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A GRASP/VND algorithm for the energy minimizing drone routing problem with pickups and deliveries☆

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ABSTRACT

In recent years, the growth of online markets in social media and auction websites, has resulted in a significant increase in direct trading between people. Unlike traditional commerce, which relies on a multi-layered supply chain, person-to-person transactions depend on courier companies for delivering the items, thus, it can be considered a third-party logistics scheme. The utilization of unmanned aerial vehicles (UAVs), also known as drones, is ideal for this type of commerce, as most of the traded items are small-sized and light-weight. Logistic companies are already experimenting with using drones in their delivery operations, as their benefits are both financial and environmental. This paper, introduces the Energy Minimizing Drone Routing Problem with Pickups and Deliveries (EM-DRP-PD), to address scenarios of direct trading between individuals, where the logistics company provides the courier service using drones. The EM-DRP-PD focuses on minimizing the total energy consumption of operations and accounts for the range constraints imposed by the drones, which is influenced by the weight of the packages carried. The formulation of the EM-DRP-PD is presented. Three variants of a Greedy Randomized Adaptive Search Procedure metaheuristic algorithm are implemented for solving the EM-DRP-PD. The algorithms are compared based on generated EM-DRP-PD benchmark instances ranging from 50 to 200 customers. The study compares both, energy and distance, objective approaches and discusses the results.

1. Introduction

Unmanned Aerial Vehicles (UAVs), also known as drones, have become a popular topic both in academic discussions and practical applications. Their versatility, together with their low cost of operation, have made them irreplaceable in a wide range of operations, such as humanitarian Search & Rescue missions (Mohd Daud et al., 2022) and state-of-the-art commercial last-mile deliveries (Aurambout et al., 2019).

The growth of online marketplaces, particularly in social media and auction websites, have resulted in a significant increase in direct trading between people. In traditional commerce, goods are transported from the seller to the customers through a complex multi-level supply chain, facilitating different elements, such as distribution centers, points of sale and final customers. Person-to-person trading differs, as it requires the pickup of the packages from multiple sellers and their delivery to the corresponding buyers. These transportation services can be considered as a third-party logistics scheme. The many, ever-changing pickup locations make the logistics operations via traditional means of transportation cost-inefficient, unpredictable and with high latency between the pickup and the delivery time. Road delivery vehicles not only are susceptible to the traffic congestion, but they are also a major contributor to it. Furthermore, traditional road vehicles have a negative environmental impact and especially in urban areas, they account for the majority of green house gas emissions, according to the European Environment Agency (European Environment Agency, 2022).

The utilization of drones is ideal for this type of commerce, which takes place in an urban environment between multiple pickup and delivery locations. Not only they are faster, avoiding traffic congestion, but also contribute to its reduction. Their advantages also apply to the environmental aspect of the replacement. Drones do not have local green house gas emissions, and even compared to electric vehicles, they are more efficient in carrying small sized and light-weight items

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between multiple sellers and buyers, as they do not have to move a multi-ton delivery vehicle just so they deliver packages weighing a few kilos.

Besides their multiple advantages, drones have certain limitations. The two most important are their battery capacity and the maximum payload they can carry. Factoring out all non-controllable parameters of the operation, such as the wind conditions and constant parameters, such as the drone weight itself, the payload weight carried is the only main variable controlling the energy consumption rate. Therefore, by controlling the payload weight and the distance traveled with it, the total energy consumption of the operation can be optimized.

In scenarios with multiple pickup and delivery locations, and considering packages of different weight classes, the order in which a drone visits the pickup and delivery locations can significantly impact the total energy consumption of the operation. By minimizing the total energy expenditure, the drones are capable to operate for longer periods of time without requiring recharge or a battery swap, which translates to better drone time utilization, improved efficiency and reduced cost of operations.

This paper, introduces the Energy Minimizing Drone Routing Problem with Pickups and Deliveries (EM-DRP-PD), to address courier operations using drones in an urban environment for direct person-to-person trading. The problem considers packages of fixed size and varying weights, which are picked-up from the sellers and delivered to the particular buyers. The drones have the ability to carry up to a certain maximum number of packages simultaneously, depending on the weight of the packages carried. Since there is no depot or distribution center in this application, the EM-DRP-PD has a base location where all drones are initially launched from, and return to after completing their operation.

The autonomy of electric vehicles is greatly affected by the weight they carry. Drones in particular, are even more sensitive to the payload weight, as a great amount of energy is spent just for level flying. Unlike the pickup and delivery approaches in literature, the EM-DRP-PD is the first drone routing problem focusing on the main factor of energy consumption. The main advantage of this approach is that it is able to model more accurately real-life applications, compared to using the flying time or the distance traveled to approximate energy consumption. Furthermore, the proposed approach takes in consideration two types of payload constraints, quantity and weight, which are also two limitations encountered in real-life applications.

The mathematical formulation of the EM-DRP-PD is presented, with the detailed description of its objective function and constraints. The assumptions of the problem are stated, and the cost calculation of the EM-DRP-PD route is illustrated with a detailed example.

For solving the EM-DRP-PD, three variants of a Greedy Randomized Adaptive Search Procedure (Feo & Resende, 1995) and Variable Neighborhood Descent (Mladenović & Hansen, 1997) (GRASP /VND) hybrid algorithm are implemented and tested. The GRASP/VND combines the exploratory properties of the GRASP algorithm and its multi-start nature, with the strong exploitative properties of the VND procedure. The VND utilizes four local search operators, implemented particularly for the EM-DRP-PD and its seller–buyer coupling. Each of the three variants of the GRASP/VND utilizes a different probabilistic rule to choose the next customer from the restricted candidate list (RCL). The GRASP/VND/U is the Unbiased variant, in which all customers in the RCL have equal probability of being chosen. The GRASP/VND/P variant applies a bias based on Proximity and GRASP/VND/R uses a bias based on the Rank of each element in the RCL.

Furthermore, the paper compares two different objectives, minimizing energy consumption, and minimizing total distance traveled, while considering the energy only as a constraint. Minimizing the total energy consumption of operations is the original objective of the EM-DRP-PD. Minimizing total distance traveled is the objective of the classical VRP. The results of each objective and its impact to total energy and total distance, are presented and discussed.

For comparing the three different GRASP/VND variants using both Energy and Distance minimizing objectives, 20 benchmark instances were created based on the instances of the classical VRP, ranging from 50 to 200 customers and 2 to 11 drones.

The main goals of the paper are summarized below:

- To introduce a novel VRP with significant practical application potential, utilizing drones with the goal of minimizing the total energy consumption of operations.
- To present the mathematical formulation of the EM-DRP-PD.
- To propose a GRASP/VND metaheuristic algorithm which effectively solves the EM-DRP-PD.
- To compare Energy and Distance minimization objectives and discuss their impact on total energy consumption and total distance.

The rest of the paper is structured as follows: Section 2 presents the related literature regarding drone routing problems. Section, 3 defines the pickup and delivery operation considered in the paper. In Section 4 the mathematical formulation of the EM-DRP-PD is presented. Section 5 describes the GRASP/VND metaheuristic algorithm proposed for solving the EM-DRP-PD and its variants. In Section 6 the computational results are presented. Finally, Section 7 discusses conclusions and suggestions for future research.

2. Related literature

The vehicle routing problem (VRP) literature, considering the utilization of drones, can be classified in two major categories. First, and most-studied, the Truck-and-Drone combination VRP class, in which a ground vehicle and an unmanned aerial vehicle cooperate to complete the service to customers. In this class of problems, the vehicles and drones can have varying degrees of coupling, from the completely independent routing and in parallel operation, to the strong synchronization requirements of vehicles serving as carriers for the drones. The second, less studied class of VRPs with drones, comprises of pure Drone Routing Problems (DRPs), without the support of a ground vehicle.

VRPs with drones of the first class, have been studied extensively since the introduction of the fist problem combining a truck and a drone by Murray and Chu (2015), the Traveling Salesman Problem with a Flying Sidekick (FSTSP). Kitjacharoenchai et al. (2019) extended the FSTSP, formulating the multiple TSP with Drones. Wang and Sheu (2019) were the first to address the VRP with Drones (VRPD) and presented the first formulation of the actual vehicle routing problem with drones. Since then, the VRPD literature has seen many contributions studying different variants of the problem, such as the cost minimizing approach of Karak and Abdelghany (2019), in which trucks are used as battery swapping stations and the energy minimizing approach (Kyriakakis, Stamadianos et al., 2022), which uses electric vans as mother-ships, and only the drones visit the customers.

