Benefits of Relocation on E-scooter Sharing - a Data-Informed Approach

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Benefits of Relocation on E-scooter Sharing - a Data-Informed Approach

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***Abstract*— E-scooter sharing lets people rent an e-scooter while the system owner manages the fleet. Relocation is fundamental to increase system utilization and revenues, but it is also an expensive task. In this paper we aim at assessing the benefits of relocation while quantifying its economic costs. For this, we rely on trace driven simulations where we build upon millions of actual rentals from two cities, Austin and Louisville. Firstly, we build prediction models to estimate which areas will present a surplus or a lack of e-scooters. We compare a simple stationary model with a state-of-art deep-learning model. Secondly, we replay the exact same traces to quantify the benefits of a relocation heuristic, comparing different system options. Our results show that relocation is fundamental to maximize the number of trips the system can satisfy. Interestingly, even a light and simple relocation policy with few relocations per hour can improve the percentage of satisfied trips by up to 42%. This can also translate in a fleet size reduction without impacting the performances. However, when projected into the economic benefits, the additional costs of relocation must be carefully considered to avoid wasting its benefits.**

I. Introduction

In the last few years, the concept of micro-mobility has gained a lot of ground, thanks also to the introduction of new transportation modes, like e-scooters. New companies started spreading e-scooters throughout different cities worldwide to offer new, dockless e-scooter sharing services. These companies are growing fast, and they have already been able to attract several hundred million dollars of investments [1]. The cost of the system setup, the short lifetime of e-scooters, and the need for frequent battery charging operations call for system optimization to maximize fleet utilization, thus revenues [2]. To this extent, relocation policies play a fundamental role in optimizing the availability of e-scooters and satisfying users' mobility demands. Notice that relocation in the context of e-scooters has peculiar characteristics. First, a single worker can relocate multiple e-scooters at the same time. Second, given the typical short trip distance, customers look only for nearby e-scooters, making the spatial granularity much more fine-grained than for, e.g., car sharing systems. Third, the mobility demand is much more variable given the more occasional usage of e-scooters [1], [3], [4].

In this work, we aim at assessing the benefits of relocation to understand how they affect the system performance and costs. What is the benefit in terms of mobility demand that the system can satisfy? Are those benefits bringing additional profit? How important is it to accurately predict the lack and surplus of e-scooters? To answer these questions, we adopt and extend our existing data-driven simulator for shared e-mobility in urban scenarios [5].[1] We rely on actual trips made available by the municipalities of Austin[2] and Louisville[3] (US). With this data, we train models that predict the expected demand at a given time and place. Then we replay a real trace via our simulator, comparing system performance. In a nutshell, we simulate a rental request observed at a given time. If an e-scooter in the nearby area exists, we rent it and make it available in the final location at the return time. If no scooter exists, we record an unsatisfied trip, i.e., a request from a user that cannot be satisfied due to a lack of a vehicle. The system also simulates the battery charging process via battery swap. On top of these processes, we introduce relocation policies.

In detail, we consider: (i) a baseline relocation solution based on the average expected demand; and (ii) an enhanced relocation informed by a deep learning predictive model. Both strategies provide the expected number of rental requests in a future given time and zone. By comparing this with the current number of e-scooters in such zone, we identify those zones with a surplus or a lack of vehicles. With this information, we simulate relocation operations. We assume that the system can move groups of e-scooters every hour, taking vehicles from those zones with the highest surplus and moving them to those zones with the most extensive lack.

The contributions of our work are: (i) The novel deep learning applications to the e-scooter usage prediction problem, and (ii) The data-driven analysis on the impact of relocation heuristics for e-scooters, considering satisfied demand for the customers and marginal profit for the operators.

Our results show that: (i) A relocation policy greatly improve satisfied demand, fleet utilization and profits; (ii) With a small fleet, relocation can improve satisfied demand by up to 42%; (iii) The more precise predictions based on deep learning are fundamental in large and heterogeneous cities like Austin; (iv) Relocation possibly translates into up to 0.7 M$ monthly additional profit in Austin.

We believe our work, albeit preliminary, paves the way for a deeper understanding of e-scooter sharing systems. For this, the accurate simulation model and the usage of real datasets allows researchers and companies to experiment and compare different solutions.

