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Impact of drone delivery on sustainability and cost: Realizing the UAV potential through vehicle routing optimization

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HIGHLIGHTS

- A green vehicle routing model to exploit the sustainability of UAVs for deliveries.
- A genetic algorithm to efficiently solve the complex model.
- Optimal solutions to validate the model and the genetic algorithm.
- Our model and algorithm minimize carbon emissions as well as delivery costs.

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ABSTRACT

An unmanned aerial vehicle (UAV), commonly known as a drone, offers the advantage of speed, flexibility, and ease in delivering goods to customers. They are particularly useful for tasks that are dull, hazardous, or dirty. Whether the use of drone delivery is beneficial to the environment and cost saving is still a topic under debate. Ideally, drones yield lower energy consumption and reduce greenhouse gas emissions, thus reducing the carbon footprint and enhancing environmental sustainability. In this research, we analytically study the impact of UAVs on CO_2 emission and cost. We propose a mixed-integer (0–1 linear) green routing model for UAV to exploit the sustainability aspects of the use of UAVs for last-mile parcel deliveries. A genetic algorithm is developed to efficiently solve the complex model, and an extensive experiment is conducted to illustrate and validate the analytical model and the solution algorithm. We find that optimally routing and delivering packages with UAVs would save energy and reduce carbon emissions. The computational results strongly support the notion that using UAVs for last-mile logistics is not only cost effective, but also environmentally friendly.

1. Introduction

E-commerce has had a revolutionary impact on the retail industry. According to the U. S. Department of Commerce [1], while total retail sales increased 5.1 percent (seasonally adjusted) from the first quarter 2016 to the first quarter 2017, e-commerce sales increased 14.7 percent. Furthermore, e-commerce's share of total retail sales has increased from 3.6 percent in 2008 to 8.5 percent in the first quarter of 2017. This, in part, has resulted in physical retail stores being closed at unprecedented rates by national chains, and a number of retailers filing for bankruptcy [2].

From the sustainability perspective, the move from brick-and-mortar stores to online purchasing and delivery has a number of advantages and disadvantages. Whether there is a net improvement in the carbon footprint depends on the type of product, the consumer buying process, urban density, transportation choices, etc. [3]. In general, physical retail stores require energy for heating and lighting and typically require additional inventory for the additional sites. E-commerce, on the other hand, is more reliant on transportation to get the product to the customer and to collect product returns, usually one item at a time.

A recent development that has the potential for improving the "last-mile" delivery of products to consumers—both from an economic and from an environmental perspective—is that of unmanned aerial vehicles (UAVs) or drones [4]. Transport activities are associated with increasing levels of environmental externalities; for example, fifteen percent of global carbon dioxide (CO_2) emissions can be attributed to the transport sector [5]. In particular, the road transport subsector has

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witnessed a dramatic increase in CO_2 emissions in recent years [6]. Since "the emissions of CO_2 are directly proportional to the amount of fuel consumed by a vehicle" [7], the prospect of replacing the gasoline/diesel requirements of a delivery vehicle with a battery-powered UAV for customer deliveries can provide substantial benefits in fuel cost as well as pollutant emission.

Unfortunately, current UAV delivery has a limited range (distance and flight time) and capacity (weight and size), so they often cannot deliver all packages by itself in one trip. Most likely, the UAV will be paired with a traditional delivery vehicle [8]. The UAV is attached to the roof of a delivery vehicle where the vehicle driver loads a package and directs the UAV to its delivery point. The delivery vehicle can make other deliveries before the UAV returns to the vehicle, docks, and prepares for another delivery. Although the UAV only serves a subset of customers, this mode of package delivery still has the potential of substantially reducing the negative environmental effects.

Thus, the objective of this research is to examine the impact of incorporating UAVs—in tandem with a traditional vehicle—into a last-mile delivery vehicle-routing model to explicitly consider the sustainability aspects of employing UAVs for last-mile parcel deliveries. We propose a mixed-integer (0–1 linear) green routing model for UAVs to exploit the sustainability aspects of the use of UAVs for last-mile parcel deliveries. A genetic algorithm is developed to efficiently solve the complex model and an extensive experiment is conducted to illustrate and validate the analytical model and the solution algorithm. We find that optimally routing and delivering packages with UAVs would save energy and reduce carbon emissions. The computational results strongly support the notion that using UAVs for last-mile logistics is not only cost effective, but also environmentally friendly.

The paper is organized as follows. In the next section, we review the literature on the "green" vehicle-routing problem as well as the use of UAVs in routing. In Section 3, an optimization model is presented to incorporate the green/fuel-economizing aspects of the routing system. A genetic algorithm is employed in Section 4 to efficiently solve the complex model. Extensive numerical analyses are conducted in Section 5, and we close the paper with a summary and suggestions for future research in Section 6.

2. Literature review

The vehicle-routing literature has a rich history, beginning with Dantzig and Ramser's [9] "truck dispatching problem" and the well-known Clarke and Wright [10] "savings" algorithm. Our research differs from the conventional literature and is relevant to two streams of new developments: (1) green vehicle routing and (2) routing with unmanned aerial vehicles. They are reviewed next.

2.1. Green vehicle routing problem

The green vehicle-routing problem (GVRP) is concerned with energy consumption. As fuel consumption constitutes the main part of the petroleum-based transport cost and since CO_2 emissions are directly affected by fuel usage, we examine the fuel-consumption, vehicle-routing problem in this subsection. Kara et al. [11] first considered the energy-minimizing vehicle-routing problem in which the load of the vehicle was incorporated into the objective. They noted that work—hence, energy consumption—is a function of weight times distance, so they utilized the total distance weighted by the number of units in the vehicle as the objective function. A mixed-integer program was formulated and used to solve small problem instances.

Kuo and Wang [12] presented a vehicle-routing problem in which the fuel consumption is a function of the payload weight and speed of the vehicle, with the speed fixed at one of three values. A tabu-search algorithm was developed to solve the model, with four approaches for identifying an initial solution. A brief experiment was conducted comparing the proposed approach to a traditional vehicle-routing algorithm that minimized the distance travelled and found that despite a four percent increase in the distance travelled, fuel savings of over eight percent can be realized.

Xiao et al. [13] also presented a model in which the fuel-consumption rate is based on the weight and distance traveled. A simulated-annealing algorithm was developed with various exchange rules. Their experimentation suggested that fuel savings of four to five percent can be achieved with little more than a two percent increase in distance travelled. MirHassani and Mohammadyari [14] developed a gravitational-search algorithm for this problem and found an average of nearly five percent decrease in fuel consumption with just under a two percent increase in distance travelled.

Further, Ćirović et al. [15] used a neuro-fuzzy logic, simulated annealing, and modified Clark–Wright algorithm to design the network to route light-delivery vehicles in urban areas. Zhang et al. [16] separated the fuel cost and the carbon emission cost, although both are formulated as linearly dependent on the fuel consumption. As with Kuo and Wang [12], the fuel consumption was formulated as a function of the payload weight and speed of the vehicle, with speed fixed at one of three values. A tabu-search algorithm based on route splitting was presented to solve the problem. Tiwari and Chang [17] use a block recombination approach to minimize distance travelled and carbon dioxide emission, while Jabir et al. [18] propose multi-objective model to address the conflict between emission and cost reduction.

More recently, Xiao and Konak [19] examine the heterogeneous GVRP with time-varying traffic congestion. Çimen and Soysal [20] employ dynamic programming to examine time-dependent GVRP with stochastic vehicle speeds. Zhou et al. [21] employ a Lagrangian relaxation-based approach to minimize greenhouse gas emissions. Leggieri and Haouari [22] use a mixed-integer linear program (MILP) and a reduction procedure to address GVRP and achieve compactness and flexibility. Turkensteen [23] find speed fluctuations may greatly increase fuel consumption by up to 80 percent, and maintain that assuming vehicle speed is fixed could lead to inaccurate outcomes for the GVRP.

Jabir et al. [24] develop a hybrid ant colony-variable neighbourhood-search algorithm to optimize the multi-depot GVRP. Li et al. [25] study the heterogeneous fixed-fleet vehicle-routing problem based on fuel and carbon emissions. Poonthalir and Nadarajan [26] use goal programming to minimize route cost and fuel consumption with varying vehicle speed.