Such approaches consider multi-layer supply chains, which form complex logistic networks with heterogeneous nodes. As a results, these networks present increased difficulties in managing and optimizing. From a managerial standpoint, coordination issues arise, as well as, increased risk in cases of disruption (Gomez et al., 2020; Kleindorfer & Saad, 2005). Multi-layer supply chains may include different vehicle types, such as trucks and drones, and multiple facility types, such as central depots, distribution centers, cross-docking facilities and points of sale. Multi-echelon vehicle routing problems have been formulated to optimize operations in such supply chains, with the Two-Echelon Vehicle Routing Problem (2E-VRP) being the most studied (Perboli et al., 2011). Variants and extensions of the 2E-VRP have been proposed, which include additional optimization elements, such as facility location, inventory and production levels (Sluijk et al., 2023). As more elements of the supply chain are being included in the optimization model, the complexity of the problem increases, and thus, difficulties arise in developing effective and efficient solution methodologies.

Well-studied algorithms must adapted, to accommodate the relations between the different elements, in order to remain effective.

Several great review papers of the VRPDs have been published recently, presenting taxonomies and classifications for the different truck and drone cooperation models, and reviewing in detail the different approaches in the literature. Macrina et al. (2020) review the existing TSPs and VRPs with drones and classifies them into four categories. Moshref-Javadi and Winkenbach (2021), provides a drone problem taxonomy along with a discussion on practical applications. In the review of Li et al. (2021) the drone integration problem is studied from a two-echelon perspective. Lastly, Chung et al. (2020), discuss the barriers of drone integration in real-world applications, highlighting the related research gaps and providing future research directions.

The proposed EM-DRP-PD is a novel drone-only routing problem, which includes both pickups and deliveries, and has the distinctive characteristic that drones provide only the courier service between specific seller–buyer customer couples, thus, there is no central depot or distribution centers. Therefore, the related literature presented in the following subsections includes DRPs and VRPs which share the same characteristics.

2.1. Drone-only routing

The pure DRP literature is less dense, as its core elements follow the traditional VRP concepts. Dorling et al. (2017) proposed two multitrip drone routing problems for delivery operations. The first one minimizes costs subject to a delivery time limitation and the second one minimizes total delivery time subject to a budget constraint. For calculating the energy consumption a linear approximation function based on payload and battery weight, is used. Coelho et al. (2017) presented a multiobjective heterogeneous UAV fleet routing problem, taking in account limited autonomy and considering multiple charging stations. In their approach different types of drones can collect and deliver packages to customers. Troudi et al. (2018) follow an energy approximation approach similar to Dorling et al. (2017) with the goal of minimizing travel distance, the number of drones used, and the number of batteries required. The proposed problem considers time windows and trip duration constraints. Liu (2019) presents a dynamic drone delivery model for delivering on-demand meals. This is a one-to-one dynamic VRP approach. It considers separate deliveries for hot and cold meals, thus a single order may be split into multiple drones. The objective function focuses on ensuring safety, minimizing lateness, and maximizing efficiency. Cheng et al. (2020) formulated a multitrip drone routing problem considering payload and travel time in the energy consumption function. They used an exact algorithm for solving the models. Kyriakakis, Marinaki et al. (2022) have formulated the covering problem in Search & Rescue operations as a DRP in order to minimize the arrival time at all locations in the area of interest.

One of the main differentiating factors between classical VRPs and DRPs is the drone energy model. Several publications have studied this particular element of the DRP. Figliozzi (2017) studied the energy efficiency of drone per unit distance and the impact of the payload. They suggest that unlike ground vehicles which are more efficient when fully loaded, drone's efficiency benefits from low delivery payloads. Kirschstein (2020) also research efficiency of drones, comparing their energy demands to those of ground vehicles. The energy model considered, takes into account internal factors such as the drone's weight, as well as externalities, such as wind conditions. Liu et al. (2017) developed a theoretical power consumption model for multi-rotor drones and validated it based on practical measurements. Experiments included different flight profiles, such as ascend, descend, hovering and level flight. Zhang et al. (2021) evaluate how energy consumption and range of operation vary with speed and payload for different models. They also provide a classification of those models, along with their scope and features.

As the related drone routing literature indicates, the researched problems considering only drones are significantly less than routing problems combining them with road vehicles. Therefore many variants of the DRP are yet to be studied, such as the one proposed in this paper, the EM-DRP-PD, which considers pickups and deliveries between pairs of customers, while accounting for weight, quantity and energy constraints.

2.2. One-to-one pickups and deliveries

Pickup and delivery problems (PDPs) cover a wide range of vehicle routing problems which have been classified into three main categories, according to Battarra et al. (2014). In the first category of *many-to-many* problems, each commodity may have several origins and destinations. In the second category, of *one-to-many-to-one* problems, some commodities are transported from the depot to the customers, while other commodities are collected to be returned to the depot. The third category consists of *one-to-one* problems, in which each commodity has exactly one pickup and one delivery node. As the EM-DRP-PD belongs to the third category, thus, the two other categories are not within the scope of this research, additional literature on those PDPs can be found in Battarra et al. (2014), Berbeglia et al. (2007) and Parragh et al. (2008). A review of dynamic variants of PDPs, which are also not directly related to the proposed problem, can be found in Berbeglia et al. (2010).

In the *one-to-one* PDP category there are two main problems studied, the Vehicle Routing Problem with Pickups and Deliveries (VRPPD) and the Dial-a-Ride Problem (DARP). The first applies to the transportation of objects, while the second one usually applies to transporting people. The DARP can be considered a specialization of the VRPPD, in which the quantity requested for transport is a single load unit. Thus, in most cases of courier services, such as the EM-DRP-PD, a dial-a-ride model is considered (Cordeau et al., 2008).

Since the first standard definition of the DARP given by Cordeau and Laporte (2003), many interesting variants of the problem have been proposed. Zhang et al. (2015) introduce the multi-trip dial-a-ride problem (MTDARP), for transporting patients from one location to another using ambulances. Chevrier Liefooghe et al. (2012) use a multi-objective approach, minimizing the number of vehicles, the journeys' duration and the delays in taxi services. Atahran et al. (2014) also use a multi-objective approach which incorporates the cost for the transportation operator, the quality of service for users and the impact on the environment. Pimenta et al. (2017) model a DARP using autonomous electric vehicles with a reliability objective. More recently, Liang et al. (2020) have studied a DARP application in ride-sharing using automated taxis, considering traffic congestion in urban road networks. In the contrary, Johnsen and Meisel (2022) autonomous vehicle DARP approach takes place in a rural environment, and considers interrelated trips. A dynamic variant of DARP has been proposed by Tafreshian et al. (2021) to address online shuttle dispatching. Detailed reviews of DARP publications can be found in Ho et al. (2018) and Molenbruch et al. (2017).

The general VRPPD has also seen several proposed variants. Yanik et al. (2014) introduced the capacitated VRP with multiple pickup, single delivery and time windows (CVRPMPDTW) for multi-product sourcing scenarios. Similarly, Wang (2018) uses VRPPD model to address the meal delivery problem where the vehicles pick up meals from multiple suppliers and deliver them to customers. A more complex scenario is addressed in Wolfinger and Salazar-Gonzalez (2021), which considers split deliveries to customers, as well as transshipment between the vehicles at designated locations. Sun et al. (2020) introduce the time-dependent profitable pickup and delivery problem with time windows, where the logistics provider uses a fleet of capacitated vehicles to transport shipment requests, for a profit, from pickup to delivery locations in an urban setting.

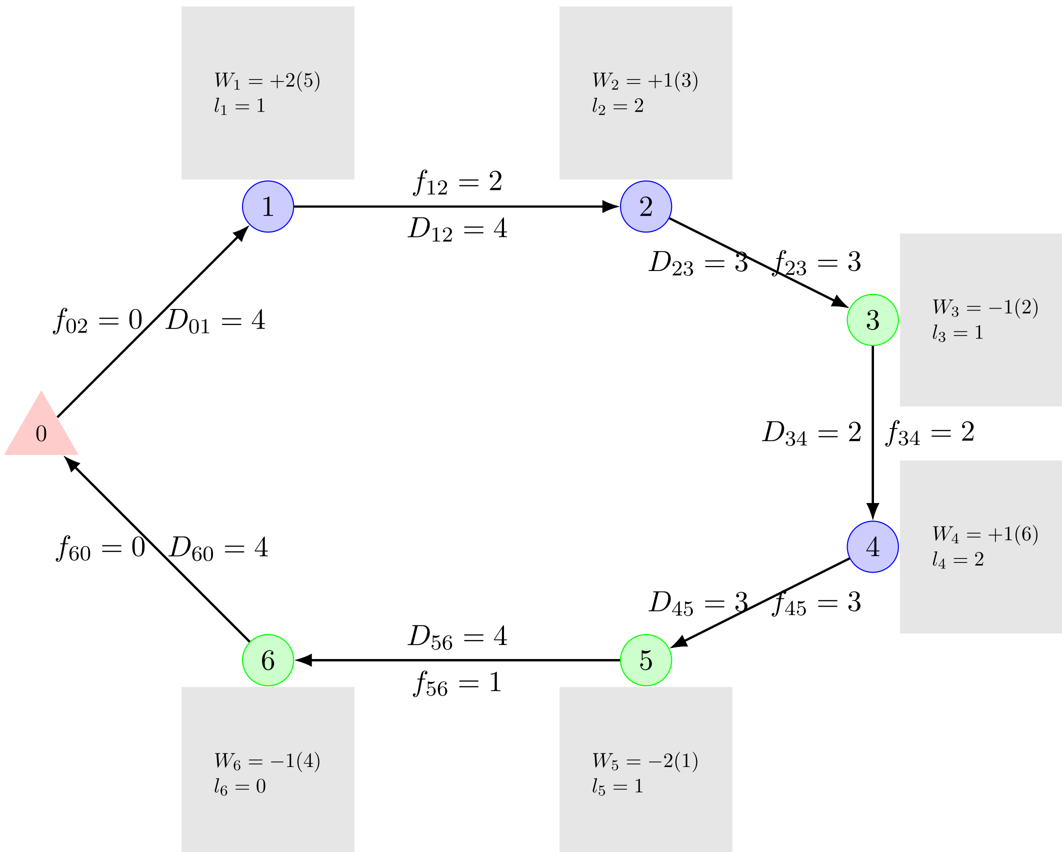

Fig. 1. Drone route example of the EM-DRP-PD.