[1]*https://smartdata.polito.it/odysseus-an-origin-destination-simulator-of-shared-e-mobility-in-urban-scenarios/*
[2]*https://doi.org/10.26000/030.000003*
[3]*https://data.louisvilleky.gov/dataset/dockless-vehicles*

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II. Related work

E-scooter sharing recently emerged as a new trending topic. The first related data and findings emerged from pilot cities like [6] and surveys like [7]. More recently, [8] analyzed the utilization of e-scooter through Twitter data. Given the growth of such a new transportation mode, researchers tried to forecast e-scooter competition with other transport modes [9]. They estimated that e-scooters could replace up to 32% of carpool, 13% of the bike, and 7% of taxi trips. Several works [1], [3], [4] show that e-scooter usage temporal pattern is different from other systems. E-scooters are more likely used in the middle of the day and on weekends, suggesting a recreational use – missing thus the two distinct morning and evening peaks typical of commuting habits [10].

Vehicle relocation is another widely covered topic, and there are many works on relocation for car-sharing and bike-sharing. Authors of [11] propose to schedule relocation at fixed times (e.g., at night) to re-balance the system. Authors of [12] design a time-independent decision schedule, only function of the current system state. In [13], authors study a time-dependent relocation based on online optimization approaches. However, e-scooter peculiar and different usage patterns make it hard to adapt these works.

Considering demand prediction, neural networks have been applied in the field of smart mobility for their ability to capture the spatio-temporal relationships inside data. In [14] researchers develop a deep learning model to predict air pollution. In our previous work [15] we predict the incoming and outcoming *flow* of different areas of the city, knowing vehicles spatial historical observations, while in [16] we estimate future car sharing usage with socio-demographic data. Deep learning models have also been used in the field of relocation strategies for sharing systems. Authors of [17] use a Convolutional Neural Network (CNN) to identify mobility patterns from unbalanced pair of stations and predicting future patterns through a Long Short-Term Memory (LSTM) recurrent neural network.

In this paper, we focus on relocation strategies considering the peculiarities of e-scooter sharing systems. To the best of our knowledge, we are the first to propose a data-driven simulation tool tailored to the e-scooter relocation problem. Although our heuristic is simplistic, it highlights the benefits and drawbacks of relocation trips with realistic demand.

III. System model and simulator

Our goal is to simulate a fleet of e-scooters in a given city. The simulator gets as input the trace of recorded trips. We then re-process all rental requests to simulate the e-scooters system management with different scenarios.

A. Spatio-temporal disaggregation of open data

For the mobility model, we rely on the open data of the municipalities of Austin and Louisville. Both offer a dataset $\mathcal{D}$ of trips recorded in the city, recording all rentals of all e-scooter sharing systems for several months. Each trip record shows the start/final time and position. Due to privacy, positions and times are rounded. Therefore, we need to recreate a possible demand trace.[4]

In detail, given a trip $i \in \mathcal{D}$, times are rounded with a granularity ΔT of 15 minutes. To produce an exact time instant to use as starting time of the trip, we generate a new timestamp t_i from a uniform distribution in $[a_i - \Delta T/2, a_i + \Delta T/2]$. This allows obtaining a continuous-time sequence of trip requests. Origin and destination information is also aggregated into different *geometries* $\tilde{o}(i)$ and $\tilde{d}(i)$. Austin offers coordinates rounded with the census blocks. Hence, we randomly pick two coordinates inside the polygon of the census block. We obtain thus a possible origin $o(i)$ and destination $d(i)$ coordinates for each trip i. In the case of Louisville, $\tilde{o}(i)$ and $\tilde{d}(i)$ are the original geospatial coordinates rounded to the second digit (with a precision of about 80 m), and we keep them as provided.

At the end of this pre-processing step, we have a new disaggregated trace where each trip in the dataset is characterized by its start time, duration, initial and final coordinates. From these, we derive trip distance and consumed energy.

B. Users' mobility and battery swap

We design an event-based simulator to study such a complex system. At any time t, each e-scooter $s \in \mathcal{S}$ is characterised by the battery state of charge $b(s) \in [0, B]$, being B the battery capacity, and location $P(s)$, that we model using a grid of 200 m x 200 m squared zones that cover the city area. Notice that we use small zones to model the fine-grained spatial properties of e-scooter mobility. At simulation start, e-scooters are randomly placed among the zones of the grid with uniform random charge $b(s) \in [B/2, B]$.

