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Using intermediate points in parcel delivery operations with truck-based autonomous drones

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Abstract

Autonomous drones are no longer science fiction but are becoming reality. Prior studies have investigated how an autonomous drone can be used in conjunction with a parcel delivery truck, but they all restricted the drones' launch/recovery sites to customer nodes visited by a truck. In practice, parcel carriers are considering the use of intermediate points (IPs), the sites found along the arcs connecting customer nodes, as drones' launch/recovery points. This means that the academic literature currently lags the industry practice. This article extends the previous works on truck-and-drone last-mile delivery by investigating the conditions under which the use of IPs is beneficial by using both theoretical and empirical approaches. Our results show that, although using IPs is an effective concept that can save the cost (time) of package deliveries by 2.189% on average, the cost saving realized by using IPs can vary notably across carriers depending on their network characteristics. Specifically, our results suggest that the benefit of using IPs becomes high when a network has the following characteristics: (1) low customer density (a small number of customers served per square mile), and (2) large number of time-sensitive packages (subject to time window constraints). Based on these findings, we provide normative implications on if, when, where, and to what extent IPs can be beneficial for the truck-and-drone joint operations in last-mile logistics.

KEYWORDS

drones, intermediate point, last-mile logistics, parcel delivery, routing, scheduling

1 | INTRODUCTION

The rapid diffusion of e-commerce raises new challenges to the last-mile delivery because it requires more direct shipments to consumers (Durand et al., 2013; Ishfaq & Raja, 2018; Lu et al., 2022; Savelsbergh & Van Woensel, 2016). Emerging technologies have been used to solve this problem, one of which is *autonomous unmanned aerial vehicles* or *drones* (Savelsbergh & van Woensel, 2016). Due to their fast speed (Transport Topics, 2017), cheap cost (Keeney, 2015), and low emissions (Goodchild & Toy, 2018), drones can bring multiple benefits, if deployed in logistics. A drone can be launched or received at a terminal (distribution center) or at any appropriate point on the road from a delivery truck (that carries drones). Firms have begun testing parcel deliveries via drones, for example: (1) DHL has been delivering medicines to islands since 2014 (Hern, 2014), (2) Amazon initiated its Prime Air deliveries in 2016 (McNabb, 2016; Weise, 2016),

and (3) UPS tested a delivery system that jointly uses a truck and a drone in 2017 (Weise, 2017). The focus of this article is to study this new mode of last-mile logistics. In particular, our interest is in the third example above, that is, the problem of jointly operating a truck and a drone.

To date, a limited number of studies have considered parcel delivery problems that combine truck(s) with drone(s) (e.g., Agatz et al., 2018; Dorling et al., 2016; Lemardelé et al., 2021; Moshref-Javadi et al., 2020; Murray & Chu, 2015). These studies, however, have restricted the drones' launch and/or recovery points to terminals and customer locations, perhaps for simplicity. No study, to the best of our knowledge, has considered using intermediate points (IPs, which are possible launch/recovery sites available along the arcs connecting customers) to operate drones.

From the practical standpoint, there are at least two advantages of using IPs in truck-and-drone joint operations. First, networks with IPs would have more available locations for

operating drones (launching and recovering points), so they would provide higher flexibility in creating drone routes than the conventional networks with no IPs. Second, networks with IPs are more likely to generate feasible truck-and-drone routing solutions than conventional networks. This is because customer nodes do not always allow drone operations (e.g., close to airports and lack of ample parking space to launch or recover a drone), so in some cases it may not be possible to generate a truck-and-drone routing solution that utilizes only terminals and customer nodes as the drone's operating sites. In such cases, however, we may still find a feasible truck-and-drone solution if we allow a truck to use IPs in addition to terminals and customer nodes as the drone's operating sites.

Given these advantages, the use of IPs is already considered in practice (e.g., Edronic, 2023; Kolodny & Brigham, 2023; Tolooie & Sinha, 2023; UPS, 2017). This means that the last-mile logistics literature currently lags the industry practice. Thus, a new research stream may be needed that addresses this relevant issue to fill the gap between academic literature and industry practice.