Although VRP variants with pickups and deliveries have been extensively studied, there is a research gap in such problems when considering the usage of drones, with their capacity and energy constraints. The study of autonomous vehicles is one of the future perspectives highlighted in Koç et al. (2020), which reviews the closely related VRP with simultaneous pickups and deliveries. Another perspective being emphasized in the same publication is the use of eco-friendly, electric vehicles. The proposed EM-DRP-PD covers both of these two elements, which state-of-the-art VRPs should consider.

3. The energy minimizing drone routing problem with pickups and deliveries

This paper combines the courier service approaches of the VRPPDs and DARPs, the drone characteristics and the energy minimization objectives, to address the following drone routing scenario:

A courier service provider utilizes a fleet of rotary wing drones, capable of vertical take-off and landing, in order to pickup parcels from sellers and deliver them to their respective buyers. The drones employed have a maximum payload quantity capacity, a maximum payload weight capacity, as well as, a maximum energy capacity. The energy consumption rate of each drone at any given time, depends on the total payload weight it carries at that moment. The drones are launched from a pre-determined launch/retrieval location, the base, and return to it after completing all deliveries from the sellers to the buyers. The goal of the operation is to service all customers while minimizing the total energy required.

The drones used, have three payload compartments and each can fit a standard-sized parcel. Each seller puts a single parcel, weighing up to a certain maximum weight on one of the three compartments. The parcel must be delivered to a certain buyer. The drone can accommodate up to three packages simultaneously, as long as the maximum payload weight limitation allows it.

In classical mechanics, work is defined as the energy transferred to or from an object via the application of force along a displacement. In practical terms, it is the product of force and displacement. The EM-DRP-PD cost structure is based on that notion, deriving from Newton's Second Law of Motion. The higher the weight of the transported parcels by the drone, the more energy it requires to transport it over a unit of distance (Kara et al., 2007). Likewise, if a certain payload weight is transported over greater distances, the total energy consumption also is higher.

In practical applications, drone energy consumption rate is affected by multiple factors. Externalities such as weather conditions, have a significant impact on drone energy consumption but cannot be controlled. Certain factors, which are controllable, such as flying speed, can be assumed to be optimal considering the conditions, due to the autonomous nature of the vehicle. The EM-DRP-PD focuses on the main controllable factor within the scope of a vehicle routing problem, which is the payload weight. By controlling the order in which customers are visited, the total energy required by a drone can be optimized.

3.1. Energy cost calculation

Let node 0 be the base location, D_{ij} the distance between nodes i and j, W_i the weight picked-up or delivered at node i, and f_{ij} the total payload weight while drone is traveling from node i to node j. The energy e_{ij} required by a drone weighing U to travel from node i to j, while carrying a total payload weight of f_{ij} is given by Eq. (1):

$$e_{ij} = D_{ij} \times (U + f_{ij}) \tag{1}$$

Fig. 1 illustrates a drone route example, for which the total route energy required is calculated based on the EM-DRP-PD. Customer nodes

Table 1
Sets, parameters, and variables of the EM-DRP-PD formulation.

Node sets & characteristics	
S	Sellers set, $S = \{1, \dots, n\}$
B	Buyers set, $B = \{n+1, \dots, 2n\}$
N	Customers set, $N = S \cup B$
V	Node set, $V = N \cup \{0, 2n+1\}$
A	Arcs set, $A = \{(i,j) \mid i \in V, j \in V, i \neq j\}$
D_{ij}	Distance from node i to node j
T_{ij}	Travel time from node i to node j
Drone parameters	
K	Set of drones
Q	Maximum payload quantity of drones
Φ	Maximum payload weight of drones
E	Maximum energy capacity of drones
U	Drone's weight, without payload
Customer parameters	
W_i	Payload weight added or subtracted at node i
P_i	Package weight picked up or delivered at node i
L_i	Payload quantity picked up or delivered at node i
Variables	
x_{ij}^k	Decision variable of drone k traversing the arc (i,j)
w_i^k	Total payload weight of drone k after visiting node i
l_i^k	Total payload quantity of drone k after visiting node i
t_i^k	The departure time of drone k from node i
f_{ij}^k	Total payload weight of drone k while traversing arc (i,j)

with blue color, denote the pickup locations, while customers with green color are the delivery locations. The gray box next to each customer i denotes the respective package pickup or delivery weight W_i, along with the corresponding customer in parenthesis. l_i denotes the parcel quantity carried by the drone after servicing customer i.

For practical purposes the drone weight U is set to 1, since all drones have the same weight. Thus, for the EM-DRP-PD route example, illustrated in Fig. 1 and presented in the previous subsection, the energy e_{ij} required at each arc (i,j) with distance D_{ij} is calculated below:

$$e_{01} = D_{01} \times (1 + f_{s1}) = 4 \times 1 = 4$$
$$e_{12} = D_{12} \times (1 + f_{12}) = 4 \times 3 = 12$$
$$e_{23} = D_{23} \times (1 + f_{23}) = 3 \times 4 = 12$$
$$e_{34} = D_{34} \times (1 + f_{34}) = 2 \times 3 = 6$$
$$e_{45} = D_{45} \times (1 + f_{45}) = 3 \times 4 = 12$$
$$e_{56} = D_{56} \times (1 + f_{56}) = 4 \times 2 = 8$$
$$e_{60} = D_{60} \times (1 + f_{60}) = 4 \times 1 = 4$$

The total energy of the route is calculated by:

$$C = \sum_{(i,j) \in route} e_{ij} = 58$$

3.2. Assumptions

As with all vehicle routing problems, certain assumptions are made for the EM-DRP-PD and are presented below:

- One parcel is picked-up or delivered at each customer location.
- The pickup and delivery process is assumed to be instantaneous.
- The time required to reach flying altitude is considered negligible and the drones are assumed to reach nominal flying velocity instantly.
- The flying altitude is assumed sufficient to avoid any structures (i.e buildings).
- No external forces affecting the drones are considered (i.e. weather conditions).

4. Mathematical formulation of the EM-DRP-PD

Let $S = \{1, \dots, n\}$ the set of pickup nodes and $B = \{n+1, \dots, 2n\}$ the set of delivery nodes, which correspond to the sellers' and buyers' set, respectively. The union of both customer type nodes is $N = S \cup B$. Nodes 0 and $2n+1$ represent the base locations, from which the drones launch from and return to, respectively. The distance between any two given nodes is given by D_{ij}. Let i be the request for parcel transfer between pickup node i and delivery node $n+i$. Each request i corresponds to the pickup and delivery of a parcel weighing P_i.

The EM-DRP-PD is defined on a directed graph $\mathcal{G} = (V, A)$ where $V = N \cup \{0, 2n+1\}$ is the node set and A is the arc set. Each drone k in the set of drones K weighs U units and can carry up to Q parcels simultaneously, the total weight of which cannot exceed the maximum payload weight Φ. The maximum energy capacity of the drones is E. Let f_{ij}^k be the total payload weight of drone k while traversing arc (i,j), t_i^k its departure time from node i and w_i, l_i the total weight and total quantity, respectively, of parcels after the service at node $i \in V$. A comprehensive description of the sets, parameters and variables used, is presented in Table 1.