Finally, there is a class of problem called the pollution-routing problem in which fuel consumption is modeled with vehicle speed as a decision variable. Bektaş and Laporte [27] noted that speeds above 40 km per hour (km/h) result in decreased fuel efficiency, so it becomes a relevant decision for heavy-duty vehicles which apply to freight transportation. Since then, a number of extensions to this model have been published, including time-dependent vehicle speeds [28,29], a heterogeneous fleet [30], multiple objectives [31,32], demand and travel-time uncertainty [33], among others.

Other green vehicle-routing research includes: alternative-fuel powered vehicles [34] and reverse logistics [35]. See Lin et al. [36] for a recent survey.

2.2. Routing with unmanned aerial vehicles

In this section, we examine the use of UAVs for package delivery, since the model we proposed integrates UAVs delivery with petroleum-based delivery vehicles. Other applications of UAV routing include military operations [37,38] and information gathering [39,40].

Sundar and Rathinam [41] investigated the situation in which a UAV serves several customers and can refuel/recharge at depots located throughout the delivery region. Mathew et al. [42] analyzed the situation in which the UAV is attached to a vehicle, and the vehicle moves to pre-specified locations from which the UAV delivers the items to all customers (i.e., the vehicle makes no deliveries). Ferrandez et al. [43] extended this to allow the vehicle to move to a customer and deliver one package while UAVs are launched using a hub configuration to serve nearby customers and return to the vehicle. Dorling et al. [44] presented a multi-trip UAV-routing problem in which the flight time of the UAVs is limited by the weight of the payload and battery. Poikonen et al. [45] study multiple homogeneous trucks carrying k drones. Each drone may dispatch from the top of the truck and returns to the top of its truck at the same location.

Little research has been conducted on the situation considered in this paper in which the delivery vehicle can make deliveries while the UAV is in flight, such that the UAV returns to the vehicle at a different point than where it departed the vehicle. Murray and Chu [46] were the first to address this scenario. But they only focused on one single vehicle—hence, a traveling-salesman problem—that is equipped with a UAV used to simultaneously visit customers not served by the vehicle. Agatz et al. [47] and Bouman et al. [48] analyzed a similar traveling-salesman problem, and provided an integer-program and a dynamic program to optimally solve small instances of the problem, and offered heuristics to solve larger problems, as well as a lower bound and an approximation result. Heuristics for this problem have also been presented by Ha et al. [49] and Ponza [50]. Wang et al. [51] extended this to the multi-vehicle situation (the vehicle-routing problem with UAVs), in which they formulated the problem with a min-max objective, determined the maximum savings that could be achieved using UAV-assisted delivery, and derived worst-case results. Coelho et al. [52] use MILP to tackle a time-dependent UAV heterogeneous fleet-routing problem. Figliozzi [53] find UAVs are more efficient in terms of energy consumption/emissions per unit distance in sparsely populated areas with low delivery density/payload. Coutinho et al. [54] provide a taxonomic review of UAV trajectory-optimization issues.

In this research, we propose a mixed-integer (0–1 linear) multi-vehicle green routing model for UAVs to incorporate the sustainability aspects of the use of UAVs for last-mile parcel deliveries as well as cost savings. A genetic algorithm is developed to efficiently solve the complex model and an extensive experiment is conducted to illustrate and validate the analytical model and the solution algorithm. We find that optimally routing and delivering packages with UAVs would save energy and reduce carbon emissions. The computational results strongly support the notion that using UAVs for last-mile logistics is not only cost effective, but also environmentally friendly.

3. Model formulation

There are various approaches to formulate the capacitated vehicle-routing problem (CVRP), including two- or three-index vehicle-flow formulations, set-partitioning formulations, and commodity-flow formulations (see, for example, [55]. Since we will be incorporating the green/fuel-economizing aspects of the routing system requiring the value of the weight in the vehicles throughout the route, we focus on the commodity-flow formulation; in particular, we will extend the model proposed by Gavish and Graves [56,57]. While Gouveia [58] and Baldacci et al. [59] have offered alternative commodity-flow formulations and exact methods for solving the CVRP, we opt for Gavish and Graves due to its clarity in presentation and ability to facilitate heuristic development. Note that most algorithms used in practice are heuristics [55], as real-life VRP often exceeds the size that can be solved optimally and solutions must often be determined quickly.

The basic capacitated vehicle-routing problem is as follows (see Appendix A for definitions of all notation). An undirected graph $G = (V, E)$ is given, where E is the set of edges with nonnegative routing costs, with $\{i, j\} \in E$ representing the edge from node i to node j. Also, $V = \{0, 1, \cdots, n\}$ is the set of all nodes, with n customers and the depot represented as node 0, and $U = V\backslash\{0\}$ is the set of nodes representing the customers (i.e., not the depot). The distance between each node is d_{ij}. Each customer has demand for q_i units; in keeping with the fuel-economizing formulation, we measure the demand in weight units.

In this research, each vehicle is outfitted with a single UAV and has a payload (weight) capacity of Q^{VEH}. There is a fixed cost associated with each vehicle/UAV tandem, c^{FIX}, as well as a variable routing cost that is a function of distance travelled and gross weight (see next paragraph). The routing cost for the UAV, c^{UAV}, is expected to be considerably less than that of the vehicle. However, there is restriction on the UAV payload (capacity), Q^{UAV}, as well as the distance the UAV can travel, D^{UAV}, and the length of time the UAV can be airborne, T^{UAV}. Note, the time restriction may include the time UAV needs to wait for the vehicle before landing. The distance between two points may differ for the vehicle versus the UAV; in fact, another potential advantage of UAVs is that they may be able to take a much more efficient route than the vehicle. For example, the vehicle may need to follow the Manhattan metric while the UAV may be able to use the Euclidean distance—so we distinguish between the two, d_{ij}^{VEH} and d_{ij}^{UAV}. It is assumed that the UAV will serve only one customer before returning to the vehicle, but can serve subsequent customers on the same route after returning to the vehicle for reloading and battery replacement.

Let y_{ij} be 1 if edge $\{i, j\} \in E$ (i.e. the vehicle travels from node i to node j); equal 0 otherwise. Let x_{ij} be the weight of the payload in the vehicle for edge $\{i, j\} \in E$. Finally, $z_{ijk} = 1$ if the UAV departs the vehicle at node i, serves customer j demand of q_j units, and returns to the vehicle at node k; equal to 0 otherwise.

An increase in the gross weight of a vehicle may substantially affect its fuel efficiency, as noted by Franzese and Davidson [60]. Since fuel is a significant portion of the variable transportation cost, it is a relevant factor to include in a vehicle-routing model. Blanco and Sheffi [61] note that the carbon footprint of transportation emissions can be estimated as a function of shipment weight (or volume) and distance traveled. The total weight of the vehicle, the UAV, and the packages is affected by routing decisions, particularly since the UAV is sometimes on, sometimes off the vehicle.[1] As the total weight in the vehicle decreases throughout the route and when the UAV is off the vehicle making a delivery, the fuel economy increases, the routing cost decreases, and the CO_2 emissions decrease. Many other factors also affect fuel economy, e.g. aerodynamic drag, tire inflation, road grade, vehicle speed, etc.