The simulator processes the trip request events obtained from the disaggregated trace. At the i-th trip request event at time t_i, the simulator checks if there is any e-scooter s with enough residual battery energy, i.e., $b(s) \geq e_i$, being e_i the energy to complete such trip, available in the same or 1-hop neighboring zones. This is equivalent to assume that customers are willing to rent only nearby e-scooters.[5] If more than one e-scooter exists, the simulator picks the scooter s^* having the highest charge $c(s)$. It then schedules a trip end event at time $t_i + \delta t_i$, being δt_i the duration of the rental as in the trace. Otherwise, if no scooter is available, it marks the request as *unsatisfied*.

When the i-th trip-end event fires, the simulator makes the e-scooter s^* back available in position $d(i)$, and updates its battery charge $b(s^*) = b(s^*) - e_i$. If $b(s^*) < b_{min}$, a charging operation is performed. We assume the system performs a *battery swap* operation. The e-scooter becomes unavailable until the operation is completed (with duration exponentially distributed, as in [4]).

[4]We consider the simplifying assumption that observed trips in the trace represent the demand. By disaggregating the trace and later reducing the fleet size, the assumption impact will be mitigated.

[5]In the worst case within 424 m with 200 m x 200 m zones.

IV. Relocation models

Here we detail the relocation strategies that we implement in the simulator to study their benefits and costs.

A. Identifying pick up and drop off zones

The core of our relocation process is the *relocation schedule generator*. It generates a new *relocation schedule* every simulated hour. Then, *relocation workers* move e-scooters as defined in the schedule. We assume the provider pays workers for the time spent to complete the relocation - like delivery workers. The relocation schedule generator receives as input the list of zones with expected surplus and lack of e-scooters. We consider two ordered lists: the first contains the *pick up* zones, where a surplus of e-scooters is expected in the next hour. The second contains *drop off* zones, where a lack of vehicles is expected. The process is greedy; hence we try to satisfy the expected trips in the next hour only. To generate such lists, we compute $\Delta(t,z)$ which represents the expected number of scooters to add to zone z at time t to exactly fulfill the expected demand:

$$\Delta(t,z) = O(t,z) - D(t,z) - S(t,z) \tag{1}$$

$O(t,z)$ is the number of vehicles that we predict will start a new trip from zone z in time [t,$t+\Delta T$], where ΔT is one hour. $D(t,z)$, instead, is the predicted number of vehicles that will end a trip in such a zone in the same time interval. The difference between these two terms gives the predicted incoming or outgoing *flow* for a given zone at a given hour. $S(t,z)$ is the current number of e-scooters present in zone z. As such, if $\Delta(t,z) > 0$, zone z is expected to have a surplus - thus being a *pick up* zone. Vice versa, if $\Delta(t,z) < 0$, zone z is expected to suffer from a lack of vehicles (*drop off* zone), and $|\Delta(t,z)|$ represents how many scooters should be placed at zone z. $O(t,z)$ and $D(t,z)$ can be estimated in different ways, as we described in the following.

B. Baseline for spatio-temporal predictions

We start from a simple stationary model for $O(t,z)$ and $D(t,z)$. In a nutshell, we assume the average past demand is a good prediction of future demand too. We consider the day type (weekday or weekend) and the hour of the day (in 24 hours), getting 48-time slots in total. For each of them, we compute the averages number of e-scooters rented (returned), for each origin (destination) zone. We use these averages to make predictions, i.e. to obtain $O(t,z)$ and $D(t,z)$ matrices. Then, we compute $\Delta(t,z)$ with $S(t,z)$ being the current state in the simulation. We refer to this estimate as to the *baseline* strategy.

C. Deep Learning for spatio-temporal predictions

To make more precise predictions about the number of incoming and outgoing flows for each zone at any given time, we consider a second model based on the deep learning model 3D-CLoST [18]. We refer to this as DNN in the following. The model has been specifically developed to capture the strong spatio-temporal dependence present in urban mobility data. 3D-CLoST is composed of different neural networks: a 3D CNN learns the spatial and temporal patterns, followed by an LSTM to reinforce the temporal correlation. A fully connected network, which considers external inputs too, completes the model. The output are the number of expected trips starting and ending in the next hour in each zone z, i.e., $O(t,z)$ and $D(t,z)$, from which we get $\Delta(t,z)$ in the simulations.

