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A Beautiful Fleet: Optimal Repositioning in E-scooter Sharing Systems for Urban Decorum

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Abstract

In recent years, many electric scooters (e-scooters) sharing companies have appeared around the world. However, a major issue that has soon become apparent is that a consistent part of the users is prone to park the e-scooters without caring about the rules of the road, abandoning them in locations and positions that greatly reduce urban decorum and may interfere with pedestrians and other vehicles. To cope with the issue of bad parking and to not compromise acceptance of e-scooters by city residents, some sharing companies have started to include correcting the position of wrongly parked scooters as an important part of their operations. In this work, we address the problem of optimally managing the actions of a set of agents who are hired by a sharing company expressly for repositioning e-scooters in order to guarantee urban decorum. We call these agents *beautificators*, since their fundamental task is to reposition scooters over short distances (even just a few meters), so to fix inappropriate and disordered parking made by users. We stress that such repositioning must not be confounded with traditional relocation made in vehicle-sharing systems to rebalance fleets in the service area: rebalancing is made over medium and long city distances and is primarily aimed at guaranteeing a balanced distribution of vehicles in the service area, better satisfying the demand and increasing the overall profit. To the best of our knowledge, such optimization problem has not yet been considered in literature and we propose to model it by Integer Linear Programming and solve it by means of a matheuristic, which offers a good performance on realistic data instances defined in collaboration with e-scooter sharing professionals.

Keywords: E-scooters; Sharing Mobility; Micromobility; Urban Decorum; Optimization; Matheuristics.

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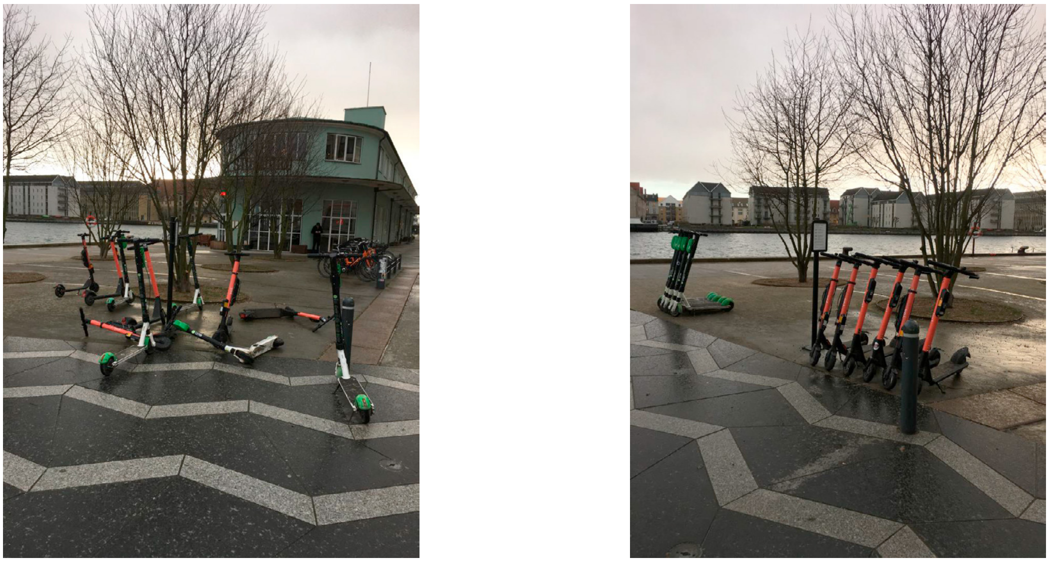

(a) Chaotically parked e-scooters (b) E-scooters repositioned by a beautificator

Fig. 1: Parking situation before and after the intervention of a beautificator (images from Gozal 2020)

