A TAILORED DATA GENERATION PROCEDURE FOR THE ALGORITHMIC ANALYSIS OF DRONE ROUTING PROBLEMS WITH ENERGY REPLENISHMENT

TECHNICAL REPORT

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ABSTRACT

In recent years, the combined deployment of drones and ground vehicles has been proven a very efficient strategy in many civil applications like delivery, agriculture, and humanitarian response, where a given set of destinations has to be visited in a short amount of time. In this work, we present a structured dataset for the *Drone Routing Problem with Energy Replenishment (DRP-E)*, which is a basic problem variant of a generic drone-lead operation, in which the drone is supported by a ground mobile charging station (rover), enabling replenishment at specific rendezvous locations on a road network. The proposed normalized dataset is able to fit a wide range of drone-, rover- and application-specific characteristics like the vehicle's speeds, the drone's battery capacity or the geographic size of the area of interest, and thus, it is flexible to ever-changing characteristics of the young drone technology and to a large variety of applications. Furthermore, the dataset is specifically tailored to analyze the effect of the most relevant parameter variations for DRP-E on the computational runtime and performance of developed solution approaches. Therefore, the dataset is well-suited to perform experimental performance analyses and comparisons of exact- as well es heuristic algorithms for DRP-E.

1 The drone routing problem with energy replenishment

The –*Drone Routing Problem with Energy replenishment (DRP-E)* is a general problem for routing the tandem of a drone and a mobile replenishment station, which we call *rover*. The drone has to visit points of interest *(destinations)* given by the set V_d with $|V_d| = n_d$. The battery capacity $e_{max} \in \mathbb{R}$ of the drone is limited and the energy drain is

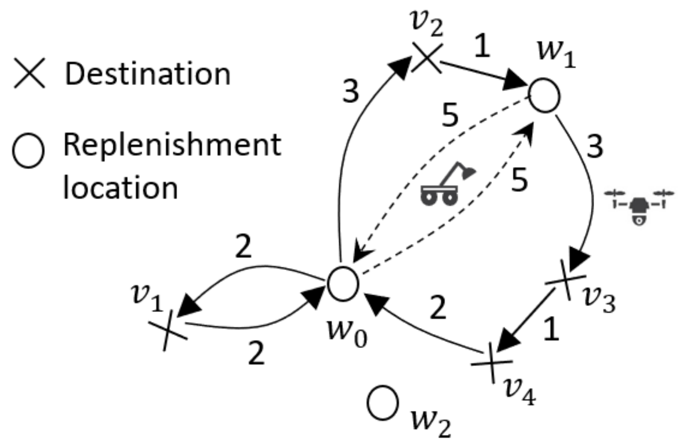

Figure 1: Illustration of a feasible solution for DRP-E: Route of the rover and the drone. Example for $n_d = 4$ destinations, $n_r = 3$ RLs, and $e_{max} = 6$. The drone travels $(w_0, v_1, w_0, v_2, w_1, v_3, v_4, w_0)$. The battery swaps take place in w_0 and w_1, so that the route of the rover is (w_0, w_1, w_0). The vehicle that arrives at a rendezvous location first has to wait for the second vehicle.

proportional to its travel time. The drone can meet the rover at a set of potential *replenishment locations (RL's)* , specified by the set $V_r, |V_r| = n_r$, which are suitable for an undisturbed battery replenishment. This obviously requires the presence of both the drone and the rover, therefore, if one of the vehicles arrives earlier, it has to wait for the other one. Both vehicles have to start and finish their routes at the depot $w_0 \in V_r$. The DRP-E consists of selecting:

- the sequence of visiting the destinations by the drone,
- suitable RL's for meetings with the rover as well as
- a schedule for the battery replenishments,

with respect to a specified objective function. One of the most common objectives is the minimization of the *makespan* of the drone's mission, but also other objective functions like cost-, or latency minimization are possible. Figure 1 illustrates a feasible solution to an exemplary instance. Depending on the problem specificity's, the drone might be allowed to hitch a ride on the rover without consuming energy, we call such joined trajectories *recharging legs*.

2 Data generation procedure

We propose a structured data set that describes a wide range of possible drone and rover characteristics that can occur in DRP-E. The dataset is focused on the most general and influential problem parameters of DRP-E, further problem-specific features like e.g. non-zero replenishment times or take-off and landing times can be easily incorporated in an extended version of the presented data set.