In more details, the first layer of 3D convolutions is employed to not compress the temporal axis of the tensor immediately after each convolution operation, preserving relevant temporal information. In cascade to the convolutional layers, there is a dense, fully connected layer of 128 units with ReLU activation function. Its purpose is to convert and resize the feature map (in input) in a vector of information that can be passed to the LSTM stage. This architecture is used to identify patterns in sequences of data points, capturing temporal dependencies.

3D-CLoST includes external features, which can influence incoming and outgoing flow. We use this feature to include the day of the week (weekdays, weekends), even if this can be exploited to include other external features such as weather conditions.

TABLE I
DATASET CHARACTERISTICS

City	N scooters	Avg trip dur.	Avg trip dist.	N zones	N trips train	N trips sim
Austin	8 350	899 s	1 288 m	2 794	4 642 309	527 776
Louisville	850	1 031 s	1 593 m	720	199 646	53 065

D. Heuristic for scheduling relocations

Given the lists of *pick up* and *drop off* zones, we need to define which relocation operations shall be implemented. This depends on the capacity of the system, e.g., the number of workers. We consider a simple greedy strategy to define which e-scooters to move from which zone to which zone.

We first associate each worker to a single *pick up* zone and to a single *drop off* zone[6]. Iteratively, we select the *pick up* zone a with largest positive Δ (i.e., the one with most predicted abundance of e-scooters) and the *drop off* zone b with the lowest negative Δ (i.e., the one with most predicted lack of e-scooters). Then we look for the closest worker to the *pick up* zone, and let him/her move a number of e-scooters equal to $\min(\Delta(t,a), |\Delta(t,b)|, max\_capacity)$. The worker will then stay idle in the drop-off zone until the next relocation schedule. $max\_capacity$ models the maximum number of e-scooters each worker can move, e.g., modeling the capacity of the support vehicle. To simplify the scenario, in the following, we set it very large and comment on this limit in the result section.

V. Parameters and performance metrics

We use for both cities the data from August 2018 to August 2019 to train the baseline and DNN models. Then

[6]This heuristic can be easily optimized by performing an actual path optimization based on relocation needs, with multiple pick up and drop off zones associated to a single worker.

TABLE II

SUMMARY OF SYSTEM PARAMETERS AND COSTS

Description	Var	Value
Scooter battery capacity	B	425 Wh [4]
Scooter efficiency	E_s	11 Wh/km [4]
Scooter cost (per year)	c_s	560 $/unit [a]
Unlock fee	f_0	1 $/trip [a]
Per minute fee	f_1	0.30 $/minute [a]
Relocation worker cost	c_w	15 $/hour [b]
Relocation vehicle cost	c_f	9.6 $/100 km [cd]
Relocation speed	w_s	20 km/h
Fleet size	N	variable
Number of relocation workers	n_w	variable

[a] *https://atommobility.com/blog-1/how-profitable-is-scooter-sharing-business*
[b] *https://www.indeed.com/cmp/Bird-Rides-Inc./salaries*
[c] *https://www.globalpetrolprices.com/USA/diesel_prices/*
[d] *https://www.fueleconomy.gov/feg/best/bestworstEPAtrucksNF.shtml*

we use the trace of September 2019 to run simulations and collect results. Dataset characteristics are summarized in Tab. I. As it can be seen, Austin e-scooter system is much bigger than Louisville. Not shown here due to lack of space, this is reflected also in a much more heterogeneous temporal and spatial demand.

In the simulations, we focus on the following indexes:

- RMSE (Root Mean Square Error): quantifies the error on the prediction of $O(t,z)$ and $D(t,z)$ for the models.
- Satisfied demand: percentage of trips that are completed over all trip requests.
- Marginal profit: revenues from satisfied trips minus costs of relocation and fleet. Here we do not consider costs related to other aspects.

Tab. II summarizes the system parameters that we keep fixed through all simulations, while we vary the fleet size N and number of workers n_w. Both affect the number of satisfied trips – thus the revenues – and costs.