The gross weight of the vehicle, w_{ij}, include the empty (tare) weight of the vehicle, b^{VEH}, plus the weight of the payload, x_{ij}, plus the weight of the UAV, b^{UAV}, if and only if the UAV is on the vehicle. This weight can be expressed as a nonlinear function:

$$w_{ij} = b^{VEH}y_{ij} + x_{ij} + b^{UAV}y_{ij}\left(1 - \sum\nolimits_{h\in U} z_{ihj}\right) \tag{1a}$$

The first term represents a vehicle's tare (unladen) weight when traveling from node i to node j. The second term is the vehicle's payload (Eq. (8) ensures it is zero if edge i, j is not selected), and the third term includes the weight of the UAV unless it departs the vehicle at node i or returns to the vehicle at node j. An alternative, linear, formulation is:

[1] It may be argued that vehicle speed should also be a decision variable, as with the pollution-routing problem; we chose not to include this as such, for the following reason. The speed of the vehicle depends on traffic congestion, whether the deliveries are urban/suburban/rural, how many stoplights are encountered, etc.; however, one of the responses by a FedEx worker on Quora.com [62] was that it averaged about 20 to 25 miles per hour. Bektaş and Laporte (2011, Fig. 1) noted that fuel consumption decreases as the speed of the vehicle increases up to 40 to 50 km/h (~25 to 30 mph). Thus, for package delivery, considering both fuel economy and the desire to serve customers as quickly as possible, it is expected that the driver will maintain a speed as great as possible within the speed limit.

$$w_{ij} \geq b^{VEH} y_{ij} + x_{ij} + b^{UAV}\left(y_{ij} - \sum_{h \in U} z_{ihj}\right) \tag{1b}$$

Since Eq. (1b) may result in a negative value for edges that are not in the solution, it is expressed as "≥" in order for the nonnegativity constraint—Eq. (18) below—to ensure those values will be zero. In either case, to calculate the routing cost of the vehicle for any edge, we take the unit cost, c^{VEH}, times the distance travelled, d_{ij}^{VEH}, times the gross weight, w_{ij} (note that c^{VEH} is measured in dollars per pound-mile and can be determined using regression analysis or estimated as discussed by [14].

The Green Vehicle Routing Problem with Unmanned Aerial Vehicles (GVRP–UAV) can then be approached in two ways. First, we examine the benefits of using UAVs on carbon emissions. To calculate the CO_2 emissions, we follow the methods used in Goodchild and Toy [4]. Eq. (2) below computes the total amount of CO_2 emissions of vehicles:

$$\sum_{i \in V} \sum_{j \in V} WAER \times d_{ij}^{VEH} \tag{2}$$

where $WAER$ is the weighted average emission rate of the vehicle. To calculate the associated total amount of CO_2 emitted by UAVs, we use the following formula:

$$\sum_{i \in V} \sum_{j \in U} \sum_{k \in V} PGFER \times AER^{UAV} \times (d_{ij}^{UAV} + d_{jk}^{UAV}) z_{ijk} \tag{3}$$

where $PGFER$ is the amount of CO_2 emitted at power generation facilities per watt-hour (Wh) used by UAVs, and AER^{UAV} is the average energy requirement of UAVs in Wh per mile. Thus, to minimize the total CO_2 emissions, including the emissions of the vehicles and the emissions of the UAVs, we have:

$$\text{Minimize} \quad \sum_{i \in V} \sum_{j \in V} WAER \times d_{ij}^{VEH} + \sum_{i \in V} \sum_{j \in U} \sum_{k \in V} PGFER \times AER^{UAV} \times (d_{ij}^{UAV} + d_{jk}^{UAV}) z_{ijk} \tag{4}$$

An alternative formulation is that of the traditional vehicle-routing objective of minimizing the total cost, including the fixed cost of the vehicles plus the variable routing cost of the vehicles as well as the variable routing cost of the UAVs:

$$\text{Minimize} \quad c^{FIX} \sum_{j \in U} y_{0j} + c^{VEH} \sum_{i \in V} \sum_{j \in V} d_{ij}^{VEH} w_{ij} + c^{UAV} \sum_{i \in V} \sum_{j \in U} \sum_{k \in V} (d_{ij}^{UAV} + d_{jk}^{UAV}) z_{ijk} \tag{5}$$

Finally, the set of constraints for both objective functions can be expressed as follows:

Subject to:

$$\sum_{j \in V} y_{ij} + \sum_{h \in V} \sum_{k \in V} z_{hik} = 1 \qquad \forall\, i \in U \tag{6}$$

$$\sum_{i \in V} y_{ij} + \sum_{h \in V} \sum_{k \in V} z_{hik} = 1 \qquad \forall\, j \in U \tag{7}$$

$$\sum_{j \in U} y_{0j} = \sum_{i \in U} y_{i0} \tag{8}$$

$$\sum_{\substack{j \in V \\ j \neq i}} x_{ji} - \sum_{\substack{j \in V \\ j \neq i}} x_{ij} + \sum_{h \in V} \sum_{j \in V} q_i z_{hij} - \sum_{j \in U} \sum_{k \in V} q_j z_{ijk} = q_i \qquad \forall\, i \in U \tag{9}$$

$$y_{ik} \geq \sum_{j \in V} z_{ijk} \qquad \forall\, i, k \in V \tag{10}$$

$$x_{ij} \leq Q^{VEH} y_{ij} \qquad \forall\, \{i, j\} \in E \tag{11}$$

$$q_j \sum_{i \in V} \sum_{k \in V} z_{ijk} \leq Q^{UAV} \qquad \forall\, j \in U \tag{12}$$

$$(d_{ij}^{UAV} + d_{jk}^{UAV}) z_{ijk} \leq D^{UAV} \qquad \forall\, i, j, k \in V \tag{13}$$

$$t_{ijk} \geq (d_{ij}^{UAV}/s_{ij}^{UAV} + d_{jk}^{UAV}/s_{jk}^{UAV}) z_{ijk} \qquad \forall\, i, k \in V, j \in U \tag{14a}$$

$$t_{ijk} \geq d_{ik}^{VEH}/s_{ik}^{VEH} y_{ik} \qquad \forall\, i, k \in V, j \in U \tag{14b}$$

$$t_{ijk} \leq T^{UAV} + M(1 - z_{ijk}) \qquad \forall\, i, k \in V, j \in U \tag{14c}$$

$$w_{ij} \geq b^{VEH} y_{ij} + x_{ij} + b^{UAV}\left(y_{ij} - \sum_{h \in U} z_{ihj}\right) \qquad \forall\, \{i, j\} \in E \tag{15}$$

$$x_{ij} \geq q_j y_{ij} \qquad \forall\, \{i, j\} \in E \tag{16}$$

$$t_{ijk} \geq 0 \qquad \forall\, i, k \in V, j \in U \tag{17}$$

$$w_{ij} \geq 0 \qquad \forall\, \{i, j\} \in E \tag{18}$$

$$y_{ij} = \{0, 1\}, y_{00} = 0 \qquad \forall\, \{i, j\} \in E \tag{19}$$

$$z_{ijk} \in \{0, 1\} \qquad \forall\, i, j, k \in V \tag{20}$$

Constraints (6) and (7) ensure that every customer is served, either by a vehicle or by a UAV. The same number of vehicles exiting and returning to the depot is ensured by Constraint (8), and Constraint (9) is a flow-balance equation that ensures the demand of each customer is satisfied. Constraint (10) synchronizes the vehicle and the UAV, such that they meet back up at the subsequent vehicle stop (y_{ik}). We will relax Constraint (10) in Section 4 to allow multiple vehicle stops before they rejoin. Constraints (11) and (12) are restrictions on the vehicle and UAV payloads, respectively. The UAV range (distance) limitation is ensured by Constraint (13), while the UAV range (time) limitation is ensured by Constraint (14c), such that the time the UAV is airborne, t_{ijk}, is the larger of the travel time of the UAV (14a) and of the vehicle (14b), where M is a very large value and s_{ij}^{VEH} and s_{ik}^{UAV} are the average speeds of the vehicle and UAV, respectively. Constraint (15) determines the vehicle weight as described in the previous paragraph. Note that a simple lower bound can be included on the payload of the vehicle at any time (Constraint 16). Finally, we can avoid the use of UAVs for a particular route (perhaps near an airport) or for a particular customer (one who cannot receive such a delivery) by simply setting $z_{ijk} = z_{hij} = 0$ for route $\{i, j\}$ or $z_{ijk} = 0$ for customer j.

The solutions to several instances using a mixed-integer program of the minimum cost formulation are presented in Appendix B. As shown in the Appendix, only small instances (up to 40 customers) can be solved optimally. While these results are useful in validating the model formulation, it is apparent that a more-efficient solution methodology is needed. Thus, we turn our attention to the development of a Genetic Algorithm to solve large-scale, realistic-sized instances.

4. Solution methodology

In the following, we briefly describe the implementation of our genetic algorithm.

