k| \to 0$:

$$\begin{aligned}
\varphi(W) &= \frac{1}{K} \sum_{k=1}^{K} 100 \cdot \frac{\Phi(W^k)}{N} \to \frac{1}{|W|} \int_{w_i}^{w_f} \frac{100 \cdot \Phi(W^k)\big|_w}{N} \, dw \\
&= \frac{100}{N \cdot |W|} \int_{w_i}^{w_f} \left[\sum_{n=1}^{N} v_n(w) \right] dw \\
&= \frac{100}{N \cdot |W|} \sum_{n=1}^{N} \left[\int_{w_i}^{w_f} v_n(w) \, dw \right].
\end{aligned} \tag{7}$$

Now, considering a specific vehicle in the fleet, $r \in \{1, \ldots, N\}$, the integral $\int_{w_i}^{w_f} v_r(w) \, dw$ will only be different to 0 during the times when the vehicle is in use, i.e., each trip of vehicle r in the time window W. These trips form a subset $\mathcal{V}_u^r \subset \mathcal{V}_u(W)$, such that $\mathcal{V}_u^r = \{u(n, t, \delta t) \in \mathcal{V}_u \mid n = r\}$. Thus, when $|W^k| \to 0$

$$\varphi(W) \to \frac{100}{N \cdot |W|} \sum_{n=1}^{N} \left[\int_{w_i}^{w_f} v_n(w) \, dw \right]$$

$$= \frac{100}{N \cdot |W|} \sum_{n=1}^{N} \left[\sum_{u \in \mathcal{V}_u^n} \left(\int_{t(u)}^{t(u)+\delta t(u)} 1 \cdot dw \right) \right]$$

$$= \frac{100}{N \cdot |W|} \sum_{n=1}^{N} \left[\sum_{u \in \mathcal{V}_u^n} \delta t(u) \right] = \frac{100}{N \cdot |W|} \sum_{u \in \mathcal{V}_u} \delta t(u)$$

$$= \frac{100}{N \cdot |W|} \mathcal{T}_u(W) = \tau_u(W), \tag{8}$$

which proves that $\varphi(W) \to \tau_u(W)$ when $|W^k| \to 0$. As a consequence, the time-based utilization rate of the fleet establishes the maximum level of accuracy of the metrics based on the number of trips. In addition, this means that the greater the sub-intervals of the division of the time window are, the bigger the deviation of the performance metrics based on the number of trips get. This set of conclusions will be visually observed in Section V-A, once we apply this mathematical framework to the real data collected in the cities of Rome and Atlanta.

C. E-Scooter Service Operator Data and Trip Information

In order to correctly separate e-scooter's data corresponding to user trips and maintenance tasks, we need to collect information regarding the precise state of the vehicle at each moment in time. This approach moves away from previous studies where input data were retrieved from the *user* API of the e-scooter service. Instead, we have developed software that is capable of accessing a public interface onto the data from the *operator*, thus including the information required to precisely know the actual state of each e-scooter in the fleet. This allows us to apply the time-based utilization rate of the fleet to this complete data set and extract the values that rigorously represent the actual performance of the e-scooter service.

An e-scooter database was collected from a 24/7 service Helbiz provides in Rome and Atlanta. Each entry includes the e-scooter's identifier, its geographical coordinates (longitude and latitude), and four Boolean flags that allow establishing the e-scooter's state: in use, out of service, or parked. Due to availability reasons, the data set corresponds to February 2021 (28 days) and contains around 796 million records. Some of these records (3.3 %) included wrong locations (outside the metropolitan area of Rome or Atlanta), which we discarded by filtering their coordinates. These raw data were conveniently processed to generate a data set of e-scooter trips, each of which includes: the e-scooter's identifier, timestamps and coordinates for its origin and destination, total distance traveled, duration, velocity, and a collection of timestamps and positions (collected every 10 seconds) that represents its trajectory. A summary of the resulting data set is shown in Table I.