1. Introduction

Electric scooters (e-scooters) have recently become a common and familiar sight in major cities around the world. Their success can be attributed to many attractive features that they offer, such as low purchase price, easiness of driving and parking and low maintenance cost. Moreover, being electrical, they represent a sustainable alternative to fossil fuel cars and may effectively contribute to reduce pollution and traffic congestion. For an introduction and overview of the benefits of (e-scooter) sharing mobility, we refer the reader to Carrese et al. (2020); Gössling (2020); Machado et al. (2018); Shaheen et al. (2020). In recent years, an increasing number of e-scooter-sharing companies has appeared around the world. A typical company distributes a shared fleet of e-scooters in a city and the vehicles can be easily rented through a smartphone application, paying a per minute fee. However, a major issue that has soon become apparent is that a consistent part of the users is prone to park the e-scooters without caring about the rules of the road, abandoning them in locations and positions that greatly reduce urban decorum and may interfere with pedestrians and other vehicles (see Fig. 1a). Many local governments have thus started to take actions, such as bans and fines, against e-scooter sharing companies for bad parking made by their users (see e.g., CBC 2019; CNN 2019).

To cope with the issue of bad parking and to not compromise acceptance of e-scooters by city residents, some sharing companies have begun to include correcting the position of wrongly parked scooters as an important part of their operations. In this work, we address the problem of optimally managing the actions of a set of agents who are hired by a sharing company expressly for repositioning e-scooters in order to guarantee urban decorum. We call these agents *beautificators*, since their fundamental task is to reposition scooters over short distances (even just a few meters), so as to fix inappropriate and disordered parking made by users (see Fig. 1b).

We stress that such repositioning must not be confounded with traditional relocation made in vehicle-sharing systems to rebalance fleets in the service area: rebalancing is made over medium and long city-distances and is primarily aimed at guaranteeing a balanced distribution of vehicles in the service area, better satisfying the demand and increasing the overall profit (e.g., Boyaci et al. 2017; Jorge et al. 2014).

To the best of our knowledge, such an optimization problem has not yet been considered in literature and we propose to model it by Integer Linear Programming and solve it by means of a matheuristic, since its solution can be challenging even for a state-of-the-art commercial optimization solver. Our new model is inspired by and based on discussions that we had with professionals from a major European e-scooter sharing company.

More in detail, we consider a sharing company that manages a fleet of e-scooters with non-swappable batteries and that has at disposal a set of beautificators that move across the service area to correct wrong parking of scooters, pursuing urban decorum. The work of the beautificators is planned over a time horizon that is subdivided into a set of equal time slots, whereas the target area is decomposed into a grid of sufficiently small elementary areas, called *zones*. Each zone contains an *hotspot*, namely a location where parked e-scooters are more likely to be rented (for example because they are closer to important landmarks, such as a subway station or a commercial center).

At the beginning of the time horizon, each beautificator starts in one of the zones and may execute three fundamental actions:

1. "beautifying" the parking of one e-scooter in the zone where he/she is located, putting the e-scooter in a different position (e.g., if the e-scooter has fallen on its side, it is put into vertical position, while if it has been left in a position of the curb that interfere with pedestrian walk, it is moved to the side of the curb);
2. repositioning an e-scooter to the hotspot of the zone;
3. moving to another zone to continue there his/her beautifying work.

Each action requires a number of time slots to be executed and is associated with a monetary value that jointly takes into account the cost and benefits of the action (in particular that of parking in line with urban decorum). The objective is to schedule the actions of the beautificators over the time horizon maximizing the total monetary value.

In order to model this optimization problem, we rely on a multiperiod graph including one node for each zone-time slot couple and where arcs between nodes represent actions that can be executed by the beautificators. The execution of actions is mathematically represented by an *unsplittable multicommodity flow model*, in which boolean flow variables model whether a beautificator does or does not execute an action and flow conservations constraints guarantee coherence of actions over space and time. Additional constraints are included to model hotspot capacity and limitations that beautificators have on moving between zones.