4.1. Design

In our design of the genetic algorithm, we adapt the following service strategy that all customers' orders must be satisfied in one day. As there is a work-hour limit (i.e., the service time of every vehicle may be no longer than 8 h), we may need more than one vehicle to deliver customers' orders. Therefore, we first determine how many vehicles are needed. Then, we divide the service area according to the number of vehicles needed. The criterion of this division is to make the number of customers served by each vehicle and the distances traveled by each vehicle to be as near to each other as possible. As a result, the service times of each vehicle will be as equal to each other as possible, to avoid the solution of one vehicle's service time being much less than 8 h, while another vehicle's service time is much more than 8 h. For example, if there are twenty customers' orders that should be satisfied, these customers are encoded as {1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20}, and the depot is encoded as {0}. If we just need one vehicle to deliver customers' orders, this vehicle serves the whole service area. If two vehicles are needed, we draw a line crossing the depot to divide the service area into two parts. The coverage of each group and the number of customers in each part should be as near to each other as possible. Each vehicle serves one part of the whole service area.

In our algorithm, we first sequence the customers. The vehicle and the UAV serve customers according to the sequence. We group customers randomly by the following method. First, a random number, $m \in [1, M]$, is generated, where M is the number of total customers served by the vehicle, with the first m customers placed into the first group. This process is repeated until all customers are grouped. If only one customer is in a customer group, the customer is served by a vehicle; otherwise, the UAV serves one customer randomly chosen from the group, and the vehicle serves the other customer(s). Based on the above strategy, we develop a GA to solve the proposed minimization problem (Model).

4.1.1. Encoding

The natural number coding method is used to encode customers and group information. For example, suppose twenty customers are encoded as 1–20, the service sequence codes are {3, 8, 6, 12, 19, 10, 1, 4, 17, 11, 2, 20, 13, 5, 7, 18, 9, 14, 16, 15}, and the group codes are {2, 1, 7, 9, 15}. Therefore, the twenty customers are divided into five groups, and the encoding result is {{3, 8}, {6}, {12, 19, 10, 1, 4, 17, 11}, {2, 20, 13, 5, 7, 18, 9, 14, 16}, {15}}.

4.1.2. Generating the initial population

In our algorithm, the service sequence of the initial individuals is optimized by dividing the service area into several subareas. For example, when two vehicles are needed, we divide the whole service area into two service group by a horizontal line crossing the depot. Taking the upper service area as an example, we divide it into eight subareas, and number the eight subareas as in Fig. 1. Then we can arrange the service sequence of the initial individuals as follows.

The customers in the first subarea are served from left to right; the customers in the second subarea are served from right to left; customers in the remaining subareas are served following the arrows in Fig. 1. The customers in the third subarea are served from left to right; the vehicle with UAV travels from right to left to serve customers in the fourth and fifth subareas. Next, the customers in the sixth subarea are served from left to right, the customers in the seventh subarea are served from right to left, and the customers in the eighth subarea are served from left to right. In the above example, customers 3, 12, 2, and 15 are served by UAV, and the last customer in each corresponding group—that is, customers 8, 11, and 16—will be the points where the UAV meets the vehicle. It should be noted that although customer 15 is in a group alone, it is served by the UAV right before the depot, as the UAV departs

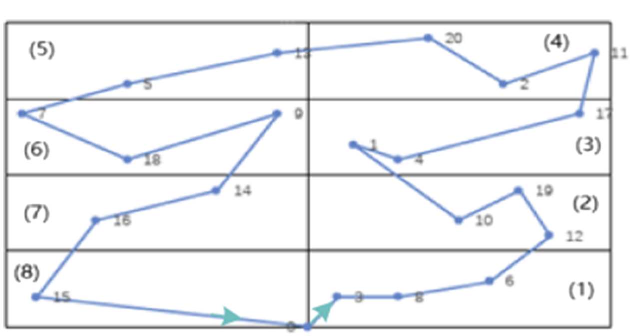

Fig. 1. An example of partitioning service area and initiating service sequence.

from customer 16 to serve customer 15, and flies back to the depot, while the vehicle directly travels back to the depot from customer 16.

4.1.3. The algorithm

Fitness Function. The fitness function can be defined as $Fit(X) = 1/C(X)$, where X is the combination of the service sequence and the grouping, and $C(X)$ is the objective function in the strategy of X.

Selection. In the selection of the optimal individual for the retention, the roulette method is applied, in which the greater the degree of individual fitness, the greater the probability of being chosen as the next generation of the parent. In the selection operation, the elite individual retention strategy is used to directly copy the individuals with the highest adaptation function into the cross-paired parent group. When all the parent individuals perform the crossover operation, the elite individual retention strategy is used again, replacing the individuals with the worst adaptive value of the group after the cross with the elite ones before crossing. Therefore, the individuals with low quality are eliminated, and the elite individuals are kept.

Crossover and Mutation. In our algorithm, double-point crossover is used, and the method of real-valued mutation is used.

Termination Conditions. When the iteration satisfies the following conditions, the result is considered as converged and the algorithm is terminated:

1) There is no significant change in the fitness value after successive iterations.
2) The population stops evolution; that is, the number of iterations reaches the set value.

4.2. Steps of algorithm

The specific steps of GA in this paper are summarized as follows:

Step 1 Determine the encoding mechanism; generate the initial population; set the crossover mutation probability and the maximum number of iterations.
Step 2 Evaluate the fitness of the current population, and find the chromosome minimizing the objective function value and the corresponding function value.
Step 3 Judge whether the termination conditions are satisfied. Output the current best chromosome and the corresponding solution if satisfied; otherwise, perform the selection operation on the current population.
Step 4 Perform cross and mutation operations on individuals of new populations.
Step 5 Evaluate the fitness of the obtained group, and go to Step 3.

5. Experimentation

In this section, we conduct the experimental study through Matlab R2015b to evaluate the proposed GVRP-GA discussed above. The configurations of the computer used (Lenovo X1 Carbon) for the experiment are: 5th Generation Intel Core i5-5200U processor (2.2 GHz base, 2.7 GHz Max Turbo, 3 MB Cache), 128 GB SSD, and 4 GB RAM. We first provide the rationales of choosing the parameter values in the experiments, and then present the results on the GVRP-GA performance.

5.1. Problem data

The demands of the customers, q_i, range from one to ten pounds. We assume 80 percent of the customers' demand are no more than 5 lb, as 86 percent of Amazon's orders are less than 5 lb [63]. Each customer's location, the x- and y-coordinates, is randomly generated uniformly between −10 and +10. The distances between the customers, d_{ij}^{VEH} and d_{ij}^{UAV}, were then determined by using Manhattan metric for the vehicles, Euclidean for the UAVs. The depot is placed at the center of the region, at the point (0, 0).

Paul Misener, Amazon's VP for global public policy [64] stated: "Prime Air is a future delivery service that will get packages to customers within 30 min of them ordering it online at Amazon.com…. The range has to be over 10 miles. These things will weigh about 55 lb each; they'll be able to deliver parcels that weigh up to 5 lb. It turns out that the vast majority of the things we sell at Amazon weigh less than five pounds." Thus, we set the weight of the empty UAV, b^{UAV}, at 55 lb; the payload capacity of UAV, Q^{UAV}, at 5 lb; and the range (maximum distance travelled) of the UAV, D^{UAV}, at 10 miles. Raptopoulos [65], the CEO of Matternet, noted that their UAVs "are able to transport two kilograms over 10 km in just about 15 min". Thus, we set the average speed of the UAV, s^{UAV} at 25 miles per hour.

As mentioned in Section 3 footnote, the average speed of a delivery vehicle is about 20 to 25 miles per hour, so s^{VEH} is set at 25 miles per hour as well. Walk-in delivery vans, or stepvans, were used to estimate the weight of the empty vehicle (vehicle curb weight plus the weight of shelving in the vehicle, plus the weight of the driver plus the weight of the UAV apparatus, but not the UAV itself), b^{VEH}, at 6,100 lb and for the payload capacity of the vehicle, Q^{VEH}, at 6,000 lb.