D. Calculation of Empirical Time-Based Utilization Rate of the Fleet

The data set formed with e-scooter trips will be used as the input for the calculation of the time-based utilization rate of the fleet, described in Section III-A. In addition to the global performance metric that we can calculate using the entire data set, we are also interested in providing information about the specific behavior that e-scooter services show during the day. Next, we describe the procedure we followed. We first separate the complete data set in subsets corresponding to each day in the month under study. For each of these subsets, we calculate the time-based utilization rate of the fleet, τ_u, in 1-minute time windows, i.e., $|W| = 1\,\text{min}$. Finally, we aggregate the values obtained for the same time windows on the same day of the week. Then, we divide each 24-hour period into 1-minute windows, i.e., $|W^k| = 1\,\text{min}$ with $k \in \{1, \ldots, 1440\}$, thus creating 1 440 time slots for each day. We calculate the time-based utilization rate of the fleet for each of these, $\tau_u(W^k)$. Finally, we obtain daily profiles of the time-based utilization rate of the fleet for different sets of days by averaging the values corresponding to the same time window on those days:

$$\left\langle \tau_u(W^k) \right\rangle_{d \in \mathcal{D}_*} \tag{9}$$

where d represents a day in the set of days $\mathcal{D}_*$, which could refer to Mondays ($\mathcal{D}_{mon}$), workdays ($\mathcal{D}_{work}$), the complete data set ($\mathcal{D}_{all}$), etc.

TABLE I

SUMMARY OF THE DATASET

city	raw records	clean records	days	trips	scooters	tsd⋆
Atlanta	172 327 798	165 491 404	28	3 394	706	0.17
Rome	623 901 766	604 204 360	28	25 186	2 559	0.35

⋆ trips per scooter-day

IV. Results

A. General Performance Figures

Let us first provide some general figures of the performance of the e-scooter service in Atlanta and Rome. Table II shows the number of e-scooters in each city, specifying the absolute and relative numbers corresponding to those that had no trips and were never out of service during the month under study. We can observe that, in Atlanta, a third of the fleet did not make any trip in the month, both because they were out of service or just because no user hired them. This is specifically problematic. First, e-scooters are parked on urban environments, thus blocking sidewalks and generating visual pollution on cities. Second, e-scooters consume energy even being in an idle state, which means that some of them will have to be recharged even when they have not been used at all, thus increasing the operative costs and the emissions associated with their transportation. Third, e-scooters that are never used constitute an extra initial cost, which serves no purpose for the operator, thus reducing their overall profit.

This same effect is also observed in Rome, with 8.9 % of the e-scooters presenting no trips during the month of the study. In addition, it is noticeable the low percentage of e-scooters that were never out of service: 12.5 % in Atlanta and 3.2 % in Rome. This implies a large number of failures in the vehicles, which inevitably imply increased operational costs for the operator. Furthermore, we can remark that 5 % and 3.5 %

TABLE II

USE OF E-SCOOTERS IN ATLANTA AND ROME

ATLANTA		#	%	
Total scooters	→	**706**		
No trips	→	236	33.4 %	
		35	5.0 % ←	relocated but not used
		64	9.1 % ←	always parked at the same place
		137	19.4 % ←	always out of service
Never out of service	→	88	12.5 %	
		24	3.4 % ←	used at least once
		64	9.1 % ←	never used
ROME		#	%	
Total scooters	→	**2 559**		
No trips	→	228	8.9 %	
		90	3.5 % ←	relocated but not used
		69	2.7 % ←	always parked at the same place
		69	2.7 % ←	always out of service
Never out of service	→	81	3.2 %	
		12	0.5 % ←	used at least once
		69	2.7 % ←	never used

Note: percentages are based on the total number of e-scooters.

of the repositioning tasks in Atlanta and Rome respectively, resulted in a useless expenditure of resources given that those replaced e-scooters were never hired during the month of study. Consequently, these first basic figures show significant inefficiencies in the design of these e-scooter services, which do not match the actual users' behavior and needs.