Since the resulting model can prove challenging even for a state-of-the-art commercial optimization solver, we propose to solve it by a *matheuristic* that combines a variable fixing procedure with an exact large neighborhood search. Computational tests on realistic instances defined in collaboration with e-scooter sharing professionals are reported and discussed, showing a remarkable performance of our modelling and algorithmic approach.

The remainder of this paper is organized as follows: in Section 2, we introduce an optimization model for beautification operations, while in Section 3 we present the matheuristic. We report results of preliminary computational tests in Section 4 and conclude the paper discussing possible directions for future research in Section 5.

2. Optimization Model

Concerning the management of the considered e-scooter sharing system, we make the following assumptions:

- the action of repositioning an e-scooter to a hotspot, excuted by a beautificator, includes beautification (in other words, the beautificator does not just move the e-scooter to the hotspot, but also sets it in a nice position that pursues urban decorum). As a consequence, an e-scooter moved to a hotspot is also considered beautified and is subtracted from the number of e-scooters that needs beautification in the zone;
- all the e-scooters in a zone require beautification;
- the time required to beautify a single e-scooter is the same for any scooter in any zone;
- the decomposition of the service area into zones is such that each zone requires the same time for repositioning a single e-scooter from any location in the zone to the hotspot.

We now proceed to introduce the system elements and the corresponding notation. The e-scooter sharing system provides services in an area that is decomposed into a set of zones Z. The beautification actions can be executed by a set of beautificators B over a time horizon in which we identify a set of discretized time instants $T = \{0, 1, \ldots, t^{\max}\}$. The time slot between any pair of consecutive time instants in T has an identical duration of Δt. A number $n_z \geq 0$ of e-scooters is located in each zone $z \in Z$ at the beginning of the planning horizon (i.e., at $t = 0$). Such e-scooters may be either located in the hotspot or out of the hotspot of the zone: we denote by n_z^{HOT} the number of e-scooters that are located in the hotspot of z at $t = 0$, whereas we denote by n_z^{OUT} the number of e-scooters that are located outside the hotspot of z at $t = 0$. Note that it holds: $n_z = n_z^{\text{HOT}} + n_z^{\text{OUT}}$.

In order to model the actions executed by the beautificators over time, we rely on a multicommodity flow model based on a graph $G(N, A)$ made up of:

- a set of nodes $N = Z \times T$, which includes one node (z, t) for each zone-time instant couple $z \in Z, t \in T$;
- a set of arcs A that is made up of four disjoint subsets, each representing one type of action that a beautificator can execute:

1. A^{BEAU} - set of *beautification arcs* $a = [(z, t), (z, t + m^{\text{BEAU}})]$ representing the action of beautifying an e-scooter in zone z. Here, m^{BEAU} is the number of time slots that are required to beautify a single e-scooter. Moreover, a beautification arc is associated with a positive $\pi_a > 0$ that represents the benefit associated with guaranteeing decorum and depends upon the zone where the beautification takes place;
2. A^{HOT} - set of *hotspot arcs* $a = [(z, t), (z, t + m^{\text{HOT}})]$ representing the action of bringing an e-scooter to the hotspot of a zone z. Here, m^{HOT} is the number of time slots that are required to move a single e-scooter to the hotspot. Moreover, a hotspot arc is associated with a profit $\pi_a > 0$ that represents the benefit associated with moving the e-scooter to a more visible and central location in the zone and depends upon the zone where the action takes place;
3. A^{MOVE} - set of *movement arcs* $a = [(z_1, t), (z_2, t + m_{z_1 z_2}^{\text{MOVE}})]$ representing the action of a beautificator who changes the zone where he/she is operating, specifically moving from zone z_1 to zone z_2. Here, $m_{z_1 z_2}^{\text{MOVE}}$ is the number of time slots that are required to move from z_1 to z_2. This type of arc is associated with a profit $\pi_a < 0$ that represents the cost of moving the beautificator;
4. A^{WAIT} - set of *waiting arcs* $a = [(z, t), (z, t + 1)]$ representing the action of a beautificator who waits in a zone for one time slot. This type of arc is associated with a null profit $\pi_a = 0$.