Given the set of satisfied rentals $SatTrips$ in one month, revenues R_{tot} are:

$$R_{tot} = \sum_{i \in SatTrips} (f_0 + f_1 \cdot \delta t_i).$$

The costs C_{rel} for the relocation set $Rels$ account for the worker's and relocation vehicles costs:

$$C_{rel} = \sum_{j \in Rels} \left(\frac{c_w}{w_s} + c_f \right) [d(b_{j-1}, a_j) + d(a_j, b_j)]$$

where $d(a_j, b_j)$ is the distance between the pick up and drop off zone of relocation j, and $d(b_{j-1}, a_j)$ is the distance between worker previous position and the next pick up zone. Remember that every hour each worker is assigned to a single relocation task - so we take into account only the actual time to complete the relocation. The monthly marginal profit becomes then:

$$P = R_{tot} - C_{rel} - N \cdot c_s/12$$

where $N \cdot c_s$ is the yearly cost of the e-scooter fleet. Notice that the chosen parameters (Tab. II) can have a significant influence on the revenues and marginal profit.

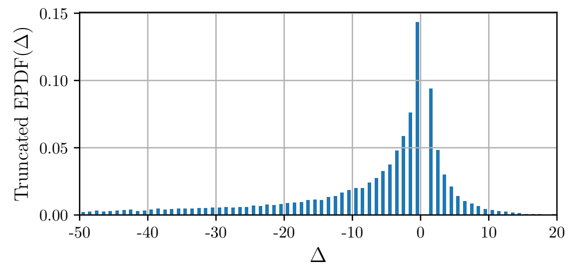


Fig. 1. Austin - EPDF for $\Delta \neq 0$. Negative Δ represents pick up zones, while positive ones are drop off zones.

TABLE III

RMSE ON THE TEST

		Model RMSE	
		Baseline	DNN Driven
Austin	Origin $O(t,z)$	6.34	0.29
	Destination $D(t,z)$	6.20	0.29
Louisville	Origin $O(t,z)$	1.38	0.23
	Destination $D(t,z)$	1.32	0.22

VI. AUSTIN AND LOUISVILLE CASE STUDIES

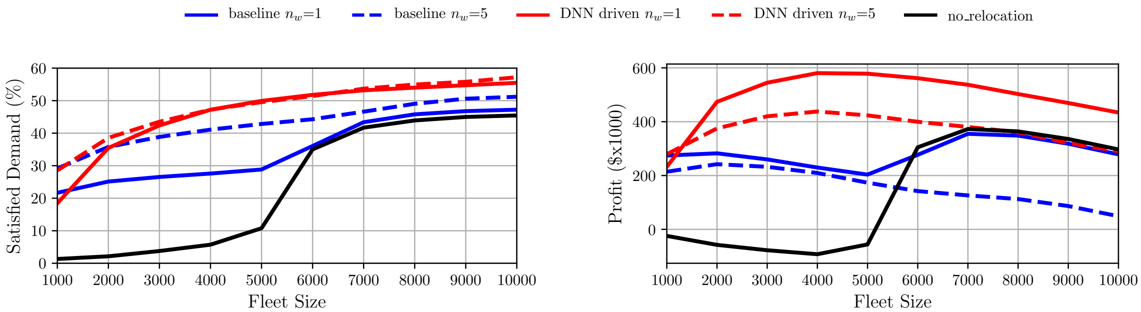
A. Analysis on predictions

We focus first on the Austin case, considering its actual configuration with $N = 8350$ e-scooters, and no relocation in place. Here, we present a preliminary analysis that is instrumental to understand the system properties. Consider the distribution of Δ in Fig. 1. It reports the Empirical Probability Density Function (EPDF) of $\Delta(t,z)$ as observed over all zones and all hours. We compute this directly from the trace, and thus it measures how unbalanced e-scooters are. Negative/positive Δ identify pick up/drop off zones. Since most of the zones neither contains e-scooter, nor need relocation, we remove the values $\Delta = 0$ (representing 98.1% of the original distribution) to ease visualization. Interestingly, negative Δ reach larger values than positive Δ, hinting to a large probability of accumulating e-scooters in some zones. On the contrary, lack of e-scooter is limited, with few cases where we observe a need of more than 10 e-scooter at a given hour. This hints that small trucks able to carry tens of e-scooters can easily suffice, i.e., $max\_capacity = 30$ would be enough.