B. Global Time-Based Utilization Rate of the Fleet

Table III shows the statistics of the time the e-scooters in Atlanta and Rome were in each state. Bold figures in the third column express the time-based utilization rate of the fleet, calculated for the entire data sets in Atlanta and Rome, and particularized for each state of the e-scooters: in use (τ_u), out of service (τ_o), and parked (τ_p). Note that these metrics are expressed as a percentage in time. The e-scooter services in Atlanta and Rome show a time-based utilization rate of the fleet of 0.20 % and 0.33 % respectively. This means that, on average, each e-scooter was only used 81 minutes in Atlanta and 134 minutes in Rome, during the entire month. Most of the rest of the time, e-scooters were parked in the cities: almost 75 % of the time in Atlanta and 90 % of the time in Rome, thus causing problems to pedestrians on sidewalks and producing visual pollution. Finally, it is also outstanding that more than 25 % of the time, e-scooters in Atlanta were out of service (almost 10 % of the time in Rome), which suggests maintenance problems that ultimately increases the operating costs of the service provider.

These empirical metrics highlight a profound problem in the provision of e-scooter services. On one hand, fleets are clearly oversize, thus significantly increasing the initial deployment costs and causing associated issues on the urban environment. On the other hand, maintenance costs are also high, which lowers the profitability of the business. And, worst of all, these metrics reflect that users are not utilizing a service that could definitely help to increase the sustainability of urban transportation.

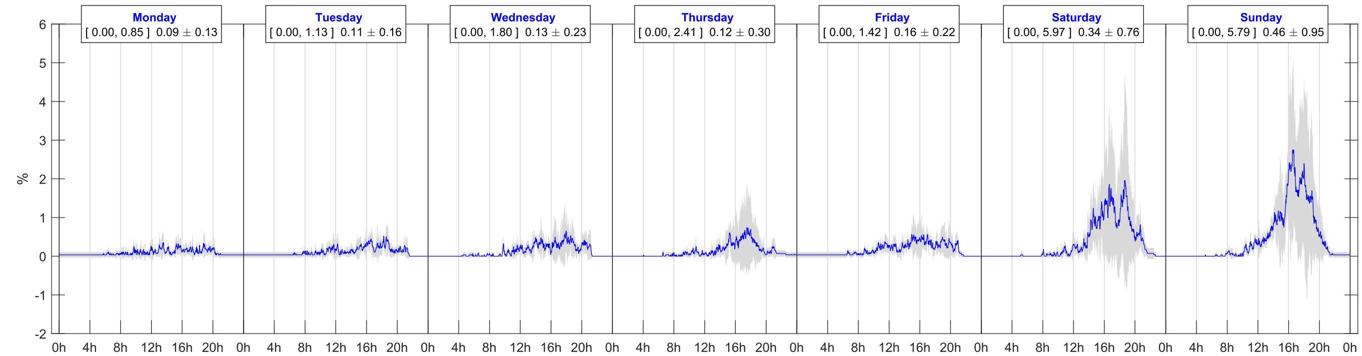
TABLE III

STATISTICS OF THE PERCENTAGES OF TIME IN EACH STATE IN ATLANTA AND ROME

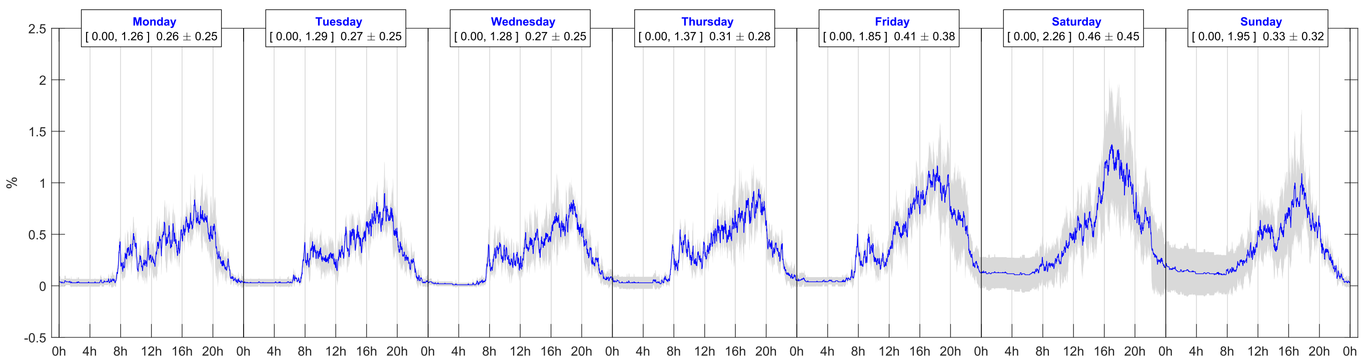
ATLANTA	min.	max.	mean (τ)	std
in use	0.0000	12.2537	**0.2021**	0.5068
out of service	0.0000	100.0000	**25.4461**	37.2212
parked	0.0000	100.0000	**74.3519**	37.1358
ROME	min.	max.	mean (τ)	std
in use	0.0000	21.3404	**0.3310**	0.6410
out of service	0.0000	100.0000	**9.8410**	18.4903
parked	0.0000	100.0000	**89.8280**	18.4414