Thus $A = A^{\text{BEAU}} \cup A^{\text{HOT}} \cup A^{\text{MOVE}} \cup A^{\text{WAIT}}$.

Given a node $(z, t) \in N$, we denote by $\delta^{FW}(z, t)$ its forward star (i.e., the subset of arcs $a = [(z, t), (\bar{z}, \bar{t})] \in A$ having (z, t) as tail node) and by $\delta^{BW}(z, t)$ its backward star (i.e., the subset of arcs $a = [(\bar{z}, \bar{t}), (z, t)] \in A$ having (z, t) as head node).

In order to model the actions of the beautificators, we rely on an multicommodity flow model in which the actions executed by the beautificators over time and space are modelled as flows moving through the graph $G(N, A)$. Specifically, we introduce a set of binary variables $x_a^b \in \{0, 1\}$ defined for every $a \in A, b \in B$, constituting unsplittable flow variables that model the actions of the beautificators and take values as follow:

$$x_a^b = \begin{cases} 1 & \text{if beautificator } b \text{ executes the action associated with arc } a \\ 0 & \text{otherwise} \end{cases} \qquad \forall a \in A, b \in B \tag{1}$$

These variables are used in the following feasibility constraints. First of all, we define a set of constraints to represent the fact that, at time instant $t = 0$, each beautificator $b \in B$ starts his/her action in a zone $z_0(b) \in Z$:

$$\sum_{a \in \delta^{FW}(z,0)} x_a^b = \begin{cases} 1 & \text{if } z = z_0(b) \\ 0 & \text{if } z \neq z_0(b) \end{cases} \qquad \forall z \in Z, b \in B \tag{2}$$

Thus a beautificator must choose exactly one of the actions available at $t = 0$ in zone z, whereas all the arcs available for actions of beautificators b in a node $z \neq z_0(b)$ must be set to 0 at t=0 (indeed, the beautificator is not located in that zone and thus cannot execute actions starting there).

The coherence of actions executed by the bautificators over space and time in the graph $G(N, A)$ is guaranteed by the following flow conservations constraints:

$$\sum_{a \in \delta^{BW}(z,t)} x_a^b = \sum_{a \in \delta^{FW}(z,t)} x_a^b \qquad \forall z \in Z, t \in T : 0 < t < t^{\max}, b \in B \tag{3}$$

Finally, we need two set of constraints to represent the upper limits on the number of beautification and bring-to-hotspot actions that can start at each time instant. First, we need to model the variable upper bound on the number of bring-to-hotspot actions:

$$\sum_{b\in B} x_a^b \leq n_z^{\mathrm{OUT}} \quad - \sum_{b\in B} \sum_{\substack{a=[(\bar{z},\bar{t}),(\bar{z},\bar{t}+m^{\mathrm{HOT}})]\in A^{\mathrm{HOT}}: \\ \bar{z}=z \,\wedge\, \bar{t}<t}} x_a^b \qquad \forall a=[(z,t),(z,t+m^{\mathrm{HOT}})]\in A^{\mathrm{HOT}} \tag{4}$$

The number of beautificators that can traverse each arc $a \in A^{\mathrm{HOT}}$ (left-hand-side of the inequality) must be less than or equal to the number n_z^{OUT} of e-scooters that are not in the hotspot of zone z at $t = 0$ minus the number of e-scooters that have been brought to the hotspot before the considered time instant t (expressed by the summation of variables x_a^b over arcs in A^{HOT} that involve zone z and start in instants $\bar{t}$ preceeding t).