The goal of this article is to extend the previous works on truck-and-drone last-mile delivery routing by studying the merits and demerits of using IPs. Because autonomous drone technology is rapidly becoming reality, it is important that we fill the aforementioned knowledge gap in a timely manner. This allows researchers and practitioners to get the scientific knowledge on how IPs can affect the truck-and-drone operations and how they should be utilized in the field before this technology becomes widely available. This article offers a valuable foundation for research on this topic by investigating if, when, and where the use of IPs can be beneficial for drone operations, and to what extent the use of IPs can help carriers meet the rapidly increasing home delivery needs. We find that although using IPs is an effective concept in general that gives considerable benefits to carriers, attainable benefits vary from one case to another depending on network characteristics such as the customer density and the proportion of packages requiring time-constrained deliveries.

2 | MOTIVATION, STUDY QUESTIONS, AND GOALS

At the beginning of this research project, we conducted a series of interviews with five executives and managers of large U.S. parcel carriers to obtain expert opinions on drone operations. Our interviews, which were conducted either by in-person meeting or via online meeting software, mainly focused on asking their levels of interest in using drones and IPs, as well as how they intend to use IPs in the truck-and-drone joint operations. The interviewees all expressed strong interests in using both drones and IPs in parcel deliveries but also indicated that they have little knowledge on how to operate trucks and drones together when IPs are available, so they are strongly interested in seeing a study that investigates the effective use of IPs. One interviewee, for example, expressed his interest in our study by stating: "We want to know any-

thing that could possibly help us use drones efficiently and effectively." This was taken as a professional endorsement that our study carries a significant practical value, which motivated us to continue conducting the study.

As we began looking at the truck-and-drone routing problem, we quickly realized that adding IPs to the problem cannot worsen the solution, that is, the cost (objective function) of the solution with IPs cannot be higher than that of the solution without IPs. This is because adding IPs to a network merely increases the feasible region of the problem without increasing the cost of carriers (strictly, there is an initial cost associated with identifying a suitable set of IPs, but it can be treated as "sunk cost"). This, however, does not necessarily mean that using IPs would always result in reducing costs. This is because there are disadvantages associated with using IPs so that, although using IPs cannot worsen the solution, it may not improve the solution either (one such disadvantage is that, because using an IP requires a truck to make an additional stop, beyond the required stops at customer nodes, it adds extra time and cost; see the discussions provided in later sections). This means that it is unclear whether the use of IPs would actually bring positive benefits to parcel carriers. Therefore, the pertinent questions are: "Are there significant economic benefits of using IPs?" and "Under what conditions can the positive benefits be realized and why?"

This article attempts to answer these questions. Answering these questions is important from the practical viewpoint. Without the correct knowledge of when and where the IPs should be utilized, practitioners may start using IPs improperly in the field once the autonomous drone technology becomes available. Answering these questions is also important from the theory perspective. Due to the lack of scholarly works on the use of IPs for the truck-and-drone last-mile operations, the literature may currently fall short with theoretical insights that can explain the conditions under which the use of IPs can be useful for such operations.

We first study the benefits of using IPs theoretically to understand not only "when and where" the benefits can be expected but also "why." We then perform a series of computational experiments to empirically contrast, under a variety of conditions, the truck-and-drone routing solutions with and without IPs to examine if the results agree with our theoretical findings regarding when and where the benefits can be realized. The most important contributions made by this study are as follows. First, because this is the first study to investigate the use of IPs, which is increasingly recognized as useful in truck-and-drone operations by practitioners but not yet by researchers, this study fills the gap between academic literature and industry practice. Second, this study provides theoretical insights into the conditions under which the truck-and-drone operations can economically benefit from the use of IPs. Developing such theoretical insights should serve as the building block of future studies that seek to advance the knowledge on truck-and-drone routing. Third, this study offers normative implications to practitioners on how to use IPs for truck-and-drone operations to achieve the best results, which may be used as practical guidelines in the field.