C. Daily Profiles of the Time-Based Utilization Rate of the Fleet

Fig. 1 shows the average time-based utilization rate of the fleet for every day of the week. Blue lines denote the mean values and gray shadings show the corresponding standard deviations. In addition, the basic statistics (minimum, maximum, mean, and standard deviation) for each type of day are included in the top boxes. Results show extremely low percentages that only exceed 1 % some times over the weekend. Once again, this clearly reflects the poor performance of the e-scooter services in Atlanta and Rome. Riders use e-scooter services in the former mainly on Saturday and Sunday afternoons, with no apparent pattern during weekdays. On its part, Rome shows an afternoon peak on weekdays, which slightly increases its height on Saturdays. In addition, we cannot observe any kind of commuter behavior on either city.



(a) Atlanta.



(b) Rome.

Fig. 1. Average time-based utilization rate of the fleet ($\tau_u(W^k)$; $|W^k| = 10$ min.): profiles by type of day in Atlanta and Rome.

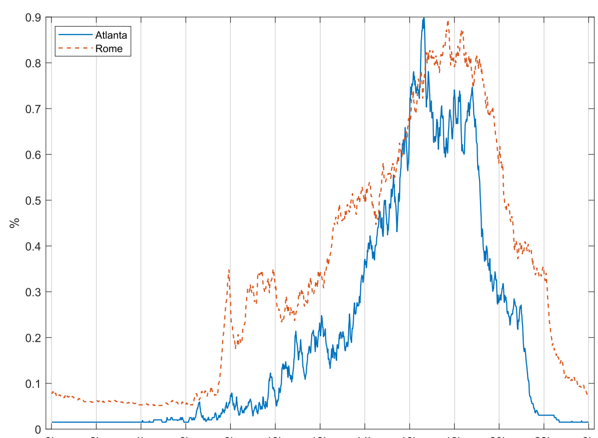


Fig. 2. Average time-based utilization rate of the fleet for the entire data sets in Atlanta and Rome.

Finally, Fig. 2 shows the profile of the time-based utilization rate of the fleet in an average day of the month under study, for each city, i.e., $\langle \tau_u(W^k) \rangle_{d \in \mathcal{D}_{all}}$, with $k \in \{1, \ldots, 1440\}$ and $|W^k| = 1$min. The statistical characterization is shown in Table IV. We can observe that the average utilization rate in Rome is higher that in Atlanta throughout the day. Moreover, we can clearly see an afternoon peak in Atlanta that is broader in Rome. Nevertheless, none of these peaks are able to exceed 1 %.

D. Economic Analysis

Finally, using the performance metrics we have developed and the collected data sets in Atlanta and Rome, we are able to analyze from an economic perspective, the e-scooter service provided in these two cities. Helbiz has a pricing structure that consists in a flat 1 € unlocking fee, plus 0.15 € per minute. Applying this rate to the real utilization of the e-scooter services in Atlanta and Rome, we can obtain the revenues they produce per unit time (day, year) and vehicle. Table V shows these results.