Then, we need to model the variable upper bound on the number of beautification actions that can be executed at every instant in every zone:

$$\sum_{b\in B} x_a^b \leq n_z \quad - \sum_{b\in B} \sum_{\substack{a=[(\bar{z},\bar{t}),(\bar{z},\bar{t}+m^{\mathrm{HOT}})]\in A^{\mathrm{HOT}}: \\ \bar{z}=z \,\wedge\, \bar{t}<t}} x_a^b \quad - \sum_{b\in B} \sum_{\substack{a=[(\bar{z},\bar{t}),(\bar{z},\bar{t}+m^{\mathrm{BEAU}})]\in A^{\mathrm{BEAU}}: \\ \bar{z}=z \,\wedge\, \bar{t}<t}} x_a^b$$

$$\forall a=[(z,t),(z,t+m^{\mathrm{BEAU}})]\in A^{\mathrm{BEAU}} \tag{5}$$

The number of beautificators that can traverse each arc $a \in A^{\mathrm{BEAU}}$ (left-hand-side of the inequality) must be less than or equal to the number n_z of e-scooters that are in zone z at $t = 0$ minus i) the number of e-scooters that have been beautified before the considered time instant t (expressed by the summation of variables x_a^b over arcs in A^{BEAU} that involve zone z and start in instants $\bar{t}$ preceding t), and ii) the number of e-scooters that have been brought to the hotspot before the considered time instant t (expressed by the summation of variables x_a^b over arcs in A^{HOT} that involve zone z and start in instants $\bar{t}$ preceding t).

Finally, the objective function attempts at maximizing the total profit that can be obtained by executing the set of actions at disposal of the beautificators:

$$\max \sum_{a\in A} \sum_{b\in B} \pi_a \cdot x_a^b \tag{6}$$

The overall optimization model, which we denote by EScooterOPT, includes the objective function (6), the constraints (2 - 5) and is based on the binary variables (1).

3. A matheuristic solution algorithm

The model EScooterOPT is a Binary Linear Programming problem that in principle could be solved by applying an optimization software like CPLEX (2020). However, for realistic instances involving many actions of the beautificators over a prolonged time horizon, CPLEX may encounter difficulties to find high quality solution within reasonable amount of time. For tackling this issue, we propose to solve the problem by a matheuristic that mixes a *probabilistic variable fixing* procedure with an *exact large neighborhood search*. Specifically, the matheuristic follows the algorithmic principles presented in (D'Andreagiovanni et al., 2015; D'Andreagiovanni and Nardin, 2015), to which we refer the reader for more details. It is mainly based on executing a cycle of variable fixing iterations that exploit a combination of a-priori and a-posteriori variable fixing measures. In our case, the a-priori measure is provided by a tighter linear relaxation of the model EScooterOPT, while the a-posteriori measure is given by the linear relaxation of EScooterOPT (where a subset of variables has been fixed in value). At the end of each cycle of variable fixing, the a-priori fixing measure is updated, evaluating how good were the applied fixing. Once a time limit is reached, the fixing cycle stops and an exact large neighborhood search is executed for trying to improve the best solution found.

At every iteration of the cycle, a *partial* solution is available and a new decision variable x_a^b is fixed in value, thus making a further step towards the definition of a *complete* solution. Given the current partial solution, the probability p_α^β of fixing a variable x_α^β whose value has not yet been fixed is given by the following formula:

$$p_\alpha^\beta = \frac{\gamma \cdot \ \tau_\alpha^\beta + (1-\gamma) \cdot \ \eta_\alpha^\beta}{\sum_{(b,a)\in NYF} \gamma \cdot \ \tau_a^b + (1-\gamma) \cdot \ \eta_a^b} \tag{7}$$

which combines the a-priori fixing measure τ_a^b with the a-posteriori fixing measure η_a^b by means of a combination factor $\gamma \in [0, 1]$, considering the set NYF of index couples (a, b) of variables whose value is not yet fixed. In the case of the problem we consider here, τ_a^b is defined from an optimal solution of the linear relaxation of EScooterOPT, strengthened by the valid inequalities found by CPLEX at the root node of its branch-and-cut procedure, whereas η_a^b is defined from an optimal solution of the linear relaxation of EScooterOPT including the valorization of the variables that has been fixed in previous steps.