The mathematical formulation of the EM-DRP-PD is the following:

$$\min F = \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} (D_{ij} \times (U + f_{ij}^k) \times x_{ij}^k) \tag{2}$$

Subject to:

$$\sum_{k \in K} \sum_{j \in N \cup \{2n+1\}} x_{ij}^k = 1, \forall i \in S \tag{3}$$

$$\sum_{j \in N} x_{ij}^k - \sum_{j \in N} x_{j,n+i}^k = 0, \forall i \in S, k \in K \tag{4}$$

$$\sum_{j \in N \cup \{2n+1\}} x_{0j}^k = 1, \forall k \in K \tag{5}$$

$$\sum_{i \in N \cup \{0\}} x_{ij}^k - \sum_{i \in N \cup \{2n+1\}} x_{j,n+i}^k = 0, \forall j \in N, k \in K \tag{6}$$

$$\sum_{i \in B \cup \{0\}} x_{i,2n+1}^k = 1, \forall k \in K \tag{7}$$

$$x_{ij}^k (t_i^k + T_{ij} - t_j^k) \leq 0, \forall (i,j) \in A, \forall k \in K \tag{8}$$

$$t_i^k + T_{i,n+i} \leq t_{n+i}^k, \forall i \in S, \forall k \in K \tag{9}$$

$$x_{ij}^k (l_i^k + L_j - l_j^k) = 0, \forall (i,j) \in A, k \in K \tag{10}$$

$$L_i \leq l_i^k \leq Q, \forall i \in S, k \in K \tag{11}$$

$$0 \leq l_{n+i}^k \leq Q - L_i, \forall n+i \in S, k \in K \tag{12}$$

$$l_0^k = 0, k \in K \tag{13}$$

$$x_{ij}^k (w_i^k + W_j - w_j^k) = 0, \forall (i,j) \in A, k \in K \tag{14}$$

$$W_i \leq w_i^k \leq \Phi, \forall i \in S, k \in K \tag{15}$$

$$0 \leq w_{n+i}^k \leq \Phi - W_i, \forall n+i \in S, k \in K \tag{16}$$

$$w_0^k = 0, k \in K \tag{17}$$

$$f_{ij}^k = w_j^k - W_j, \forall (i,j) \in A, k \in K \tag{18}$$

$$0 \leq f_{ij}^k \leq \Phi \times x_{ij}^k, \forall (i,j) \in A, k \in K \tag{19}$$

$$\sum_{i \in V} \sum_{j \in V} (D_{ij} \times (U + f_{ij}^k) \times x_{ij}^k) \leq E, \forall k \in K \tag{20}$$

$$x_{ij}^k \in \{0, 1\}, \forall (i,j) \in A, k \in K \tag{21}$$

$$L_i = \begin{cases} -1, & \text{if } i \in B \\ 1, & \text{if } i \in S \\ 0, & \text{otherwise} \end{cases} \tag{22}$$

$$W_i = \begin{cases} -P_i, & \text{if } i \in B \\ P_i, & \text{if } i \in S \\ 0, & \text{otherwise} \end{cases} \tag{23}$$

The objective function (2) minimizes the total energy consumption. Constraints (3) and (4) ensure that each pair of pickup and delivery nodes are served exactly once and by the same drone. Constraints (5)–(7) forces all drones to begin their route from the base and return to it after completing their route. Constraints (8) and (9) force the vehicle to visit the pickup node before its corresponding delivery node. Constraints (10)–(12) impose the quantity limitations on the drones, while (13) force them to begin their route empty. Similarly to the quantity constraints, (14)–(16) impose the payload weight limitations on the drones for both pickup and delivery nodes, while (17) ensures they initially carry no payload. Constraints (18) and (19) limit the arc payload weight between 0 and Φ for the arcs used by the drones and forces it to be zero otherwise, while (20) impose a limit on the total energy consumption of each drone. Lastly, (21) define the binary variable scope, (22) sets the quantities at each node depending on its type and (23) sets the weight of the package depending on whether it is picked up or delivered.

5. The proposed GRASP/VND metaheuristic

The Greedy Randomized Adaptive Search Procedure (GRASP) (Feo & Resende, 1995) is an iterative optimization process, with each iteration consisting of two phases, a solution construction phase, and a local search phase. In the first phase, a feasible solution is built utilizing a randomized greedy scheme, and in the second phase, the constructed solution undergoes a local search procedure until a local minimum is reached. The algorithm keeps the best overall solution. The GRASP iterations terminate when some termination criterion, such as the maximum number of iterations, is satisfied.

In the solution construction phase, a randomized greedy mechanism provides feasible solutions incorporating both greedy and random characteristics in the solution building process. At each step of this phase, a node is added to a partial solution. To select the next node to be added in the incomplete solution, a candidate list is used, called the Restricted Candidate List (RCL). The elements of the RCL are determined based on a greedy function, thus, these nodes are the best candidates. The choice among the best candidate nodes of the RCL can either be random or have a bias based on an attribute.

The heuristic method is adaptive since the benefits associated with every element are updated during each iteration of the construction phase to reflect the changes brought on by the previous nodes. This selection mechanism allows for different solutions to be generated at each iteration of the GRASP algorithm.

In the local search phase, the generated solution initializes the process. In an iterative manner, the current solution is replaced by a better solution in the neighborhood of the current solution. The local search terminates when no further improvement is possible in the defined neighborhoods.

Since its introduction, the GRASP algorithm has seen many extensions and hybridizations with other successful algorithms. A Path Relinking approach was used in Aiex et al. (2005), Laguna and Marti (1999), and Marinakis (2012) has proposed the Expanding Neighborhood Search algorithm as the second phase for the GRASP.

The proposed GRASP/VND implementation uses the Variable Neighborhood Descent (VND) (Mladenović & Hansen, 1997) algorithm as a local search procedure in the second phase of the metaheuristic. The GRASP and VND hybrid approaches have been proven effective in solving a number of different VRPs, such as the one commodity pickup and delivery VRP (Hernández-Pérez et al., 2009), the single truck-and-trailer routing problem with satellite depots (Villegas et al., 2010), and the school bus routing problem with bus stop selection (Schittekat et al., 2013). A recent review of GRASP implementations can be found in Resende and Ribeiro (2019).

In this paper, the following three variants of the GRASP are implemented, each utilizing a different approach for choosing the next customer from the RCL.

- **GRASP/VND/U:** No bias in choosing among the customers of the RCL. Therefore, all customer in the RCL have equal probability of being chosen.
- **GRASP/VND/P:** Bias based on the proximity $PBias_{ij} = 1/d_{ij}$ of each customer in the RCL, where d_{ij} is the distance of customer j from the last inserted node i in the route.
- **GRASP/VND/R:** Bias based on the rank r_j of each customer in the RCL, $RBias_{ij} = \frac{|RCL|+1-r_j}{|RCL|}$. The rank is determined based on the distance d_{ij} of customer j from the last inserted node i in the route, with the closest customer having the rank of 1.

All three variants utilize the same VND procedure as the local search phase. The outline of the GRASP/VND algorithms is presented in Algorithm 1.

Algorithm 1: GRASP/VND Outline

Input: $instance, Iter_{GRASP}, \alpha$
Result: S_{best}
for $iter \leftarrow 1$ *to* $Iter_{GRASP}$ **do**
  $S \leftarrow$ ConstructGRASPSolution $(instance, \alpha)$;
  $S_{improved} \leftarrow$ VND$(Iter_{VND}, S)$;
  if *Cost*$(S_{improved}) <$ *Cost*(S_{best}) **then**
    $S_{best} \leftarrow S_{improved}$;
return S_{best};

5.1. Solution construction

The solution construction process of the GRASP requires the generation of a restricted candidate list at each step of inserting a node in a route, containing the most promising customers to be visited at that step of construction. The implemented approach uses a value-based RCL. This type of RCL construction process utilizes a parameter $\alpha \in [0, 1]$ to determine whether a customer is eligible to be added based on its distance from the last inserted node. Let i be the last inserted node in the route, and d_{max}, d_{min} the maximum and minimum distance between the current node and the possible candidates. A candidate node $l \in L$, is added in the RCL only if the condition in Eq. (24) is true. L is the list containing all the nodes not yet visited (pickup and delivery) and for which the transition is feasible, thus, their insertion in the route would not violate the payload quantity, payload weight, and energy capacity constraints.

$$d_{il} \le d_{min} + \alpha(d_{max} - d_{min}) \tag{24}$$

Algorithm 2 presents the value-based RCL construction method for the GRASP/VND.

5.2. Variable Neighborhood Descent

The Variable Neighborhood Descent (VND) is a deterministic variant of the Variable Neighborhood Search algorithm originally proposed by Mladenović and Hansen (1997) and has been used as a local search

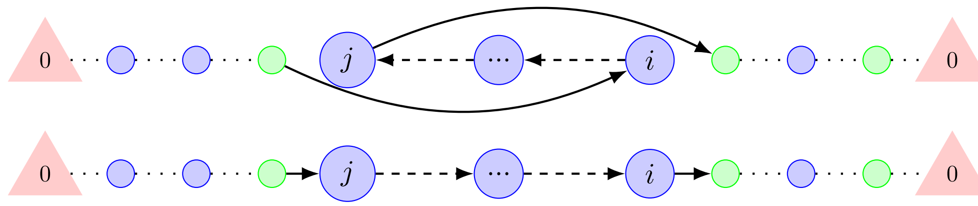

Fig. 2. 2-Opt operator example.