TABLE IV
STATISTICS OF THE TIME-BASED UTILIZATION RATE OF THE FLEET IN ATLANTA AND ROME

city	min.	max.	mean (τ_u)	std
Atlanta	0.0000	6.0907	**0.2041**	0.5163
Rome	0.0000	2.3447	**0.3351**	0.3316

TABLE V
REVENUES OF THE E-SCOOTER SERVICES IN ATLANTA AND ROME

city	€/day	€/year	€/scooter-day	€/scooter-year
Atlanta	429.39	156 728.72	0.61	222.00
Rome	2 729.27	996 183.62	1.07	389.29

Let us first focus on the city of Rome. Even considering the extremely low utilization rate of the fleet (0.3351 %), the e-scooter service in Rome is capable of producing annual revenues close to 1 million euros. This means that the actual efficiency of the service does not dramatically impact on the final income. In addition, each e-scooter produces 389.29 € a year, which significantly reduces the amortization period of the initial investment required. From the point of view of the operator, these two facts constitute a major advantage as they guarantee the economic viability of the business. However, from a broader perspective, this implies a serious issue as it detaches the operator from global sustainability objectives, which will ultimately reinforce the inefficiency of the system and result in a significant increase of the subsequent problems: visual pollution, obstacles on sidewalks, and relocating tasks using emitting vehicles.

On its part, the expected annual revenue of the e-scooter service in Atlanta drops below 200 000 €. As compared to Rome, this shows a substantial difference that cannot be exclusively attributed to the dissimilar utilization rates in each city: 0.2041 % vs. 0.3351 %. Instead, we could find a plausible reason in the high percentage of vehicles in Atlanta that were always out of service during the month under study (19.4 %), which effectively reduces the available fleet of the operator.

V. Discussion

A. Estimation Errors of Performance Metrics Based on Number of Trips

In practical terms, performance metrics of the efficiency of e-scooter and other shared mobility services are calculated by averaging the values obtained in a set of sub-intervals of the time window under study. This procedure means that those metrics that are based on the number of trips rather than on time, are floored by the presence of journeys extending along more than one sub-interval. Thus, the greater the sub-intervals they consider, the higher the deviation from the actual performance they show.

In Section III-B, we mathematically analyzed the impact of the selected division of the time window W on the accuracy of the resulting performance metric. Let us remind that we can subdivide W into K sub-intervals W^k, with $k \in \{1, \ldots, K\}$, of equal length $|W^k|$ as in Equation 3. As we demonstrated in Equation 6, the time-based utilization rate of the fleet, $\tau_u(W)$ provide a unique value, independent of the specific division we select. Nevertheless, performance metrics based on the number of trips, like $\varphi(W)$, could only reach this value in the limit, i.e., dividing W in a set of sub-intervals of infinitesimal length, $|W^k| \to 0$, as demonstrated in Equation 8.

Applying this mathematical analysis to the data sets corresponding to Atlanta and Rome, we can visually observe this effect. Fig. 3 shows the values of the time-based utilization rate of the fleet, $\tau_u(W)$, and the utilization rate of the fleet based on the number of trips, $\varphi(W)$, for different lengths of the sub-intervals, $|W^k|$, in which we divide the time window W that covers the entire month under study. We can clearly observe that $\tau_u(W)$ (solid green line) is invariable with respect to the length of the sub-intervals we select $|W^k|$. On the contrary, $\varphi(W^k)$ significantly deviates from the actual performance value as we increase the length of the time intervals we choose for the calculation, meeting the value of the time-based utilization rate on the fleet in the limit $|W^k| \to 0$.

This effect would lead to significant errors in the estimation of the performance of an e-scooter service when using a metric based on the number of trips instead of the time in use.