Once a fixing round has been completed, the measure τ is updated by evaluating the quality of fixing, according to the following formula that exploits the concept of optimality gap:

$$\tau_a^b(i) = \tau_a^b(i-1) + \sum_{s=1}^{\sigma} \Delta\tau_a^b(s) \qquad\qquad \Delta\tau_a^b(s) = \tau_a^b(0) \cdot \left(\frac{OG(v^{\mathrm{AVG}}, u) - OG(v_s, u)}{OG(v^{\mathrm{AVG}}, u)} \right) \tag{8}$$

where $\tau_a^b(i)$ is the a-priori measure of fixing (a, b) at the i-th execution of the cycle and $\Delta\tau_a^b(s)$ is the modification to the value of the a-priori measures, computed over a summation that considers the last σ solutions that have been generated. Moreover, u is an upper bound on the optimal value of the problem, v_s is the value of the s-th feasible solution built in the last construction cycle, v^{AVG} is the average of the values of the last σ solutions that have been generated. The optimality gap OG(v,u) measures how far is the value v of a solution from the upper bound u and is defined as $OG(v, u) = (u - v)/v$. The role of formula (8) is to update the a-priori measure rewarding (penalizing) those fixing that have led to a solution with lower (higher) optimality gap in comparison to the moving average value v^{AVG}.

With the aim of improving the best solution found or repairing a partial solution that cannot lead to a feasible complete solution, we propose to combine the fixing procedure with an Integer Linear Programming (ILP) heuristic corresponding to an *exact* variable large neighborhood search made: the adjective "exact" means that the search is formulated as an ILP problem that is solved, possibly at its optimum, by a software like CPLEX (see e.g., Blum et al. 2011). The rationale at the basis of this approach is that, even though CPLEX may find difficulties when solving the full optimization problem, it may instead effectively and efficiently solve suitable subproblems corresponding to the (large) neighborhood of a solution. The neighborhood we consider is obtained from a given solution $\bar{x}$ allowing to flip the binary value of at most k variables in $\bar{x}$. This condition is expressed by the following constraint, stating that the hamming distance between $\bar{x}$ and a feasible solution x must not exceed k:

$$\sum_{(a,b)\in A\times B:\ \bar{x}_a^b=0} x_a^b + \sum_{(a,b)\in A\times B:\ \bar{x}_a^b=1} (1 - x_a^b) \ \leq\ k \tag{9}$$

The exact search is then applied using as basis a solution $\bar{x}$ and solving EScooterOPT with included constraint (9). The pseudocode of the overall algorithm, denoted by *MH-EScooter*, which we adopted for our preliminary computational tests is presented in Algorithm 1. The algorithm is essentially founded on two cycles, namely an external one that is executed until reaching a time limit and an internal one that attempts at constructing σ feasible solutions. Before entering the cycles, a tight linear relaxation of EScooterOPT is solved and used for initializing the values of the a-priori fixing measures. At each round of the internal cycle, the iterative fixing procedure based on formula (7) is run. If the resulting fixing leads to an infeasible solution, the exact ILP-based search is executed with the aim of repairing the fixing. At the end of the construction phase of solutions, the exact ILP-based search is applied to the best solution found with the aim of trying to further improve it.