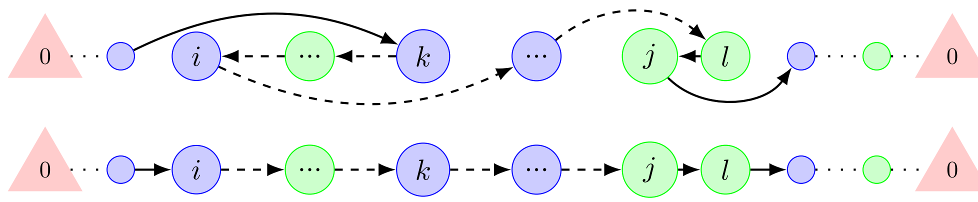

Fig. 3. Pair-Swap operator example.

Algorithm 2: Value-based RCL construction

Data: d, i, α, L
Result: RCL
$d_{min} \leftarrow \min\{d_{il} | l \in L\}$;
$d_{max} \leftarrow \max\{d_{il} | l \in L\}$;
$RCL \leftarrow \{\}$;
for l *in* L **do**
  if $d_{il} \leq d_{min} + a(d_{max} - d_{min})$ **then**
    $RCL \leftarrow RCL \cup \{l\}$;
return RCL;

routine in many metaheuristic algorithms. It utilizes a set of neighborhood operators, which are applied to the incumbent solution visits in order to improve it.

In this paper, a Pipe-VND (P-VND) scheme is used, where the search continues in the same neighborhood as long as it improves the incumbent solution. When no further improvement can be made by the same neighborhood operator, the search continues in the next neighborhood. This process is repeated until no further improvement can be made by any neighborhood operator.

Let $N = \{N_1, N_2, ..N_{k_{max}}\}$ be a set of operators that map a given solution to a neighborhood structure $N_k(S)$. Algorithm 3 shows the Pipe-VND procedure utilized.

Algorithm 3: Variable Neighborhood Descent

Data: $S, N = \{N_1, N_2, ..N_k\}, Iter_{VND}$
Result: S
$S' \leftarrow S$;
for $iter \leftarrow 1$ *to* $Iter_{VND}$ **do**
  $R_i, R_j \leftarrow RandomDroneSelection(S)$;
  for $k \leftarrow 1$ *to* k_{max} **do**
    repeat
      $S \leftarrow S'$;
      $S' \leftarrow N_k(S, R_i, R_j)$;
    until *Cost(S′) ≥ Cost(S)*;
    $S' \leftarrow S$;
return S;

To complement the exploitation of solutions, the VND procedure utilizes a set of local search operations. Although the operators are well-studied in the literature, the seller-buyer pairing characteristic of the EM-DRP-PD requires special attention in implementing them. The operators used are the following:

- **2-Opt:** The operator takes consecutive customers of the same type (sellers or buyers) in a range of positions $[i, j]$ in a single route and reverses their positions. Illustrated example in Fig. 2.
- **Pair-Swap:** The operator takes a seller–buyer pair at positions i, j of a single route and swaps their positions with another seller–buyer pair at positions k, l of the same route. Illustrated example in Fig. 3.
- **2-2 Exchange:** The operator takes a seller–buyer pair at positions i, j of a route R_m and exchanges their positions with another seller–buyer pair at positions k, l of a different route R_n. Illustrated example in Fig. 4.
- **2-0 Relocation:** The operator takes a seller–buyer pair at positions i, j of a route R_m and inserts them at positions p, q of a different route R_n. Illustrated example in Fig. 5.

6. Computational results

The algorithms were coded in C++ and compiled with GCC 12.1. All tests were conducted using an Intel® Core™ i5-11400F CPU (4.3 GHz boost clock speed) with 15.4 GB RAM running Fedora 36 Workstation.

The algorithms were tested on 20 newly generated EM-DRP-PD instances. The number of customers ranges from 50 to 200 and the number of drones from 2 to 11. The instances are based on the well-known CMT instances proposed by Christofides et al. (1979) for the CVRP. The depot of the original instances is used as the base of the drones. The customers are split into two groups, sellers and buyers, and each seller-buyer pair has a payload weight demand in the range of $[1, 3]$. The groups were generated by randomly choosing customers in pairs, as in this particular application of person-to-person trading, everyone is both a potential buyer and seller. The algorithms are executed 10 independent times for each instance.

6.1. Parameter settings and sensitivity

The GRASP/VND variants have few parameter values which must be determined before execution. Table 2 displays the parameters, their description and the values tested.

The parameter values regarding the iterations, $Iter_{GRASP}$ and $Iter_{VND}$ of the algorithms, were determined by testing large enough values for which the algorithm could not further improve solutions. The most important parameter, with a significant impact on the behavior of the algorithm and its ability to explore the solution space, is parameter

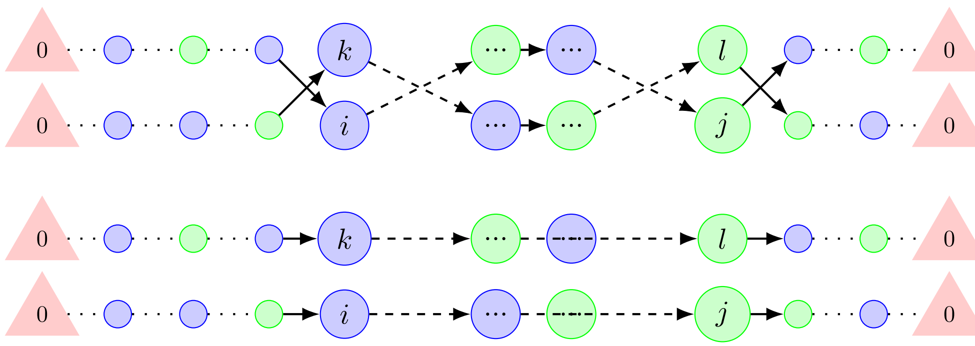

Fig. 4. 2-2 Exchange operator example.

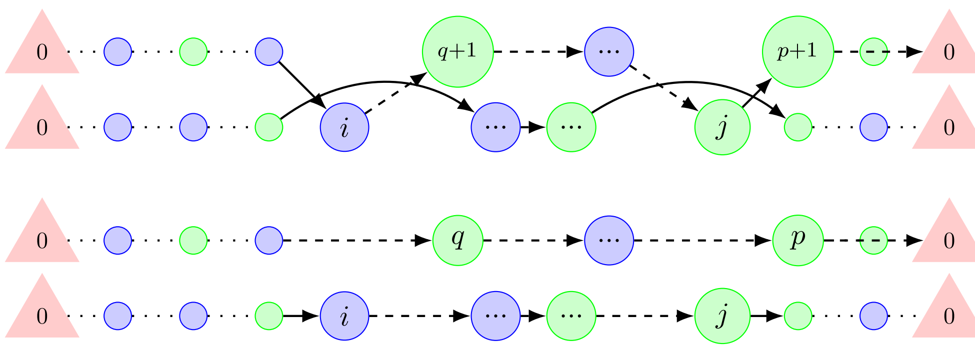

Fig. 5. 2-0 Relocation operator example.

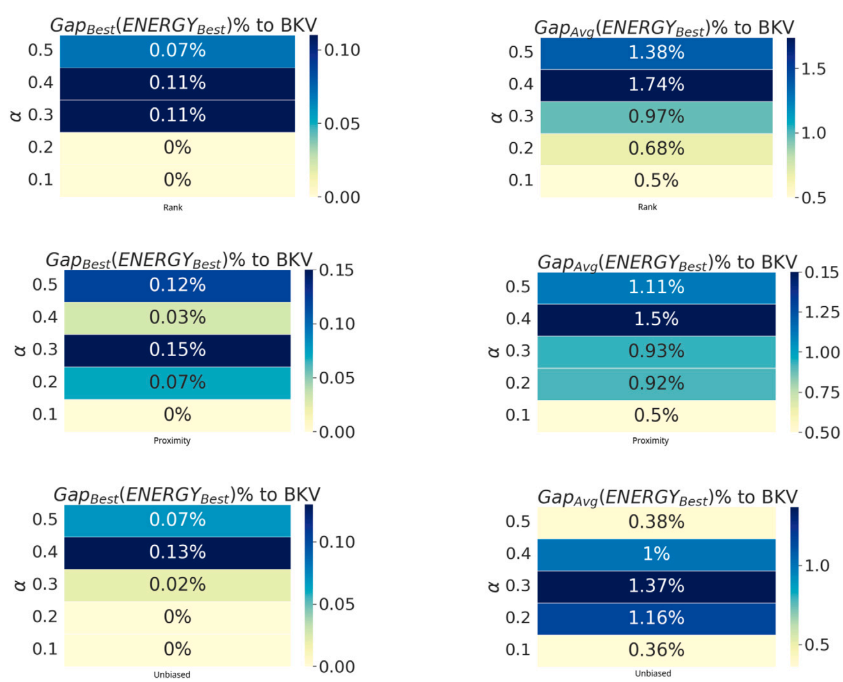

Fig. 6. Best (left) and average (right) gap of the solutions found to the BKV for each instance, by each parameter value and GRASP/VND variant.