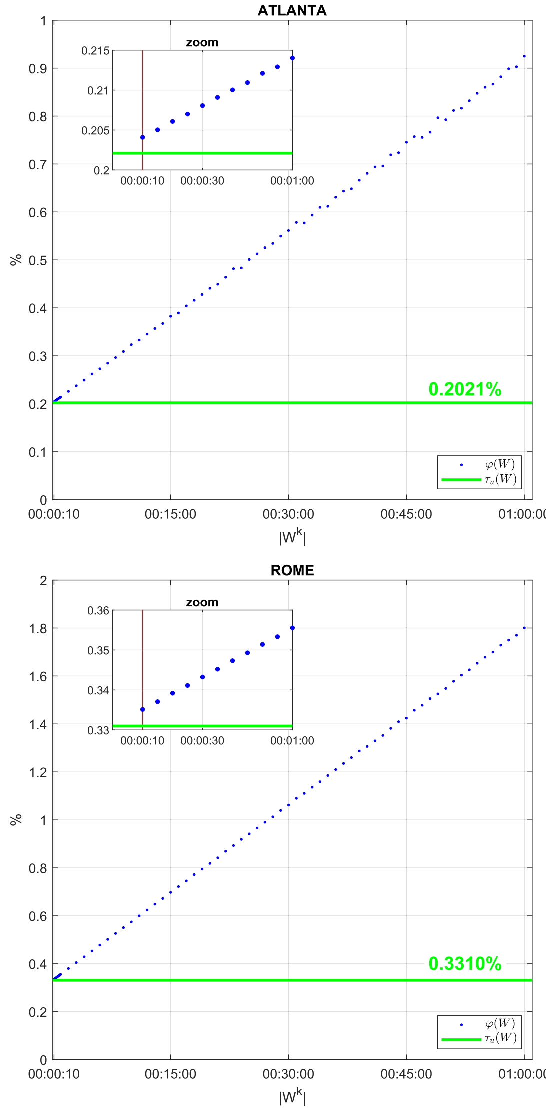


Fig. 3. Convergence.

Table VI shows the values of the utilization rate of the fleet based on the number of trips, $\varphi(W)$ and their deviation in percentage from the actual performance, for different lengths of the selected sub-intervals W^k. As we can observe, errors exceed 5 % as soon as the length of the sub-intervals is greater than 1 minute, and they can go beyond 400 % using 60-minute sub-intervals.

B. Importance of the Database

As described in Section III-C, the data of this study were collected from an *operator* API instead of a *user* API. This implies a significant leap in the quality and completeness of the data we use to calculate meaningful performance metrics that characterize e-scooter services. Particularly, the data set we used provided us with information regarding the specific state of each vehicle: in use, out of service, or parked. First, this allows us to precisely separate trips performed by riders from others related to relocation or maintenance tasks. Second, it gives us exact information about the e-scooters that are out of service, which we use to differentiate e-scooters that have

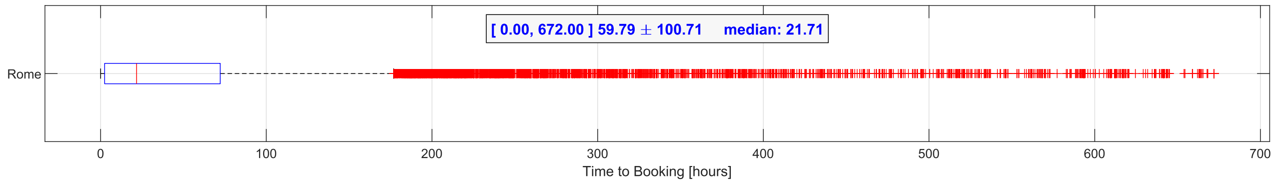


Fig. 4. Box plot of TtB using operator's data in Rome. The insert shows the minimum and maximum, average, standard deviation, and median.

TABLE VI
ESTIMATION ERRORS

ATLANTA

$\|W^k\|$	$\varphi(W)$	% error
10 sec.	0.2041 %	0.9816 %
30 sec.	0.2081 %	2.9452 %
1 min.	0.2140 %	5.8915 %
5 min.	0.2622 %	29.7158 %
15 min.	0.3825 %	89.2677 %
30 min.	0.5613 %	177.7352 %
45 min.	0.7454 %	268.8100 %
60 min.	0.9249 %	357.6425 %

ROME

$\|W^k\|$	$\varphi(W)$	% error
10 sec.	0.3351 %	1.2452 %
30 sec.	0.3432 %	3.6986 %
1 min.	0.3555 %	7.4141 %
5 min.	0.4531 %	36.8930 %
15 min.	0.6976 %	110.7506 %
30 min.	1.0619 %	220.8167 %
45 min.	1.4242 %	330.2855 %
60 min.	1.8004 %	443.9531 %