3 | LITERATURE REVIEW

There is a growing interest in the academic literature for utilizing drones. Drones have been used in a number of areas, for example, surveillance (Shen et al., 2020), terrain examinations (Torres et al., 2016), data gathering (Sujit et al., 2013), agriculture (Chamaria, 2016), humanitarian logistics (Zhang et al., 2021), and parcel delivery. This section focuses on reviewing the literature on drone operations for parcel delivery routing problems. Readers who are interested in other applications of drones are referred to a recent literature review by Otto et al. (2018). We divide the relevant literature into three groups, that is, deliveries performed by drones only, deliveries performed by a truck and a drone(s) (traveling salesman problem with drones: TSP-D), and deliveries performed by multiple trucks and multiple drones (vehicle routing problem with drones: VRP-D).

3.1 | Parcel deliveries by drones only

These studies do not involve collaborations between trucks and drones. As such, they are similar to the traditional VRP except that they route drones rather than trucks.

Dorling et al. (2016) developed a model for a delivery problem by a fleet of drones. They solved the problem both by minimizing the cost and by minimizing the total delivery time, subject to a budget constraint. Liu (2019) considered online dispatch operations of a fleet of drones that deliver on-demand meals and developed a mixed-integer programing model. This model, which incorporated real-world constraints (e.g., hot meal and cold drink must be delivered by different drones even if they belong to the same order), was solved by an optimization-drive, progressive algorithm. Simulated instances were tested by the author to validate the proposed algorithm.

3.2 | TSP-D studies

These studies considered parcel delivery operations performed by one truck assisted by one or more drones using the traditional TSP framework. Murray and Chu (2015) are among the earliest to consider this problem. They introduced a variant of the TSP (called the Flying Sidekick TSP or FSTSP) in which a drone works together with a truck to deliver parcels and showed that the delivery time becomes notably less with the use of a drone. In their settings, the drone is autonomous, which can deliver parcels to customers by itself, therefore reducing the stops made by trucks. They developed a mixed-integer program and several heuristics. Agatz et al. (2018) examined a similar problem (where a drone may be launched and recovered only at customers' sites) and presented an integer program and several heuristics to solve large instances.

Several studies extended Murray and Chu (2015). Ha et al. (2018) considered a similar problem in which the cost, rather than the delivery time, is minimized and developed two heuristics. Bouman et al. (2018) proposed an exact dynamic programing algorithm for the TSP-D considered by Agatz et al. (2018) and showed that their algorithm can solve larger problems. Carlsson and Song (2018) used continuous approximation methods to solve the TSP-D. Their theoretical analysis and numerical experiments showed that the efficiency gained by adding a drone to a truck is proportional to the square root of the ratio of the speeds of the truck to that of the drone. Ha et al. (2020) developed a new hybrid genetic algorithm that can find better TSP-D solutions than the existing approaches. Poikonen et al. (2019) analyzed the TSP-D problem with one truck and one drone and created four heuristics. They showed that the delivery-time saving attainable by adding a drone can be larger than 30%.

Liu et al. (2020) studied one-truck one-drone delivery problem, in which a drone can visit multiple customers in one flight, and developed a two-stage algorithm. They found that the use of lighter parcels and larger capacity drone battery would bring higher cost savings. Yoon (2018) developed a mixed-integer linear program for a delivery problem by one truck and multiple drones. They solved small instances (9–10 customers) and showed that the cost saving from deploying multiple drones could be as large as 30%. Murray and Raj (2020) developed a mixed-integer program for the TSP-D with one truck and multiple drones and solved instances with up to 100 customers using a 3-phased heuristic. Raj and Murray (2020) extended Murray and Raj (2020) by considering varying speeds of drones. They showed that the model with varying speeds can give more time savings than the model with a fixed speed. Luo et al. (2021) considered a TSP with one truck assisted by multiple drones, in which multiple visits can be made by a drone per flight. They solved this problem using a tabu search and showed that the ability of a drone to make multiple visits per flight can generate over 20% saving in delivery time when compared to the model that allows only a single visit per drone flight.

3.3 | VRP-D studies

Perhaps, the first study to consider the VRP-D is Wang et al. (2017). They considered the VRP-D, in which each truck can take multiple drones. Their problem assumed that: (1) Drones would travel the same street network as trucks (rather than Euclidean arcs), (2) drones' battery capacity is unlimited, and (3) drones can only be released or recovered at customer sites. They theoretically derived a few worst case results on VRP-D to show the maximum savings that can be attained by using drones. Several studies followed and extended Wang et al. (2017).