α. For this parameter the recommended range of values in the literature has been used in a sensitivity test to determine the best values for this particular implementation.

Fig. 6 displays the best gap of the best solution found using the respective parameter value and the best known value (BKV) for each instance. Although for multiple values of parameter α, the three variants were able to obtain quality results, it can be observed that lower values benefit their overall performance. In particular, $\alpha = 0.1$ was

Table 2
Parameter description and settings.

Parameter	Description	Values tested
$Iter_{GRASP}$	Number of iterations	2000
$Iter_{VND}$	Number of the local search iterations	100
α	Controls the greediness and randomness	$\{0.1, 0.2, 0.3, 0.4, 0.5\}$

Table 3
Energy results obtained using the Energy objective for the three variants of the GRASP/VND metaheuristic. (BKV in bold, best distance values among them underlined.)

Instance	GRASP/VND/R			GRASP/VND/P			GRASP/VND/U		
	$ENERGY_{best}$	$ENERGY_{avg}$	$DIST_{best}$	$ENERGY_{best}$	$ENERGY_{avg}$	$DIST_{best}$	$ENERGY_{best}$	$ENERGY_{avg}$	$DIST_{best}$
PD1a	**1785.77**(2)	1803.67	793.35	1789.38(2)	1801.14	781.81	1789.38(2)	1804.35	803.07
PD1b	1728.65(2)	1748.36	795.71	1728.46(2)	1747.22	787.49	**1727.62**(2)	1748.61	793.33
PD1c	1963.63(3)	1980.74	823.47	**1961.02**(3)	1979.82	824.74	1961.45(3)	1981.18	817.83
PD1d	**2140.07**(3)	2146.00	847.10	**2140.07**(3)	2145.83	853.14	2141.58(3)	2146.14	849.62
PD3a	**3086.29**(4)	3127.66	1 284.39	3098.22(4)	3131.11	1 319.97	3090.76(4)	3131.57	1 310.17
PD3b	3007.21(4)	3049.58	1 288.63	**2992.41**(4)	3049.50	1 303.79	3017.84(4)	3045.45	1 263.63
PD3c	4451.44(6)	4515.87	1 677.05	4456.17(6)	4504.30	1 687.31	**4437.31**(6)	4514.41	1 711.71
PD3d	3739.09(5)	3783.50	1 492.75	3726.70(5)	3784.84	1 464.64	**3710.87**(5)	3782.81	1 463.07
PD4a	4733.00(6)	4793.66	1 963.72	**4711.93**(6)	4791.00	1 933.34	4725.27(6)	4825.75	1 964.43
PD4b	4784.93(6)	4857.92	1 964.78	**4772.64**(6)	4847.54	1 931.20	4805.22(6)	4891.62	1 951.76
PD4c	**6598.30**(9)	6727.41	2 550.17	6651.60(8)	6715.35	2 599.91	6612.65(9)	6739.51	2 544.24
PD4d	7273.55(9)	7347.76	2 791.25	**7220.94**(9)	7340.00	2 709.01	7245.83(9)	7370.62	2 756.26
PD5a	**6658.49**(9)	6797.72	2 713.22	6658.87(9)	6785.32	2 739.45	6684.64(9)	6845.03	2 761.21
PD5b	6919.51(9)	7039.87	2 751.01	6897.87(9)	7038.06	2 785.08	**6896.74**(9)	7084.78	2 791.62
PD5c	**8342.19**(11)	8554.44	3 303.84	8376.45(11)	8530.10	3 297.20	8378.92(11)	8601.02	3 310.95
PD5d	**9298.19**(12)	9458.99	3 504.42	9316.15(12)	9510.53	3 535.14	9302.43(12)	9571.77	3 523.94
Average	4781.89	4858.32	1 909.05	**4781.18**	4856.35	1 909.58	4783.03	4880.29	1 913.55
Total	76 510.31	77 733.15	30 544.86	**76 498.88**	77 701.66	30 553.22	76 528.51	78 084.62	30 616.84

observed to be the common best value for all three GRASP/VND variants both in the best and average gap of the solutions found. All three implementations exhibit very similar sensitivity to the parameter, as the gaps obtained follow, more or less, the same range of values. An interesting finding is the Gap_{Avg} obtained by the GRASP/VND/U for $\alpha = 0.5$. The combination of a large RCL together with the increased randomness of the unbiased transition rule, seems to benefit this variant much more compared the biased approaches. The gap is calculated by the formula in Eq. (25):

$$Gap(Value) = 100 \times (Value - BKV)/BKV \tag{25}$$

6.2. EM-DRP-PD results - Energy objective

This sections presents the results of the computational experiments on the instances using the proposed EM-DRP-PD objective, which is the minimization of the total energy consumption.

Table 3 displays the results obtained by the three variants using the Energy objective approach. The first column denotes the names of the instances. Columns 2, 5, 8 are the best energy values obtained by the GRASP/BND/R, GRASP/VND/P and GRASP/VND/U, respectively. In parentheses are the number of drones used in the solution. Columns 3, 6, 9 display the average energy values found for the variants. Lastly, columns 4, 7, 10 present the best total distance values found, using the Energy objective approach.

All three variants were able to provide quality results. More specifically, GRASP/VND/R found 7 BKVs, the GRASP/VND/P 6 BKVs, while the GRASP/VND/U was able to obtain 4 BKVs. The difference on average best results between the proximity and rank variants is only 0.01% and the difference between the arguably best performing algorithm, GRASP/VND/P, and the worst performing, GRASP/VND/U, is 0.04%. In terms of average energy values obtained, there is a similar pattern observed, where GRASP/VND/P is marginal better than GRASP/VND/R with a difference of 0.04% and the GRASP/VND/U being the worse with a 0.5% difference to the best performing variant. Furthermore, there is no observable differences in solution quality relative to the number of customers in the instances, as all variants are able to obtain BKVs or marginally inferior solutions for a wide range of customer populations. Thus, there is no clear evidence to strongly suggest that one variant is superior to another in the total energy minimization objective.

Although the total traveled distance is not the objective of the EM-DRP-PD, it is useful to explore the results of the three variants with respect to that metric also. As observed, the relative performance of the GRASP/VND variants in the distance metric is similar to the energy results. In this metric, the GRASP/VND/R is slightly better than the GRASP/VND/P, with a difference of just 0.02%, while the unbiased variant is the worst performer on average with a difference of 0.23%. These results, further suggest that the differences in performance between the rank-biased and proximity-biased variants are minimal, and a clearly superior algorithm cannot be determined.

Table 4
Computational time required by the three variants of the GRASP/VND metaheuristic.

Instance	GRASP/VND/R $TIME_{avg}(s)$	GRASP/VND/P $TIME_{avg}(s)$	GRASP/VND/U $TIME_{avg}(S)$
PD1a	34.55	34.71	33.53
PD1b	37.10	37.01	36.38
PD1c	37.70	37.45	34.81
PD1d	21.37	21.77	20.15
PD3a	87.27	89.12	79.19
PD3b	90.78	92.59	83.73
PD3c	21.79	22.34	20.66
PD3d	64.06	65.23	58.97
PD4a	93.91	97.93	84.12
PD4b	91.76	95.56	83.88
PD4c	26.33	27.16	23.87
PD4d	53.10	54.95	48.45
PD5a	101.48	106.22	89.88
PD5b	100.09	105.28	89.83
PD5c	34.04	35.80	30.98
PD5d	73.38	76.15	66.48
Average	60.54	62.45	55.30
Total	968.71	999.27	884.91

Table 4 displays the average computational time required by each variant of the EM-DRP-EP. In terms of the computational time required, GRASP/VND/U is, on average and in total, the fastest among the three variants tested on the EM-DRP-PD instances. The GRASP/VND/U is on average 11.4% faster than the GRASP/VND/R approach and 8.6% faster than the GRASP/VND/P variant. Part of these differences may be attributed to the unbiased choice rule which does not require the computation of any probabilities, unlike the other two variants. The difference in computational time between the two biased variants, is on average 3%, with the GRASP/VND/R being the fastest among the two.

6.2.1. Statistical comparison

Between the three GRASP/VND variants tested, the GRASP/VND/P approach, is observed as the best performing algorithm on the average and the total energy of the solutions obtained. Nevertheless, the differences in those metrics compared to the other two variants are marginal,

Table 5
Wilcoxon signed-rank test of the GRASP/VND variants' results on EM-DRP-PD instances.