Industrial Engineer magazine [8] noted "the typical medium-duty delivery truck gets only about 5.5 mpg and costs about $1 a mile to operate…the HorseFly's fuel costs are only 2 cents a mile." As we measure the variable cost of the UAV, c^{UAV}, and the vehicle, c^{VEH}, in dollars per pound-mile, the variable routing cost of the UAV, c^{UAV}, was set at $0.00036364 per pound-mile, and the variable routing cost of the vehicle, c^{VEH}, was set at $0.00016 per pound-mile. Finally, the fixed cost of the vehicle and UAV, c^{FIX}, set at $500 per vehicle, which is large enough such that the number of vehicles is minimized first, then the routing costs are taken into consideration.

5.2. Illustrative example

We first present the results of the genetic algorithm for a 200-customer instance. The location and weight of the 200 customers are shown in Appendix C. Two vehicles are required to serve the customers within an eight-hour day; the service times of each vehicle are 5.58 and 5.61 h. The routing of the vehicles and UAVs is shown in Fig. 2. The results are as follows:

Carbon emissions. The first vehicle has carbon emissions of 175.81 Kg and its UAV has carbon emissions of 0.13 Kg, for a total of 175.94 Kg. The second vehicle has carbon emissions of 176.76 Kg and its UAV has carbon emissions of 0.13 Kg, for a total of 176.89 Kg. Thus, the total carbon emissions equals 352.83 Kg. If UAVs were not utilized, two vehicles would still be sufficient; however, the carbon emissions would be 420.31 Kg, so a reduction of 67.48 Kg (16.1 percent) in carbon emissions would be realized.

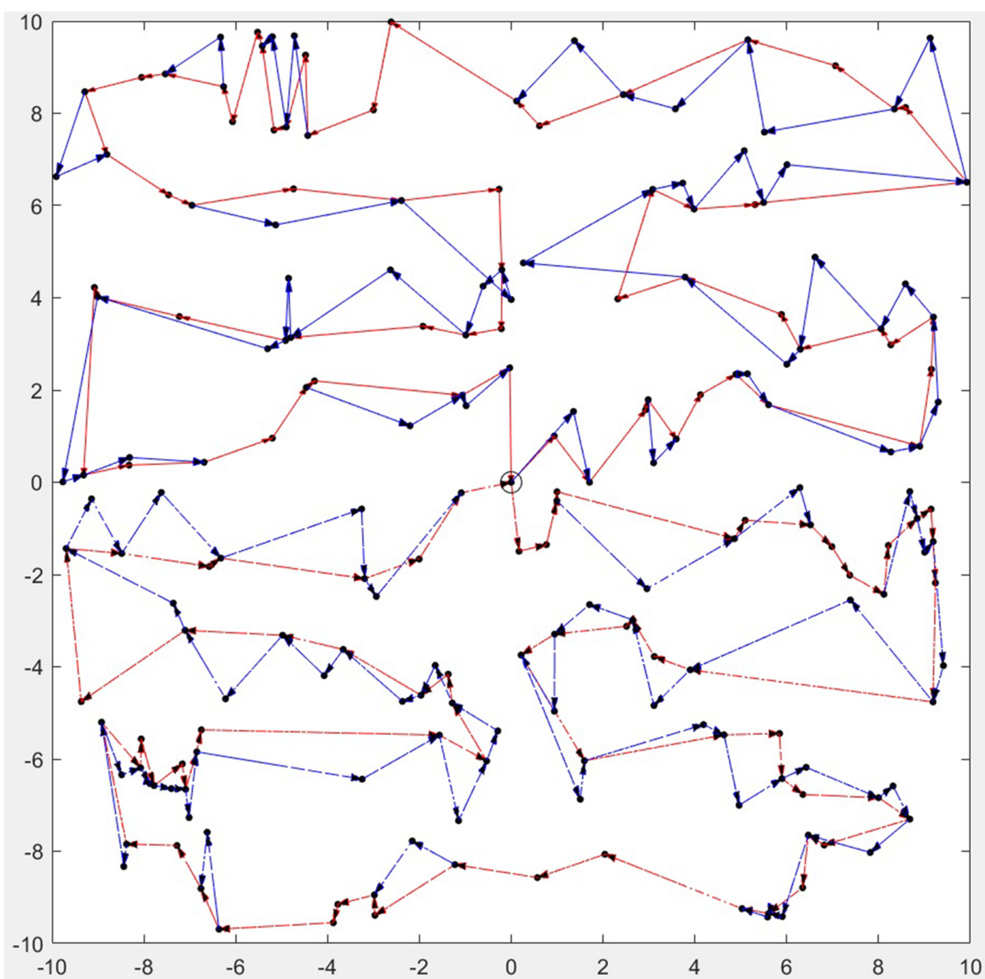

Fig. 2. Routing of vehicles and UAVs.

Cost: The first vehicle has variable costs of $131.86 and its UAV has variable costs of $2.10, for a total of $133.96. The second vehicle has variable costs of $127.39 and its UAV has variable costs of $2.08, for a total of $129.47. Thus, the total variable cost is $263.43, and the total cost with two vehicles (including the $500 fixed cost of each) is $1,263.43. If UAVs were not utilized, the total variable cost would be $354.26, so a savings of $90.83 (25.6 percent) in variable costs would be realized.

5.3. Results on the performance of the genetic algorithm

We now extend our analysis to instances of 200, 300, 400, and 500 customers, comparing the situations when UAVs are used with those in which they are not used. We first evaluate the effect of UAVs on carbon emissions, then consider the effect on fixed and variable routing costs.

5.3.1. Effect of UAVs on carbon emissions

We first examine the benefits of the use of UAVs on the carbon emissions. In our case, we set the $WAER$ of all vehicles to 1.2603 Kg per mile, the $PGFER$ to 3.773×10^{-4} Kg per Wh, and the AER^{UAV} to 3.3333 Wh per mile (see Goodchild and Toy [4] for details). Table 1 shows the results of carbon emissions without UAVs, Table 2 shows the results of carbon emissions with UAVs, and Table 3 compares the CO_2 emissions with the use of UAVs and without UAVs.

As expected, as the number of customers increases, the number of vehicles required and the carbon emissions also increase. However, it is apparent from these tables that one of the benefits of the use of UAVs for last-mile delivery is a potential reduction in the number of vehicles required. The 300-, 400-, and 500-customer instances all require one fewer vehicle when UAVs are used. Also illustrated in the tables is the reduction of CO_2 emissions. An emission reduction of over twenty percent, on average, can be realized with the use of UAVs. Even without a reduction in the number of vehicles—as in the 200-customer case, discussed in the previous subsection—the use of UAVs can bring about a sixteen percent reduction in carbon emissions.

Also presented in Tables 1 and 2 are the computational resources needed to run the genetic algorithm and get the results. Obviously, the added complexity of the model by incorporating the use of UAVs results in greater CPU times; however, the run times are still within a reasonable range for practical use.

5.3.2. Effect of UAVs on routing costs

We now turn our attention to the traditional vehicle-routing objective of cost minimization. Table 4 shows the variable routing costs without UAVs, Table 5 shows the variable routing costs with UAVs, and Table 6 compares the costs with and without the use of UAVs.

As mentioned in the previous subsection, a benefit of the use of UAVs is a potential reduction in the number of vehicles required. Obviously, this will have a considerable impact on the fixed costs of routing. Perhaps more importantly, though, is the impact on the variable costs. As illustrated in Table 6, variable costs are reduced by an average of over thirty percent through the use of UAVs. This alone would likely justify the use of UAVs for last-mile delivery.

Comparing Tables 3 and 6, we can find that the computational results strongly support the notion that using UAVs is not only conducive to cost reduction, but—as the variable cost is the expenditure on fuel—also substantially reduces the carbon footprint. Thus, there is a high correlation between reduction of costs and reduction of CO_2 emissions that can be easily seen through the illustration of Fig. 3, which presents the 400-customer case. To generate the graph, we set the number of iterations at 1,500. During the run, we output the best cost and the corresponding emission of CO_2 every 30 iterations. As a result, we obtained 50 sets of costs and CO_2 emissions.

Table 1
Results of carbon emissions without UAVs.