Poikonen et al. (2017) revised the worst case results of Wang et al. (2017) by considering the limited battery life of

a drone and by using different distance metrics for trucks and drones. They found that if using different distance metrics for trucks and drones, the model could generate higher time savings. Wang and Sheu (2019) also expanded the work of Wang et al. (2017) by developing a path-based VRP-D model and a branch-and-price algorithm that can solve the instances with up to 15 customers. They report that the cost saving attained by the VRP-D over the VRP ranges between 12% and 29%. Schermer et al. (2019) introduced a mixed-integer linear programming model of the VRP-D and developed valid inequalities that reduce the feasible region. They solved instances with up to 100 customers by using a metaheuristic and showed that trucks could reduce the delivery time by roughly 20%–50% if assisted by drones.

3.4 | Gap and contributions

In summary, our review of literature suggests that, to date, no truck-and-drone study has considered using IPs as drones' launch and/or recovery points. Consequently, the truck-and-drone literature currently lacks the knowledge of if, when, where, and to what extent the use of IPs would be beneficial to parcel carriers that jointly operate trucks and drones. This article seeks to fill this knowledge gap in the literature by using both theoretical and empirical approaches.

4 | THEORETICAL ANALYSES

4.1 | Scope and assumptions

This section theoretically studies if, when, where, and why IPs can provide economic benefits to parcel carriers. Because it is known in the logistics literature that the cost of operating a vehicle(s) in a network is highly dependent on the characteristics of the network (e.g., Ballou & Agarwal, 1988; Bell & Griffis, 2010), we posit that the benefit of using IPs in a network may also be affected by the characteristics of the network, as well as by the properties of the IPs added to the network. Given this notion, we utilize graph theory to perform our analyses in this section.

Because this is the first study to consider IPs in the truck-and-drone routing literature, we focus on studying the simplest form of the problem, namely, the *TSP-D*, in which one truck and one drone are considered. Albeit using the simplest form, our study can still provide realistic implications, as it incorporates several conditions that are often ignored by previous studies, which include (1) delivery time windows, (2) out-of-route miles (extra distance a truck must travel to reach the drone's launch/recovery sites located off the main road), and (3) zones where drones cannot be operated by regulations. The assumptions employed in this study are listed in Table 1.

These assumptions are either taken from the literature (e.g., Agatz et al., 2018; Murray & Chu, 2015) or derived from practitioner interviews. Most assumptions should be intuitive,

but two of them may require further explanations. First, we employ the first assumption because in the trucking (including parcel delivery) industry, the largest operating cost is time-dependent (e.g., driver pay, fuel cost, and equipment depreciation cost, all of which are functions of vehicles' operating time, e.g., Lu et al., 2022; Suzuki, 2008). This assumption is in line with both (1) previous truck-and-drone routing studies, most of which minimized the vehicles' operating time (see the TSP-D and VRP-D studies cited in Section 3), and (2) inputs received from practitioners during our interviews. Second, we employ the fourth assumption based on the expert opinions given by practitioners. Our interviewees stated that when identifying IPs, they would carefully evaluate suitable IP candidates in advance and pick up only a few good ones for each arc, so that only a small number of IPs should be considered per arc in our study.