Algorithms	w-value	p-value	H_0
GRASP/VND/P - GRASP/VND/R	55.0	0.7764	Not Rejected
GRASP/VND/P - GRASP/VND/U	53.0	0.6909	Not Rejected
GRASP/VND/R - GRASP/VND/U	61.0	0.7435	Not Rejected

especially compared to the GRASP/VND/R. In order to statistically compare the three variants, the non parametric, Wilcoxon signed-rank test is employed.

Table 5 displays the results of the statistical comparison between the implemented GRASP/VND variants in pairs. The first column denotes the two variants compared. Column 2 displays the w-value and column 3 displays the corresponding p-value. The last column indicates whether the null hypothesis H_0 can be rejected with the risk to reject the null hypothesis when H_0 is true, being less than 5%.

The null hypothesis H_0 assumes that the true mean of the algorithms compared is equal, while H_1 assumes the true mean of the two algorithms differ. The statistical test results confirm the discussion made on the results obtained by the algorithms. The results suggest that the null hypothesis H_0 cannot be rejected for any pair of variants, with a risk less than 5%. Therefore, although the GRASP/VND/P was able to obtain marginally the best results in total and on average, its performance is statistically indifferent to the other two variants.

6.3. EM-DRP-PD results - Distance objective

This subsection presents and discusses the results obtained on the EM-DRP-PD instances, using the total distance traveled by the drones as the minimization objective. The energy of the drones is considered only as a constraint.

Table 6 displays the computational results using the Distance objective approach. The first column denotes the names of the instances. In columns 2, 5, 8 are the best energy values obtained by the GRASP/VND/R, GRASP/VND/P and GRASP/VND/U, respectively. Columns 3, 6, 9 display the average energy values found for the variants. Lastly, columns 4, 7, 10 present the best total distance values found.

Using the Distance objective approach, the on average best results in the total traveled distance metric where provided by the GRASP/VND/R implementation. The GRASP/VND/P results were on average 0.24% worse, while the GRASP/VND/U variants was the worst performer with a 0.48% average distance surplus. For the total energy consumption metric, the proximity-biased algorithm results are on average 0.23% better than the unbiased variant, and 0.44% better than the proximity-biased variant.

In contrast to the Energy objective's results, the results using the Distance approach on the distance metric, exhibit larger differences. Nevertheless, all three variants were able to obtain best distance values for several of the instances. Similarly to the Energy objective, it is observed that the GRASP/VND variant with the best energy value obtained for a certain instance, does not necessarily obtain the best distance value also. Therefore, it is worth comparing the differences between the two objectives and discussing their effect in both of those metrics.

6.4. Comparison of energy and distance objectives on the EM-DRP-PD

In the classical VRPs, using road vehicles, a routing solution requiring less trucks would almost always be preferable to a solution requiring more trucks. This is intuitive considering the high acquisition cost of road vehicles, their maintenance costs, fuel cost, and the cost of the driver.

In the case of the EM-DRP-PD, which utilizes autonomous drones, such costs are insignificant compared to traditional vehicles or not applicable at all, and the focus of the operation is to minimize the energy required to complete the service to the customers. Furthermore, the weight of the drone itself, is a fraction of the maximum payload weight it can carry. For example, the Amazon Prime Air UAV is estimated to weigh 5.5 kg, while being able to carry up to 14 kg of payload (Jung & Kim, 2017). In some cases, this characteristic makes routing two drones instead of one, more energy efficient than a single drone carrying more payload weight. Therefore, for the EM-DRP-PD, requiring additional drones, is preferable as long as it minimizes the total energy consumption of the operation, even if the total distance traveled increases.

In order to compare the two objectives in terms of total distance traveled and total energy consumed, the best solutions obtained by each approach among all variants of the GRASP/VND metaheuristic are aggregated in Table 7. The first two columns indicate the instance names and the corresponding number of customers they consider. Columns 3 and 7 are the best energy result values found by the Energy objective approach and the Distance objective approach, respectively. Columns 4 and 8, present the energy value results as gaps to the best energy values obtained. Similarly, Columns 5 and 9 are the best distance results found by the Energy and Distances objective approaches, respectively, and columns 6 and 10 present the corresponding gap values to the best distance values obtained.

As expected each objective approach is able to obtain the best solutions for the corresponding objective. This confirms the need to use different objective approaches, depending on weather the total energy or total distance should be minimized. The total energy required in all instances using the Energy objective approach is 6.12% lower than the total energy required using the Distance objective approach. Similarly, the total distance traveled in all instances using the Distance objective approach is 5.37% lower than the distance traveled using the Energy objective approach.

In terms of the average gap percentages obtained in the instances, the average $Gap(Distance_{best})$ of the Energy objective approach is 7.03% and the average $Gap(Energy_{best})$ of the Distance objective is 6.54%. This finding suggests that using the Distance objective approach, a slightly better energy outcome should be expected, percentage-wise, than doing the opposite, thus, using the Energy objective approach and expecting the distance outcome. Although this holds true on average, the difference is very small and should be further examined.

In order to have a more complete overview of the results differences between the two objective approaches, in the two performance metrics, the solutions obtained are visualized. Fig. 7 presents the $Gap\%$ to the BKVs for the energy (top) and distance (bottom) metrics, for the two objective approaches, in relation to the number of customers in the benchmark instances. The data presented include all the solutions obtained from the experiments.

In the case of the distance metric, a strong pattern is observed. As the number of customers in the instances increase, the gap differences between the two objective approaches tend to decrease, with overlapping values being present. For the 50 customer instances, only outlier results of the Distance objective overlap with the Energy objective gaps. The gap differences decrease significantly for the 100 and 150 customer instances, however, for the 200 customer instances, a slight increase is noticeable compared to the 150 customer instances.

In the case of the energy metric, this pattern, although present, is less observable. In the energy metric the majority of solutions obtained by the Distance objective is distinctly inferior to the solutions obtained using the Energy objective approach, independent of the customers in the instances. The median Gap_{Energy} value remains above 10% for all instances, using the Energy objective. Using the Distance objective, the median Gap_{Energy} value is less than 5% for all instances, with only outlier results exceeding this threshold.

Table 6
Energy results obtained using the Distance objective for the three variants of the GRASP/VND metaheuristic. (Best energy values among them underlined, best distance values in bold.)

Instance	GRASP/VND/R			GRASP/VND/P			GRASP/VND/U		
	$ENERGY_{best}$	$ENERGY_{avg}$	$DIST_{best}$	$ENERGY_{best}$	$ENERGY_{avg}$	$DIST_{best}$	$ENERGY_{best}$	$ENERGY_{avg}$	$DIST_{best}$
PD1a	1897.41(2)	2062.67	704.77	1810.06(2)	2063.91	**698.79**	1875.97(2)	2067.60	703.66
PD1b	1857.06(2)	2028.73	686.90	1815.45(2)	2028.78	**686.71**	1824.40(2)	1993.47	691.69
PD1c	2136.11(3)	2297.18	707.29	2201.78(3)	2324.60	717.07	2190.14(3)	2309.87	**702.85**
PD1d	2293.75(3)	2429.64	**769.00**	2242.02(3)	2406.77	777.08	2329.56(3)	2430.19	778.89
PD3a	3358.64(4)	3572.47	**1 226.58**	3331.03(4)	3574.76	1 229.33	3327.35(4)	3602.91	1 230.78
PD3b	3306.68(4)	3467.75	1 203.33	3267.58(4)	3498.56	1 198.83	3243.43(4)	3508.45	**1 159.83**
PD3c	4843.68(6)	5029.77	**1 588.17**	4763.92(6)	5010.23	1 606.49	4798.14(6)	5049.89	1 607.76
PD3d	4033.16(5)	4325.25	1 417.60	4073.80 (5)	4291.82	1 421.82	4089.66(5)	4341.06	**1 409.32**
PD4a	5117.85(6)	5457.99	1 882.75	5119.22(6)	5482.48	**1 863.37**	5090.50(6)	5502.98	1 902.22
PD4b	5261.21(6)	5472.94	1 867.16	5215.62(6)	5499.68	**1 861.71**	5152.68(6)	5523.84	1 881.67
PD4c	7087.78(8)	7468.83	2 426.45	6871.08(8)	7410.13	**2 425.70**	7145.73(8)	7469.43	2 441.08
PD4d	7684.02(9)	8030.65	**2 617.67**	7797.56(9)	8050.31	2 635.64	7723.24(9)	8067.18	2 624.42
PD5a	7207.47(8)	7631.30	2 589.70	7213.80(8)	7573.05	2 622.77	7240.55(8)	7701.47	**2 583.45**
PD5b	7402.68(9)	7808.93	**2 632.66**	7369.659(9)	7793.16	2 652.44	7353.51(9)	7871.84	2 638.17
PD5c	9030.98(10)	9463.56	3 142.56	9029.50(10)	9417.74	**3 099.91**	8842.98(10)	9488.06	3 155.42
PD5d	9745.36(11)	10 229.54	**3 350.47**	9779.39(11)	10 185.80	3 386.31	9861.21(11)	10 293.08	3 441.30
Average	5141.49	5423.58	**1 800.82**	5118.84	5413.24	1 805.25	5130.57	5451.33	1 809.53
Total	82 263.84	86 777.20	**28 813.06**	81 901.46	86 611.78	28 883.97	82 089.05	87 221.32	28 952.51

Table 7
Best results obtained by each objective among all GRASP/VND variants.