4. Preliminary computational results

The optimization model EScooterOPT and the matheuristic MH-EScooter were used to plan the actions of a set of beautificators considering realistic instances that refer to the city of Rome, Italy, and were defined in collaboration with e-scooter sharing professionals. The instances considers a downtown district of Rome that is decomposed into a set of 30 zones, in which a fleet of 75 e-scooters is deployed and 5 beautificators may operate overnight to execute beautifications and hotspot repositioning operations, according to the model EScooterOpt. We considered 10 instances, each associated with a different initial distribution of the e-scooters over the zones. The planning horizon is from 11:00 PM to 5:00 AM and is decomposed into 36 time slots of 10 mins each, thus defining a set T including 37 time instants. The profit coefficients associated with arcs were defined taking into account the potential profit that an

Algorithm 1 MH-EScooter

compute a (tight) linear relaxation of EScooterOPT and use it to initialize the values τ_a^b
let x^* denote the best solution found
while a global time limit is not reached **do**
  for $s := 1$ to σ **do**
    iteratively construct a complete solution $\bar{x}$
    if $\bar{x}$ is associated with an infeasible fixing
      run the exact search based on (9) to $\bar{x}$
    end if
    if $\bar{x}$ is feasible and its value $v(\bar{x})$ is such that $v(\bar{x}) > v(x^*)$
      update the best solution found $x^* := \bar{x}$
    end if
  end for
  update τ_a^b according to (8)
end while
apply the exact search based on (9) to x^* and update it if a better solution is found
return x^*

e-scooter may generate over one day when positioned in a specific zone at the beginning of the day. As optimization solver, we employed CPLEX and the computational tests were run on a 2.70 GHz Windows-based machine equipped with 8 GB of RAM, applying a global time limit of 1 hour for both CPLEX and the matheuristic. In MH-EScooter, the combination factor γ was set equal to 0.5, thus balancing the combination of the a-priori and a-posteriori measures; the number of solutions whose construction is attempted in each execution of the internal was set equal to 5; the final exact search was assigned a time budget of 10 minutes of the overall 1-hour time budget.

The results of the tests are reported in Table 1, where "ID" is the instance identifier, v^* denotes the value (in EUR) of the best solution found by CPLEX and MH-EScooter within the time limit and $\Delta v^*\%$ is the percentage increase of the objective value that MH-EScooter offers with respect to CPLEX. The first important comment that can be made is that CPLEX experiences difficulties to identify high quality solutions. This can be attributed to the dense time-space graph that includes a very large number of arcs representing beautification, repositioning to hotspots and movement between zones of the beautificators over the overnight time horizon. The metaheuristic is instead able to find solutions of increased objective value that grant an average increase of about 14% with respect to CPLEX. The increase in value is particularly significative for the first three instances (I1, I2, I3) and can reach 20%. This performance has been considered remarkable by professionals and encourage us to enlarge the computational experience to other sets of larger instances and to deepen the understanding of the mechanisms of the heuristic and the impact of parameter tuning.

Table 1: Computational results

ID	v^* (CPLEX)	v^* (MH-EScooter)	$\Delta v^*\%$
I1	313	376	20.12
I2	347	409	17.86
I3	352	386	9.65
I4	406	474	16.74
I5	392	438	11.73
I6	424	467	10.14
I7	403	462	14.64
I8	397	451	13.60
I9	375	419	11.73
I10	361	394	9.14

5. Conclusions and Future Work

In this paper, we have addressed the problem of optimally managing agents hired by an e-scooter sharing company specifically for repositioning scooters that are left in wrong locations and positions by users. We have called such agents *beautificators*, since their essential task is to pursue urban decorum, and we have proposed an optimization model for scheduling their activities over time in a target territory. Since the resulting optimization model, corresponding to a multi-period variant of an unsplittable multicommodity flow problem may result challenging for state-of-the-art optimization software, we have proposed a matheuristic for its solution. For highlighting the potentialities of the new approach, we conducted computational tests on realistic instances, indicating that the matheuristic offers solution of improved value with respect to a commercial software. As future work, we intend to study mathematically strengthened version of the model we proposed and refinements of the matheuristic algorithmic approach, also extending the model to other more complex decisional dimensions that are related to the management of shared mobility fleet (e.g., dimensioning the fleet and beautifying staff and planning their territorial deployment).

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