We generate instances by randomly uniformly scattering a given number of destinations n_d in a square $l \times l, l \in \mathbb{N}$. The placement of RLs should ensure the feasibility of instances. Unfeasible instances occur when at least one destination has no close-by RL, such that the battery life of the drone is insufficient even for a visit in a direct return flight. Possible workarounds in the literature include dismissal of infeasible instances (cf. Poikonen and Golden, 2020) or calculation of e_{max} as a function of the realized positions of $v \in V_d$ and $w \in V_r$ (Gonzalez-R et al., 2020). For the sake of data generation transparency, and similar to Karak and Abdelghany (2019), we decided to place RLs in the nodes of a uniform grid instead (see Figure 2), having as a consequence that the number of RLs should possibly be *quadratic* (e.g. 9=3x3, 16=4x4, 100=10x10. In smaller settings, this restriction might be more difficult to adhere to). A randomly selected RL is set to be both the initial and target depot of the drone's and rover's routes. We use the Euclidean metric to measure the distances flown by the drone. Because the rover is usually restricted to moving on a street network, in order to realistically address this limitation, we use the Manhattan metric for the rover. The chosen metrics follow a commonly observed convention in benchmark data sets in the drone routing literature, see, for instance, Dell'Amico

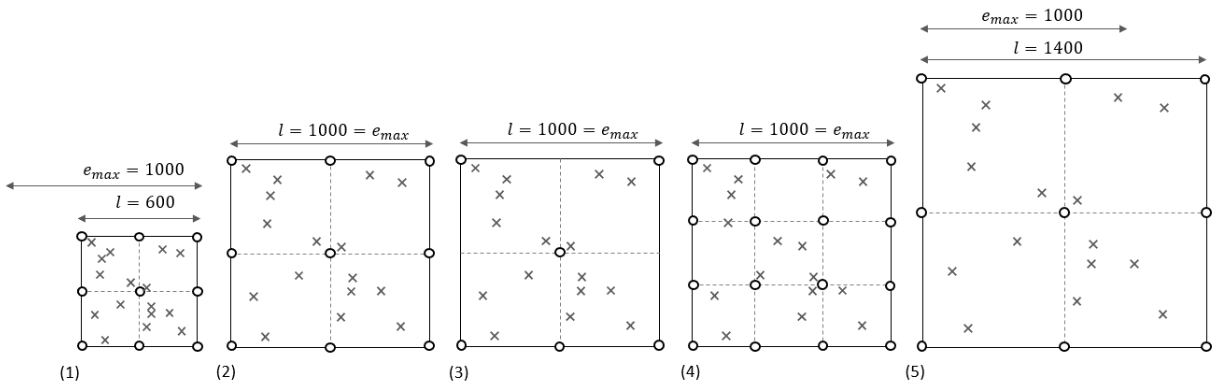

Figure 2: Examples of generated instances for Small
(1): DenHigh, (2): Basis, (3): LocLow, (4): LocHigh, (5) DenLow. To keep the proportion of destinations and RLs at 3 in LocLow for Small, n_r had to be set to a non-quadratic number 6.

et al. (2020); Ha et al. (2018); Betti Sorbelli et al. (2023); ; Murray and Chu (2015). One of the usual motivations is that this constellation of metrics mimics an urban scenario.

We generate two data sets:

- Small data set (*Small*) contains instances of moderate size with $n_d := 16$ destinations and $n_r \in \{6, 9, 16\}$ RLs, thus up to 32 locations in total.
- Large data set (*Large*) contains instances with $n_d := 100$ destinations and $n_r \in \{36, 49, 100\}$ RLs thus up to 200 locations in total.

Each data set contains 9 settings with 10 instances each, making 180 instances in total.

We specify instance settings having in mind the drone speed of 10m/sec with the maximal flight time of about 30 minutes and the rover moving at the rate of 5m/sec. Since the ratio of the vehicle speeds and not their absolute values are essential to the performance of solution algorithms, we normalize the drone speed to 1 and condense further instance characteristics to a few essential details. Such normalization makes our results more informative in view of ever changing characteristics of the young drone technology. For example, if we set in our basic setting, called Basis (cf. Table 1), the *time unit* $TU := 2$ seconds and the *length unit* $LU := 20$ m, we receive vehicle speeds of 10m/sec and 5m/sec as considered by Poikonen and Golden (2020), combined with the realistic maximal drone flight time $e_{max} = 33$ minutes (cf. Stolaroff et al., 2018).