Number of customers	Number of vehicles	Service time of each vehicle (hours)				Emissions of each vehicle (Kg)				Total emissions (Kg)	CPU times (sec.)
200	2	6.69	6.65			210.7852	209.5249			420.3101	125.5
300	3	7.04	6.63	5.99		221.8128	208.8947	188.7299		619.4375	138.3
400	4	5.41	5.35	5.46	4.85	190.3933	188.2817	192.1529	170.6853	741.5133	158.7
500	4	5.92	6.51	6.35	5.92	217.1016	238.7384	232.8708	217.1016	905.8123	219.0

Table 2
Results of carbon emissions with UAVs.

Number of customers	Number of vehicles	Service time of each vehicle (hours)			Emissions of each vehicle (Kg)			Emissions of each UAV (Kg)			Total emissions (Kg)	CPU times (sec.)
200	2	5.58	5.61		175.8119	176.7571		0.1321	0.1308		352.8318	1028.9
300	2	6.83	7.19		215.1962	226.5389		0.1761	0.1635		442.0747	1228.0
400	3	5.66	7.86	6.51	162.6644	225.8907	187.0927	0.1409	0.2037	0.1654	576.1578	1163.6
500	3	7.90	7.38	7.64	247.9267	231.6075	239.7671	0.1937	0.1918	0.2000	719.8868	1236.9

Table 3
Comparison of the results of carbon emissions without UAVs and with UAVs.

Number of customers	Number of vehicles		Number of vehicle reduction if UAVs are Used	CO_2 emissions (Kg)				Emission reduction if UAVs are used	
	Without UAVs	With UAVs		Without UAVs	With UAVs			Quantity (Kg)	Percentage (%)
					From vehicles	From UAVs	Total emissions		
200	2	2	0	420.3101	352.569	0.2629	352.8319	67.4782	16.05
300	3	2	1	619.4375	441.7351	0.3396	442.0747	177.3628	28.63
400	4	3	1	741.5133	575.6478	0.5100	576.1578	165.3555	22.30
500	4	3	1	905.8123	719.3013	0.5855	719.8868	185.9255	20.53

Table 4
Results of variable costs without UAVs.

Number of customers	Number of vehicles	Service time of each vehicle (hours)				Cost of each vehicle (dollars)				Total variable cost (dollars)	CPU times (sec.)
200	2	6.69	6.65			177.95	176.31			354.26	125.5
300	3	7.04	6.63	5.99		191.59	181.08	164.60		537.29	138.3
400	4	5.41	5.35	5.46	4.85	155.03	152.39	155.90	138.40	601.74	158.7
500	4	5.92	6.51	6.35	5.92	175.87	175.52	176.30	179.50	707.26	219.0

Table 5
Results of variable costs with UAVs.

Number of customers	Number of vehicles	Service time of each vehicle (hours)			Cost of each vehicle (dollars)			Cost of each UAV (dollars)			Total variable costs (dollars)	CPU times (sec.)
200	2	5.58	5.61		131.86	127.39		2.10	2.08		263.45	1028.9
300	2	6.83	7.19		144.92	152.10		2.80	2.60		302.40	1228.0
400	3	5.66	7.86	6.51	120.53	138.90	139.84	2.24	3.24	2.63	407.42	1163.6
500	3	7.90	7.38	7.64	169.48	159.00	157.34	3.08	3.05	3.18	495.17	1236.9

Table 6
Comparison of the results of costs without UAVs and with UAVs.

Number of customers	Number of vehicles		Number of vehicle reduction if UAVs are used	Variable costs (dollars)		Percentage of variable cost reduction if UAVs are used (%)	Total costs (dollars)		Percentage of total cost reduction if UAVs are used (%)
	Without UAVs	With UAVs		Without UAVs	With UAVs		Without UAVs	With UAVs	
200	2	2	0	354.26	263.45	25.63	1354.26	1263.45	6.71
300	3	2	1	537.29	302.40	43.72	2037.29	1302.40	36.07
400	4	3	1	601.74	407.42	32.29	2601.74	1907.42	26.69
500	4	3	1	707.26	495.17	29.99	2707.26	1995.17	26.30

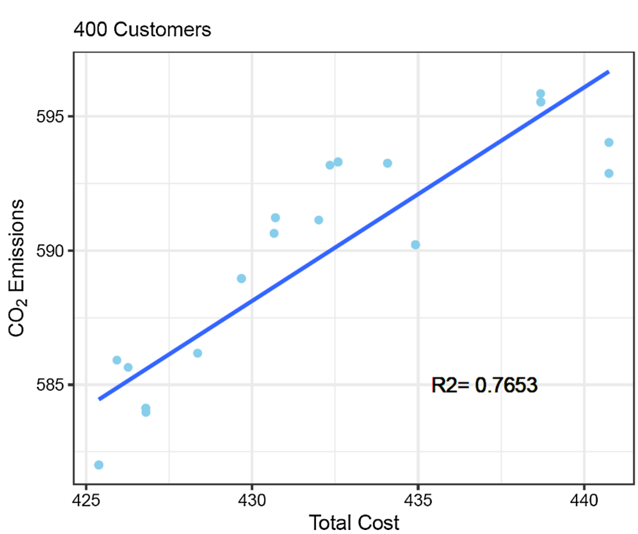

Fig. 3. Relationship between cost reduction and CO_2 emissions.

6. Conclusion

We developed a vehicle-UAV green routing model to investigate the use of UAVs to save cost and fuel consumption for last-mile deliveries. An optimal model to minimize the total cost is proposed and a genetic algorithm, GVRP-GA, is designed to solve large problem instances. The experimental results show that the use of UAVs can help save fixed costs by reducing the total delivery time and the number of vehicles required, because UAVs and vehicles deliver parcels jointly. Perhaps more importantly, the use of UAVs can save variable costs, which is primarily the expenditure on fuel. As a result, the consumption of fuel and the subsequent carbon emissions can be substantially reduced.

We would like to point out that logistics is at the center of supply chain, and transportation is the most visible aspect of supply chain that accounts for 33% of the logistics costs. Using drones to transport commercial packages is a new industry trend, as seen in Amazon, Google, UPS, Walmart, JD.com, Alibaba, etc. It can greatly change energy use in the transportation and distribution sector. Drones can help minimize the time needed to deliver all packages. In this research, we offer managers an effective model to create competitive edges by optimally coordinating vehicles and their UAVs. Shifting smaller-package delivery from trucks to drones would result in savings of overall energy used. We analytically and numerically show that when adequately deployed, UAV delivery would cut down energy use and CO_2 emissions. Thus, to realize the environmental benefits of drone delivery, firms should carefully plan and control the routing and co-ordination of the vehicles and the drones. Operational decisions can be effective in reducing transportation costs, reduce the greenhouse effect, and improve the environment [66,67].

The current technology of battery-powered delivery UAVs limits their range (delivery distance and flight time) and payload capacity (weight and size of parcel). Future research should focus on alternative power sources, such as fuel cells [68,69]. This would relax the constraints currently limiting the utilization of UAVs, and may provide additional cost savings and CO_2 reduction when using UAVs in tandem with traditional delivery vehicles for last-mile parcel delivery.

Acknowledgement

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Appendix A. Notation.

Sets:	
V	The set of all nodes, $V = \{0, 1, \cdots, n\}$, where n is the number of customers and node 0 is the depot.
U	The set of all customers, $U = V \{0\}$.
E	The set of edges, where $\{i, j\} \in E$ represents the edge from node i to node j.
Variables:	
x_{ij}	The weight of the payload (in pounds) in the vehicle for edge $\{i, j\} \in E$.
y_{ij}	Equal to 1 if edge $\{i, j\} \in E$ is in the solution (i.e., the vehicle travels from node i to node j), equal to 0 otherwise.
z_{ijk}	Equal to 1 if the UAV departs the vehicle at node i, serves customer j demand of q_j units, and returns to the vehicle at node k; equal to 0 otherwise.
t_{ijk}	The time (in hours) the UAV is airborne after departing the vehicle at node i, serving customer j, and returning to the vehicle at node k.
w_{ij}	The gross weight of the vehicle (in pounds) over edge $\{i, j\} \in E$, including the weight of the empty vehicle, the weight of the payload, and the weight of the UAV if it is on the vehicle.
Parameters:	
b^{VEH}	The weight of the empty vehicle (tare weight, in pounds).
b^{UAV}	The weight of the empty UAV (in pounds).
q_i	The demand of customer i (in pounds).
Q^{VEH}	The payload capacity of the vehicle (in pounds).
Q^{UAV}	The payload capacity of the UAV (in pounds).
d_{ij}^{VEH}	The distance from node i to node j for the vehicle (in miles).
d_{ij}^{UAV}	The distance from node i to node j for the UAV (in miles).
D^{UAV}	The range (maximum distance travelled) of the UAV (in miles).
T^{UAV}	The range (maximum time airborne) of the UAV (in hours).
s_{ik}^{VEH}	The average speed of the vehicle to travel from node i to node k (in miles per hour).
s_{ij}^{UAV}	The average speed of the UAV to travel from node i to node j (in miles per hour).
c^{FIX}	The fixed cost of the vehicle and UAV (in dollars).
c^{VEH}	The variable routing cost of the vehicle (in dollars per pound-mile).
c^{UAV}	The variable routing cost of the UAV (in dollars per mile).