Focus now on the ability of the two models to predict how many e-scooters will be requested in the next hour in each zone. Tab. III reports the RMSE for both cities and prediction models, and for $O(t,z)$ and $D(t,z)$. The lower the RMSE, the better. As expected, the DNN model can greatly improve the predictions. However, in Louisville, the baseline model already provides good predictions. This is due to the smaller size of the city and its more homogeneous usage patters with respect to Austin.

B. Austin extensive analysis

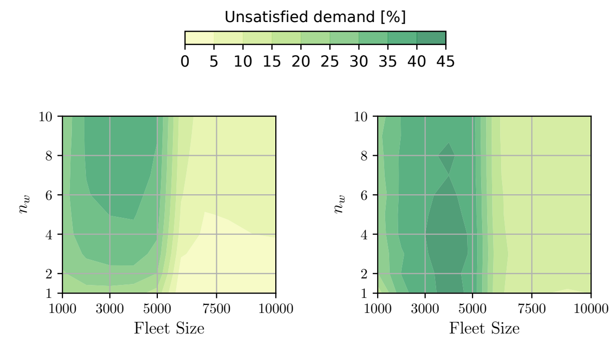
We now run simulations to compute the metrics of interest, activating the relocation policies and varying the fleet size N. Let us start showing the percentage of satisfied trips in Austin, shown in Fig. 2(a), with $n_w = 1$ and $n_w = 5$



(a) Satisfied demand

(b) Monthly marginal profit

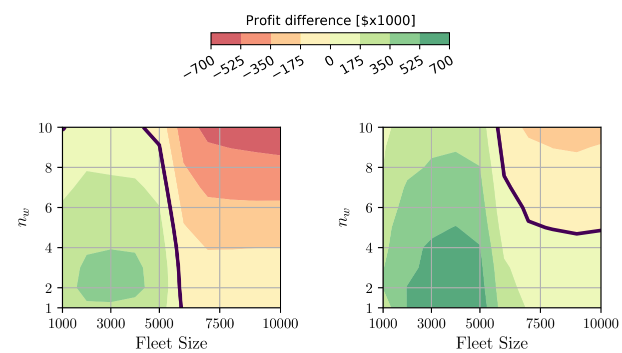
Fig. 2. Austin case study.



(a) Baseline

(b) DNN Driven

Fig. 3. Austin - Additional satisfied demand w.r.t. no relocation.



(a) Baseline

(b) DNN Driven

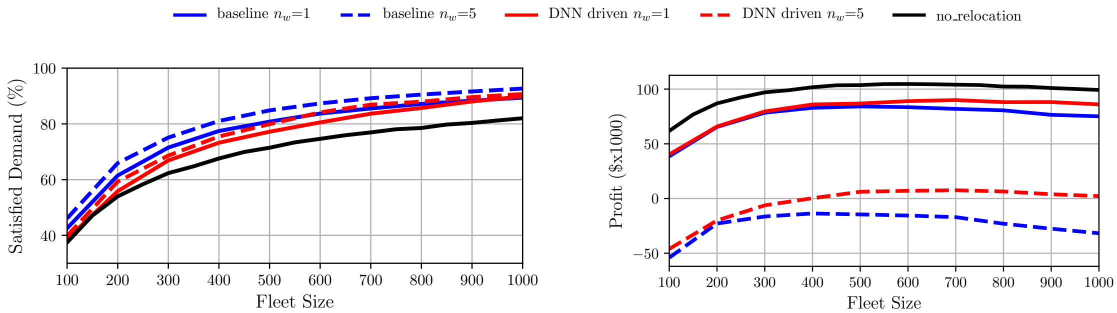
Fig. 4. Austin - Monthly marginal profit difference w.r.t. no relocation.

workers. Solid black curve reports results with no relocation. A system with a small fleet would not be able to cope with the users' demand. With N larger than 6000, the system is able to satisfy about 40% of the demand, and increasing the number of e-scooters has little benefits.