We control the following factors and use one-factor-at-a-time design around the basic settings (marked in bold):

- *Rover* speed $\delta \in \{1, \mathbf{\frac{1}{2}}, \frac{1}{3}\}$ *TU/LU*. The lower is δ, the larger is the impact of the waiting times for the rover on the routing decisions of the drone.
- *Energy capacity* $e_{max} \in \{750, \mathbf{1000}, 1250\}$ *TU*.
- *The ratio of the number of destinations and RLs* $\frac{n_d}{n_r} \approx 1, 2$ or 3. Given $n^d = 16$ for Small and $n_d = 100$ for Large, we set $n_r \in \{6, \mathbf{9}, 16\}$ for Small and $n_r \in \{36, \mathbf{49}, 100\}$ for Large to achieve these values.
- *The number of destinations per square unit (density)* $d \in \{8, 16, 45\} \times 10^{-6}$ LU^{-2}. To achieve these values, we set $l \in \{600, \mathbf{1000}, 1400\}$ LU for Small and $l \in \{1500, \mathbf{2500}, 3500\}$ LU for Large.

The one-factor-at-a-time design is an established strategy to conserve a tractable amount of investigated parameter settings, but even more importantly, it allows to emphasize clearly the effect of the variation of a specific parameter on the problem complexity or the performance of an algorithm. What results are 8 additional settings to the Basis setting, which conserve all the parameter values of Basis but one, for which they increase or decrease the reference value, see Table 1. The nine investigated settings are labeled *Basis, RoverSpeedLow, RoverSpeedHigh, EnergyLow, EnergyHigh, RLDensityLow, RLDensityHigh, DensityLow, DensityHigh*.

Table 1: Overview over the nine settings in each data set – Small and Large

Setting	Replenishment station speed δ	Energy capacity e_{max}	Location ratio $\frac{n_d}{n_r}$	Density d $(\times 10^{-6})$
Basis	$^1/_2$	1000	2	16
RoverSpeedLow	**$^1/_3$**	1000	2	16
RoverSpeedHigh	**1**	1000	2	16
EnergyLow	$^1/_2$	**750**	2	16
EnergyHigh	$^1/_2$	**1250**	2	16
RLDensityLow	$^1/_2$	1000	**3**	16
RLDensityHigh	$^1/_2$	1000	**1**	16
DensityLow	$^1/_2$	1000	2	**8**
DesityHigh	$^1/_2$	1000	2	**45**

References

F. Betti Sorbelli, C. M. Pinotti, and G. Rigoni. On the evaluation of a drone-based delivery system on a mixed euclidean-manhattan grid. *IEEE Transactions on Intelligent Transportation Systems*, 24(1):1276–1287, 2023.

M. Dell'Amico, R. Montemanni, and S. Novellani. Matheuristic algorithms for the parallel drone scheduling traveling salesman problem. *Annals of Operations Research*, 289, 06 2020. doi:10.1007/s10479-020-03562-3.

P. Gonzalez-R, D. Canca, J. Andrade, M. Calle, and J. Leon-Blanco. Truck-drone team logistics: A heuristic approach to multi-drop route planning. *Transp. Res. Part C Emerg. Technol.*, 114:657–680, 05 2020.

Q. M. Ha, Y. Deville, Q. D. Pham, and M. H. Hà. On the min-cost traveling salesman problem with drone. *Transportation Research Part C: Emerging Technologies*, 86:597–621, 2018.

A. Karak and K. Abdelghany. The hybrid vehicle-drone routing problem for pick-up and delivery services. *Transp. Res. Part C Emerg. Technol.*, 102:427–449, 03 2019.

C. C. Murray and A. G. Chu. The flying sidekick traveling salesman problem: Optimization of drone-assisted parcel delivery. *Transp. Res. Part C Emerg. Technol.*, 54:86–109, 2015.

S. Poikonen and B. Golden. Multi-visit drone routing problem. *Comput. Oper. Res.*, 113:104802, 2020.

J. K. Stolaroff, C. Samaras, E. R. O'Neill, A. Lubers, A. S. Mitchell, and D. Ceperley. Energy use and life cycle greenhouse gas emissions of drones for commercial package delivery. *Nat. Commun.*, 9(1):409, 2018.