Appendix B. Model optimization

In this appendix, we present the results of applying a mixed-integer program (MIP) to the cost-minimization formulation of Section 3. We first present a lower bound on the number of vehicles required, in order to provide the MIP solver a means of efficiently terminating branches; for example, a 25-customer problem took over 28 min to solve without the bound, and less than 3 min to solve with it. We then provide the parameters used for these instances and the results from a commercially-available MIP solver.

Lower bound. Sometimes, the mixed-integer program maintains a lower bound on the solution (cost) that would require fewer vehicles than can possibly be achieved due to the vehicles' capacities. Thus, we can include a lower bound on the number of vehicles, calculated as follows:

Step 1. Let $p = \left\lfloor \sum_{i\in U} q_i \big/ Q^{VEH} \right\rfloor$, the total weight to be delivered divided by a vehicle's capacity.
Step 2. Identify the p largest demands that can be satisfied by a UAV from the depot; hence, z_{0jk} can equal one, and those demands will not need to be on a vehicle…call them $q_1', q_2', \ldots, q_p'$.
Step 3. The lower bound is then $LB^{VEH} = \left\lceil \left(\sum_{i\in U} q_i - \sum_{j=1}^{p} q_j'\right) \Big/ Q^{VEH} \right\rceil$.

We can then add a constraint to the mixed-integer program for a lower bound on the number of vehicles required: $\sum_{j\in U} y_{0j} \geq LB^{VEH}$.

Parameters. The locations and demands of the first n customers are taken from Appendix C, and the values used for the remaining parameters are as follows (see Section 5.1):

- Fixed cost of vehicle/UAV tandem = 500
- Variable routing cost of vehicle = 0.00016
- Variable routing cost of UAV = 0.02
- Maximum travel distance of UAV = 10
- Maximum flight time of UAV = 10
- Weight of vehicle = 6100
- Weight of UAV = 55
- Average speed of vehicle = 25 (using the Manhattan metric for vehicle distances)
- Average speed of UAV = 25 (using the Euclidean metric for UAV distances)
- Capacity (payload weight) of the UAV = 6
- Capacity (payload weight) of the vehicle = 30, 40

Note: the capacity (payload weight) of the vehicle was set to 30 and to 40 in order to get multiple vehicles required; if it were set to a more-practical value for these small problems, only one vehicle would be needed.

Results. The results in Table B1 were obtained using the CPLEX solver (Version 12.6.2, using an *i*7-980 3.33 GHz, clocked at 4.00 GHz, processor with 12 GB of RAM). The mixed-integer program was able to find optimal solutions for problem instances up to n= 40 customers. Since MIP run times tend to be a function of the number of binary variables, these are also listed those in the table; note, the number of binary variables is $(n + 2)(n + 1)^2$; the number of continuous variables is also $(n + 2)(n + 1)^2$. The optimal solution uses the default CPLEX parameters for the MIP solver; the CPU time

Table B1
Optimal solutions.

Binary				Optimal solution		Genetic algorithm solution		
n	Variables	Q^{VEH}	LB^{VEH}	Total cost	CPU time	Total cost	Deviation	CPU time
20	9,702	30	3	1,586.7	35.77	1,600.1	0.85%	37.55
		40	3	1,582.0	38.38	1,625.5	2.75%	38.09
25	18,252	30	4	2,101.0	44.38	2,233.8	6.32%	45.90
		40	3	1,592.6	172.53	1,675.7	5.22%	40.65
30	30,752	30	5	2,617.2	131.05	2,688.1	2.71%	53.12
		40	4	2,104.4	129.95	2,114.4	0.47%	51.54
35	47,952	30	5	2,620.4	1,881.59	2,730.4	4.20%	54.87
		40	4	2,107.0	929.48	2,110.6	0.17%	52.66
40	70,602	30	5	2,625.2	35,169.53	2,653.8	1.09%	58.12
		40	4	2,109.0	15,975.69	2,117.1	0.38%	55.29

(in seconds) reflects the time to identify and verify the optimal solution.

It is obvious from these results that a mixed-integer program will not be a satisfactory means of solving practical routing problems with hundreds of customers. Hence, the need for an efficient solution methodology is necessary. Also shown in Table B1, then, are the results of the Genetic Algorithm presented in Section 4; as shown, the GA is quite effective in finding good solutions—an average deviation of less than 2.5 percent from optimal—with a reasonable amount of CPU time.

Appendix C. Location and weight of customers

Customer no.	Customer location	Weight of order	Customer no.	Customer location	Weight of order	Customer no.	Customer location	Weight of order	Customer no.	Customer location	Weight of order	Customer no.	Customer location	Weight of order
1	6.2945 2.8864	3	41	8.1158 −2.4278	5	81	−7.4603 6.2316	6	121	8.2675 0.6565	1	161	2.6472 −2.9855	5
2	−8.0492 8.78	7	42	−4.43 7.5189	3	82	0.9376 1.0031	1	122	9.1501 2.4495	2	162	9.2978 1.7409	4
3	−6.8477 −5.8452	6	43	9.4119 −3.9751	3	83	9.1433 −0.5815	8	123	−0.2925 −5.3902	3	163	6.0056 6.8862	1
4	−7.1623 −6.1047	7	44	−1.5648 −5.4816	4	84	8.3147 −6.5858	2	124	5.8441 −5.4467	1	164	9.1898 −1.286	3
5	3.1148 −3.778	3	45	−9.2858 8.4676	1	85	6.9826 −1.3959	1	125	8.6799 −7.3037	4	165	3.5747 8.0976	3
6	5.1548 9.595	6	46	4.8626 −1.2226	1	86	−2.1555 −7.7776	5	126	3.1096 −4.8387	3	166	−6.5763 −1.8256	1
7	4.1209 1.8979	4	47	−9.3633 −4.7558	6	87	−4.4615 2.0569	1	127	−9.0766 4.2243	3	167	−8.0574 −5.5651	6
8	6.4692 −7.6516	6	48	3.8966 −4.0665	2	88	−3.658 −3.6244	2	128	9.0044 −1.5167	1	168	−9.3111 0.1572	4
9	−1.2251 −8.2897	5	49	−2.3688 −4.7504	3	89	5.3103 6.0203	2	129	5.904 −9.4156	2	169	−6.2625 8.5771	3
10	−0.2047 4.6066	6	50	−1.0883 −0.2278	1	90	2.9263 1.5705	2	130	4.1873 −5.2543	4	170	5.0937 −0.823	3
11	−4.4795 9.2618	2	51	3.5941 0.9361	2	91	3.102 0.4227	2	131	−6.7478 −5.3681	3	171	−7.62 −0.222	1
12	−0.0327 2.4812	9	52	9.1949 3.5827	6	92	−3.1923 −2.0897	1	132	1.7054 −2.6513	1	172	−5.5238 9.7596	6
13	5.0253 −9.2452	3	53	−4.8981 7.7034	9	93	0.1191 8.2657	2	133	3.9815 5.9237	5	173	7.8181 −8.0258	4
14	9.1858 −4.7626	3	54	0.9443 −3.2929	7	94	−7.2275 3.5946	3	134	−7.0141 −7.2689	4	174	−4.8498 4.4245	2
15	6.8143 −7.8648	7	55	−4.9144 3.0751	6	95	6.2857 −0.1165	2	135	−5.1295 5.581	2	175	8.5853 4.3007	5
16	−3.0003 8.0744	3	56	−6.0681 7.8185	6	96	−4.9783 −3.3167	1	136	2.3209 3.9749	1	176	−0.5342 −6.0438	1
17	−2.9668 −9.3892	5	57	6.6166 4.8815	4	97	1.7053 0.0004	8	137	0.9945 −0.4016	4	177	8.3439 8.0944	6
18	−4.2832 2.1973	8	58	5.144 2.3533	4	98	5.0746 7.1888	4	138	−2.3911 6.1098	2	178	1.3564 1.5344	1
19	−8.4829 −6.3416	1	59	−8.921 −5.2014	6	99	0.616 7.7302	5	139	5.5833 −9.4265	4	179	8.6802 −0.202	3
20	−7.4019 −6.6415	2	60	1.3765 9.5736	5	100	−0.6122 4.2539	2	140	−9.762 0.0094	2	180	−3.2575 −0.5782	2
21	−6.7564 −8.8076	10	61	5.8857 3.6394	2	101	−3.7757 −9.1514	5	141	0.5707 −8.5711	8	181	−6.687 0.433	5
22	2.0396 −8.0654	9	62	−4.7406 6.363	4	102	3.0816 6.3509	1	142	3.7843 4.4488	6	182	4.963 −7.0027	1
23	−0.9892 3.1921	2	63	−8.3236 0.3719	5	103	−5.4205 9.4595	8	143	8.2667 2.9798	1	183	−6.9524 6.0066	2
24	6.5163 −0.924	4	64	0.7668 −1.3522	3	104	9.9227 6.5063	2	144	−8.4365 −8.3306	5	184	−1.1464 −7.3366	1
25	−7.8669 −6.5322	1	65	9.238 −2.1812	1	105	−9.9073 6.6276	1	145	5.4982 6.0673	7	185	6.3461 −8.7906	1