Instance	# Cust.	ENERGY Objective				DISTANCE Objective			
		$ENERGY_{best}$	$Gap(E_{best})\%$	D_{best}	$Gap(D_{best})\%$	$ENERGY_{best}$	$Gap(E_{best})\%$	$DIST_{best}$	$Gap(D_{best})\%$
PD1a	50	1785.77	0.00	781.81	11.88	1810.06	1.36	698.79	0.00
PD1b	50	1727.62	0.00	787.49	14.68	1815.45	5.08	686.71	0.00
PD1c	50	1961.02	0.00	817.83	16.36	2136.11	8.93	702.85	0.00
PD1d	50	2140.07	0.00	847.10	10.16	2242.02	4.76	769.00	0.00
PD3a	100	3086.29	0.00	1284.39	4.71	3327.35	7.81	1226.58	0.00
PD3b	100	2992.41	0.00	1263.63	8.95	3243.43	8.39	1159.83	0.00
PD3c	100	4437.31	0.00	1677.05	5.60	4763.92	7.36	1588.17	0.00
PD3d	100	3710.87	0.00	1463.07	3.81	4033.16	8.69	1409.32	0.00
PD4a	150	4711.93	0.00	1933.34	3.76	5090.50	8.03	1863.37	0.00
PD4b	150	4772.64	0.00	1931.2	3.73	5152.68	7.96	1861.71	0.00
PD4c	150	6598.30	0.00	2544.24	4.89	6871.08	4.13	2425.70	0.00
PD4d	150	7220.94	0.00	2709.01	3.49	7684.02	6.41	2617.67	0.00
PD5a	200	6658.49	0.00	2713.22	5.02	7207.47	8.24	2583.45	0.00
PD5b	200	6896.74	0.00	2751.01	4.50	7353.51	6.62	2632.66	0.00
PD5c	200	8342.19	0.00	3297.20	6.36	8842.98	6.00	3099.91	0.00
PD5d	200	9298.19	0.00	3504.42	4.59	9745.36	4.81	3350.47	0.00
Average		4771.29	0.00	1894.12	7.03	5082.44	6.54	1792.26	0.00
Total		76 340.78		30 306.01		81 319.10		28 676.19	

7. Conclusions

In this paper, the first drone routing problem with pickup and deliveries, with the goal of minimizing total energy consumption was introduced, namely, the Energy Minimizing Drone Routing Problem with Pickups and Deliveries. This novel VRP considers person-to-person trading scenarios where the logistic company provides third-party courier services to pick up the parcel from the seller and deliver it to the buyer.

The presented problem accounts for payload weight, payload quantity and energy limitations, while minimizing the total energy consumption of the operation. The energy function used is based on the definition of work in classical mechanics, thus, it considers both, the payload weight and the distance traveled. This approach, focusing on the payload weight as the main energy consumption factor, provides a more accurate approximation of the real-life application, compared to using the distance or travel time as the only consumption contributor.

The mathematical formulation of the EM-DRP-PD was presented and described, along with the assumptions made. For solving this novel problem three variants of a hybrid GRASP/VND metaheuristic algorithm were tested. The variants, particularly implemented for the problem at hand, differ in the probabilistic rule of choosing the next customer to be added in the incumbent partial solution. The GRASP/VND/U variant used an unbiased choice among the customers in the RCL, the GRASP/VND/P variant used a bias based on the proximity of the customers, and GRASP/VND/R used a bias based on the rank of the customers in the RCL. In all variants, the GRASP algorithm was combined with a VND procedure as local search, comprising of four neighborhood operators, specifically implemented to address the buyer–seller coupling of the EM-DRP-PD.

For assessing the performance of the algorithms in solving the EM-DRP-PD, 20 benchmark instances were created. The instances ranging from 50 to 200 customers, both sellers and buyers, are based on well-known VRP benchmark instances.

In order to better evaluate the behavior of the algorithms, the sensitivity of the GRASP/VND variants to the most important of their parameters', α, was tested. Lower values of the parameter were observed to provide the most quality solutions, for all variants.

The EM-DRP-PD was solved by the GRASP/VND variants using two objective approaches, one considering the total energy consumption and the other using the total distance traveled of the classical VRP. For the Energy objective, although the GRASP/VND/P was able to obtain the best energy values on average, GRASP/VND/R had the most number of BKVs found. Its superiority could not be statistically proven. The differences in both the energy and distance metrics for the

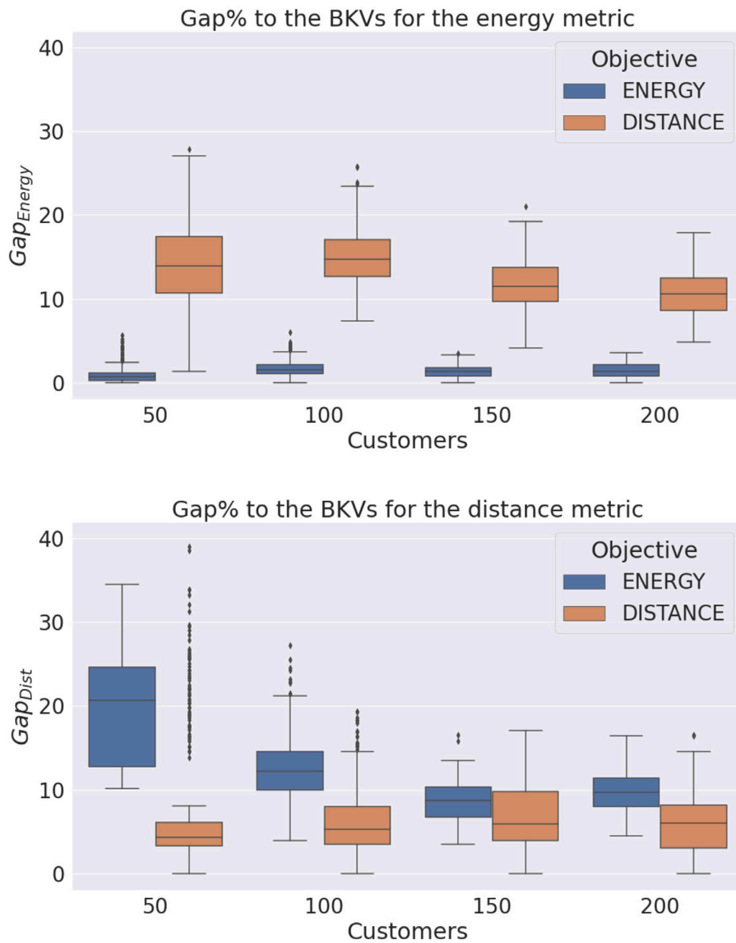

Fig. 7. The *Gap%* of each objective approach to the best solutions obtained by the energy (top) and distance (bottom) metrics, for the number of customers tested.

GRASP/VDN/R and GRASP/VND/P were marginal. For the Distance objective, similar performances were observed. The GRASP/VND/P was the best performing variant, with the lowest energy values on average, while being second to the GRASP/VND/R in the distance metric. Overall, no single variant could be statistically identified as the superior approach for solving the EM-DRP-PD.

The research compared the Energy minimizing objective approach and the Distance minimizing objective approach, in order to study the total energy and total distance properties of the solutions obtained. As expected each approach is able to provide the best results for its respective metric. The average gaps to the BKVs of the opposite objective was similar for both approaches, although the Distance objective had marginally lower values. Further analysis, based on the number of customers of the instances, indicated that the gap difference between the two approaches tends to decrease as the number of customers increases. This trend is more prevalent in the case of the total distance metric. These insights highlighted the differences in the obtained results between the two objective, for both the energy and distance metrics.

As the efforts for eco-friendly and emission-free logistics amplify, novel means of transportation such as drones, will become more common, especially for delivery operations in urban environments. The proposed EM-DRP-PD, addresses one of the possible practical applications of drones in logistics, with the goal of minimizing total energy consumption. Future work includes the expansion of the proposed EM-DRP-PD model, to include additional drone launch/retrieval bases, with additional characteristics such as battery swaps. Furthermore, stochastic elements and their impact in drone routing applications, such as weather conditions, are worth investigating.

CRediT authorship contribution statement

Nikolaos A. Kyriakakis: Conceptualization, Methodology, Software, Investigation, Formal analysis, Writing – original draft. **Stylianos Aronis:** Software, Investigation, Formal analysis, Writing – original draft. **Magdalene Marinaki:** Conceptualization, Supervision, Writing – review & editing. **Yannis Marinakis:** Conceptualization, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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