Relocation significantly increases satisfied demand, especially for small fleets. Notice how with relocation we can obtain the same satisfied trip percentage with a much smaller fleet size than without relocation. Intuitively, it is fundamental to move e-scooters where customers are looking for them. DNN offers the best results, improving by up to 42% the satisfied demand w.r.t. no relocation. Even for large fleet size, relocation allows 10% improvements in satisfied demand. Interestingly, $n_w = 1$ suffices with the accurate predictions offered by DNN, while the rough prediction based on averages requires more relocation operations every hour to see some benefits. In a nutshell, one relocation per hour is already enough to improve system performance, provided the pick up and drop off zones are accurately predicted using the DNN model. This is confirmed by observing how many e-scooters are moved for each relocation/worker. With $N = 8000$ and $n_w = 1$, on average we move 28.4 vehicles with the DNN Driven predictions, while this reduces to 5.0 for the baseline ones. With $n_w = 5$ workers, the e-scooters moved for each relocation reduces to 10.2 for DNN and 3.1 for baseline. The additional workers move few e-scooters, bringing little overall benefits for DNN.

Focus now to the monthly marginal profit shown in Fig. 2(b). For all systems, marginal profit increases with N when this is beneficial to improve the satisfied demand (left part of the figure). On the contrary, increasing the fleet size too much increases costs, reducing profits (right part of the figure). Focusing on $n_w = 1$ with DNN, the system results always more profitable than a system with no relocation. That is, the extra-cost of relocation always pays-off in terms of additional revenues. With $N = 4000$, we move on average only 415 e-scooters per day. This allows a difference in marginal profit of 670 000 $ with respect to the case without relocation, for which we obtain a negative marginal profit. This is not true for the baseline model: as soon as $N > 5000$, the additional revenues are totally consumed by the relocation costs. With $n_w = 5$, revenues would reduce w.r.t. no relocation even for the DNN predictions, highlighting the need to accurately balance the benefits and costs of workers.

To better gauge the trade-offs between increased fraction of satisfied demand, and extra cost, Fig. 3(a) and Fig. 3(b) show the additional satisfied demand with respect to no relocation for the baseline and the DNN models, respectively. Results are reported as heatmap. The greener the color, the higher the benefits. As expected, all combinations lead to improvement in satisfied trips. As already seen in Fig. 2(a) the largest advantages are obtained for small fleet size. Interestingly, with the baseline we need up to $n_w = 10$ workers to reach a 40% gain in satisfied demand. Instead, with DNN, n_w has little impact. With more than 6 workers, the performance even slightly decreases: likely too many scooters result offline while they are relocating between



(a) Satisfied demand

(b) Monthly marginal profit

Fig. 5. Louisville case study.

zones.

We now project these figures into the additional monthly marginal profits with respect to no relocation. Results are shown in Fig. 4(a) and Fig. 4(b). Black lines highlight a null difference (marginal profit are equal with and without relocation). The coarse prediction offered by the baseline model call for an accurate selection of both N and n_w. Indeed, for $N > 5500$, relocation results in reduction of profit. In general, increasing n_w reduces the benefits. For DNN predictions, the marginal profits are always higher than a system without relocation, provided $n_w < 4$. Again, more workers do not pay off for the extra costs, and $n_w = 1$ always results the best configuration. For the baseline prediction, benefits are more limited and $n_w = 2$ is the best trade-off.

C. Louisville case study

Here we repeat the whole study for Louisville, showing the main differences to the Austin use case. Recall that the usage of e-scooters in Louisville is much more homogeneous, and with a much smaller system (Tab. I).

Focus first on the percentage of satisfied requests in Fig. 5(a). Even without relocation, the satisfied demand grows up to 80% with 1000 scooter, and it increases by about an additional 10% with relocation. Here, the prediction based on the baseline works similarly to the DNN predictions, especially for $N > 600$. This happens because the system already performs quite well, and the zones that needs relocation are quite few. When projected in marginal profit, Fig. 5(b) shows that the profit is maximum without relocation. This is because relocation results too expensive compared to the extra revenues, and thus it is not sustainable with few trips in a city.

VII. Conclusion

In this paper we quantified the benefits of applying relocation to an e-scooter sharing system. We applied a DNN predictive strategy to find zones where there will be a lack or a surplus of scooters in the next hour and compared it to a baseline statistic strategy. Few workers performing few relocations per hour proved to be enough to improve satisfied demand and revenues. Moreover, with a relocation strategy, we can satisfy the same trips considerably reducing the fleet. However, it is important to note that the additional economic costs of relocation in some cases can make the overall system less profitable.

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