TABLE VII
COMPARATIVE ANALYSIS OF TTB VALUES GENERATED FROM USER AND OPERATOR DATA SETS IN ROME

Data set	Average	Median
[35]	18.49 h	2.05 h
Present work	59.79 h	21.71 h

no trips because they are not available from those that are simply not rented by users. This state information completes the data we require to perform exact performance calculations of the efficiency of the fleet and the mobility service it provides. On the contrary, the lack of this information usually leads to inaccurate conclusions. Thus, research in the shared mobility field is often floored by the quality of the input data scientists have access to, reducing the impact of their work. Let us highlight this observation using the remarkable work in [34] as an illustrative example. The authors characterize the performance of e-scooter services in 30 European cities, including Rome. To this end, they use the *time to booking* (TtB), calculated as the time between two consecutive trips, as a metric of the utilization efficiency of the system. They collect data from the user APIs of two operators, recording the positions of the available e-scooters at periodic moments in time. Using the traditional approach, they estimate that an e-scooter starts a trip when it disappears from the set of available vehicles, and ends it when it appears back again. In order to highlight the importance of the completeness of the information included in the database, we have implemented the calculation of the TtB and applied it to our data set in Rome. Figure 4 shows the box plot resulting from our database. In addition, Table VII shows the comparative analysis of the results obtained using information from a user API ([34]) and an operator API (the present work).

We must bear in mind that the periods of time under study are different and we have no confirmation about data belonging to the same operator. However, the substantial difference between the results from both works cannot be explained by these factors, given that they ultimately reflect the behavior of e-scooter services in the same city. This is most likely due to the lack of complete information in the data set used in [34] that did not allow the authors to correctly identify parked vehicles. Consequently, e-scooters that were never used within the period of time under study were directly excluded from their calculations. Nevertheless, having a data set with complete information allows us to include these e-scooters in the calculation of the TtB, which reaches significantly higher values that highlight the major inefficiencies the service actually shows.

VI. CONCLUSION

E-scooters have a great potential to contribute to the sustainability of modern cities, complementing public transport and providing users with a clean, flexible, and enjoyable mobility mode. However, in order to turn it into reality, we must understand the capabilities and limitations of this type of service.

To this end, we have defined the time-based utilization rate of the fleet, as a performance metric capable of precisely representing the efficiency of e-scooter and, in general, shared mobility services. Our time-based approach deviates from traditional metrics that use the number of trips as their basic reference, which heavily depend on the time interval they choose for their calculations. In fact, we have mathematically demonstrated that metrics based on the number of trips can only reach the accuracy of our time-based utilization rate of the fleet selecting infinitesimal time windows. We have applied this performance evaluation to the cities of Atlanta and Rome. Thus, we have constructed a data set by accessing the operator's information that includes the state of each e-scooter at any moment in time. This allowed us to precisely separate e-scooters user trips from others that were due to maintenance or relocating tasks, and extract those that were parked on the street. To the best of our knowledge, this is the first time that this information is retrieved in scientific analyses in the shared mobility field, which may shed light on the importance of employing complete information in order to extract accurate conclusions. This data set corresponds to February 2021, given the availability of data, which served the purpose of demonstrating how the proposed metrics can be applied to real data. However, having a single month of data hampers the study of seasonal or pandemic effects, which will be conducted in future research works.

Results from the cities of Atlanta and Rome showed extremely low utilization rates of the fleet: 0.2021 % and

0.3310 % respectively. In addition, e-scooters were often out of service: more than 25 % in Atlanta and almost 10 % in Rome. This evident inefficiency leads to issues on the urban environment (obstacles, visual pollution, etc.) and on the profitability of the service. Nevertheless, the economic analysis of the e-scooter service in these two cities resulted in expected revenues close to 1 million euros in Rome, which seems to reflect that the business is somehow disconnected from the major inefficiencies of the service. This fact ultimately obstructs the improvement of the provision of this type of mobility as operators are not forced to pay attention to a factor that is not dramatically reducing their income. The utilization rate of the fleet allows municipalities to impose efficiency targets to operators, which would add an exogenous cost that would link their overall revenue to efficiency.

Furthermore, the utilization rate of the fleet could lead to spatial analyses of the efficiency of e-scooter services. These studies could also consider the integration of micromobility with public transport, highlighting the differences observed when it acts as complementary, auxiliary or substitute to it [35].

In conclusion, we need to find ways to promote the use of e-scooter services in order to avoid its main concerns and leverage the evident advantages of this transport mode to meet the mobility and environmental needs of cities.

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