26	7.3739 −2.0148	2	66	−8.3113 0.5375	5	106	−2.0043 −1.664	3	146	−4.8026 3.1372	4	186	6.0014 2.5595	2
27	−1.3717 −4.1603	6	67	8.213 −1.367	2	107	−6.3631 −9.6903	1	147	−4.7239 9.6813	3	187	−7.0892 −6.6566	3
28	−7.2786 −7.8757	4	68	7.3858 −2.5518	2	108	1.5941 −6.0376	1	148	0.9972 −0.2062	4	188	−7.1009 −3.2101	6
29	7.0606 9.0326	6	69	2.4411 8.4066	10	109	−2.981 −8.9465	6	149	0.265 4.7572	5	189	−1.9638 −4.6176	6
30	−8.4807 −1.5433	8	70	−5.2017 0.9574	1	110	−7.5336 8.8547	9	150	−6.3218 −1.6451	2	190	−5.2009 9.661	5
31	−1.6547 −3.9709	3	71	−9.0069 4.022	4	111	8.0543 3.3268	2	151	8.8957 0.7825	2	191	−0.0001 3.9621	3
32	−0.2149 3.3306	2	72	−3.2456 −6.4374	2	112	8.0011 −6.8397	4	152	−2.6151 9.9816	9	192	−7.7759 −6.5776	5
33	5.605 −9.348	5	73	−2.2052 1.224	2	113	−5.1662 7.6373	10	153	−1.9218 3.3835	5	193	−8.0709 −6.1913	3
34	−7.3605 −2.6217	2	74	8.841 −0.7855	4	114	9.1227 9.6328	1	154	1.5042 −6.8719	3	194	−8.8044 7.1105	5
35	−5.3044 2.8953	3	75	−2.9368 −2.4746	2	115	6.4239 −6.1815	5	155	−9.6919 −1.4349	4	195	−9.1395 −0.3596	3
36	−6.6202 −7.5878	1	76	2.9823 1.7901	2	116	4.6344 −5.4762	4	156	2.9549 −2.3076	4	196	−0.9815 1.6597	1
37	0.9402 −4.9639	2	77	−4.0736 −4.1912	3	117	4.8939 2.3418	4	157	−6.2209 −4.6944	1	197	3.7355 6.4875	2
38	−6.3298 9.6533	1	78	−2.6303 4.605	5	118	2.5124 −3.1225	1	158	5.6045 1.6814	3	198	−8.3775 −7.8446	7
39	8.5877 8.1262	1	79	5.5143 7.5931	1	119	−0.2642 6.3552	3	159	−1.2828 −4.7854	5	199	−1.0643 1.8871	2
40	−3.873 −9.5497	1	80	0.1702 −1.4948	8	120	0.2154 −3.7456	4	160	6.3526 −6.7703	3	200	5.8966 −6.4247	5

For a better understanding of customers' location, we also illustrate this data in Fig. C1:

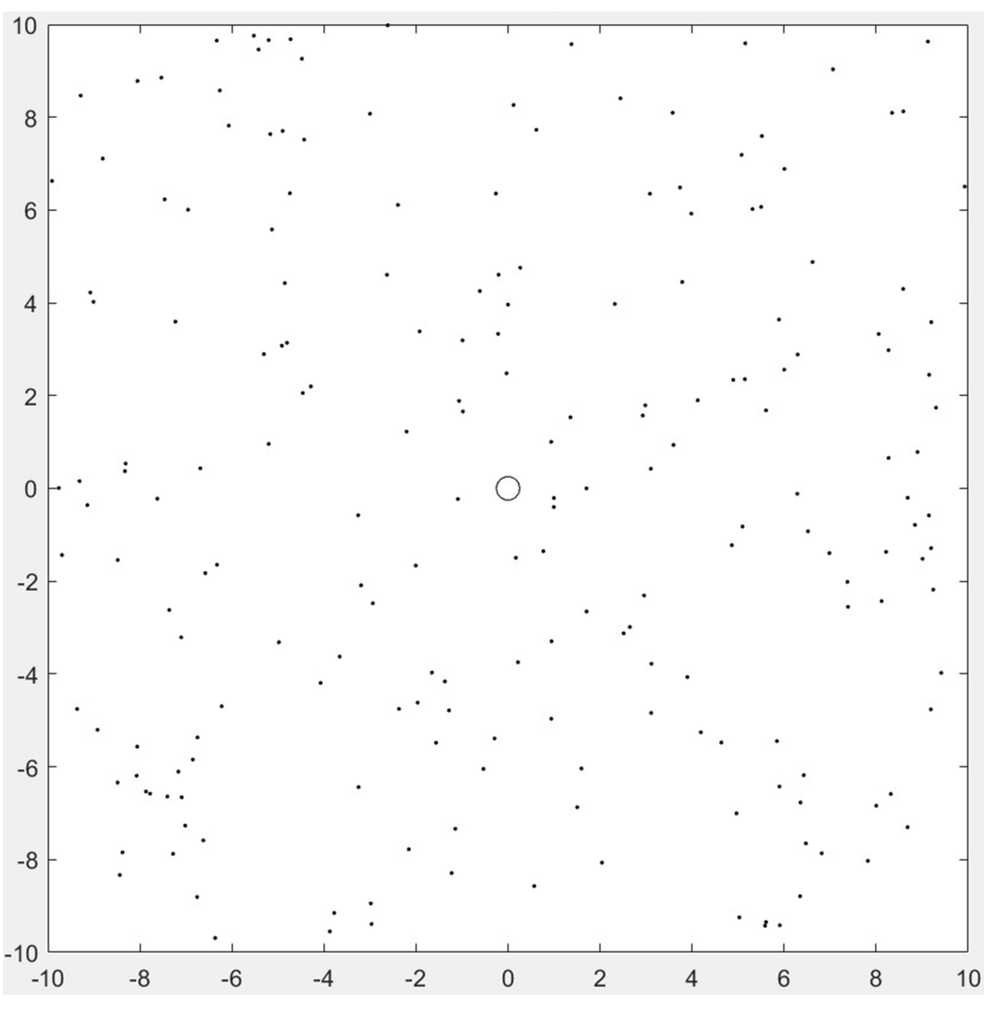

Fig. C1. Location of customers.

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