4.2 | Benefit of using IPs

The major benefit of using an autonomous drone is that it cuts the time needed to complete a set of deliveries. Note that without a drone, a driver must visit all customers in person, so that all delivery tasks (visiting customers) must be performed sequentially. However, if a driver can use an autonomous drone, the driver can let the drone service certain customers while he/she visits other customers, so that some tasks can be processed simultaneously (parallel processing), which is known to be more efficient (takes less time) than sequential processing (e.g., Ba'Its et al., 2020; Wang et al., 2017). Parts (a) and (b) of Figure 1 show the comparison of a sequential (no drone) and a parallel (with drone) processing of delivery tasks (calculation details are available on request).
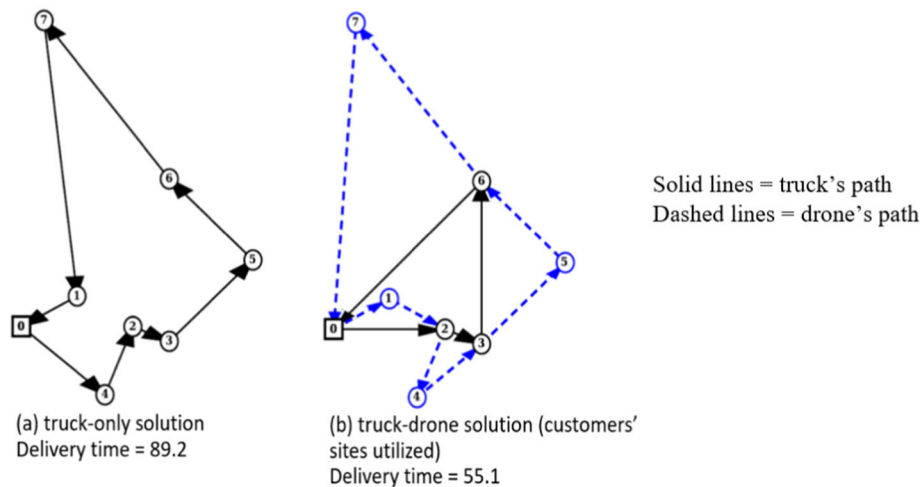
Note, however, that when a driver is allowed to use only the customer nodes as the drone's launch and recovery points (denoted hereafter as DLR points), operational inefficiencies may exist due to the presence of waiting time by either a drone or a driver (truck). Figure 2 shows an example of a drone's flight, in which the drone is launched from customer node a, visits customer node b by itself, and proceeds to the recovery point. If only customer nodes can be used as DLR points, the drone must be recovered at either node c or d, which results in a waiting time of 5 min for the truck (if using c as the recovery point) or the drone (if using d as the recovery point). Such waiting time (by truck or drone) can delay the delivery completion time, that is, the time the truck returns to the depot with the drone (we discuss this issue more with an example in the next section).

Such inefficiencies, however, can be eliminated or minimized if a driver can use IPs. In Figure 2, for example, the waiting time of both the drone and the truck becomes zero if q (an IP) can be used as the recovery point (to supplement this contention, a different example with a similar outcome is provided in online Appendix G). This is the main advantage of using IPs. The use of IPs, however, has disadvantages too. One such disadvantage is that, because using an IP requires a truck to make an additional stop, beyond the stops needed at

TABLE 1   Assumptions.

1. The goal of parcel carriers is to minimize the time it takes for a delivery truck (driver), together with a drone, to complete all the assigned delivery tasks (minimize the return time of the truck, with a drone, to the terminal)

2. A drone carried in a truck is an autonomous vehicle such that it can (1) fly its intended path without being guided by humans, and (2) wait for the truck in the air (by hovering) at the recovery point if it arrives there earlier than the truck

3. The drone can be operated (launched and/or recovered) at the depot (terminal), customers' sites, or IPs on arcs (operating a drone while the truck is in motion is not allowed for safety reasons)

4. In each arc, the number of IPs that are suitable as a drone's launch and/or recovery points (e.g., locations that are not in the vicinity of airports and that have open air spaces) is limited

5. A drone can deliver one package per flight due to the payload and flight range restrictions

6. A truck carries replacement batteries for the drone, so that the drone can be dispatched from the truck multiple times in each truck route

7. The time needed to attach batteries to a drone and that to load parcels onto the drone, which must be incurred every time a drone is launched, are fixed (constants)

8. A drone can service only a subset of customers whose packages weigh less than the maximum payload of the drone and whose locations are outside of the restricted zones (e.g., near airports)

Abbreviation: IPs, intermediate points.

(a) truck-only solution
Delivery time = 89.2

(b) truck-drone solution (customers' sites utilized)
Delivery time = 55.1

Solid lines = truck's path
Dashed lines = drone's path

FIGURE 1   A truck route with and without an autonomous drone.

FIGURE 2   Example of a drone flight.

Note: truck's arcs reflect surface roads so that they may not necessarily be straight lines, whereas drone's arcs reflect flight paths so that they are straight lines.

Solid lines = truck's path
Dashed lines = drone's path
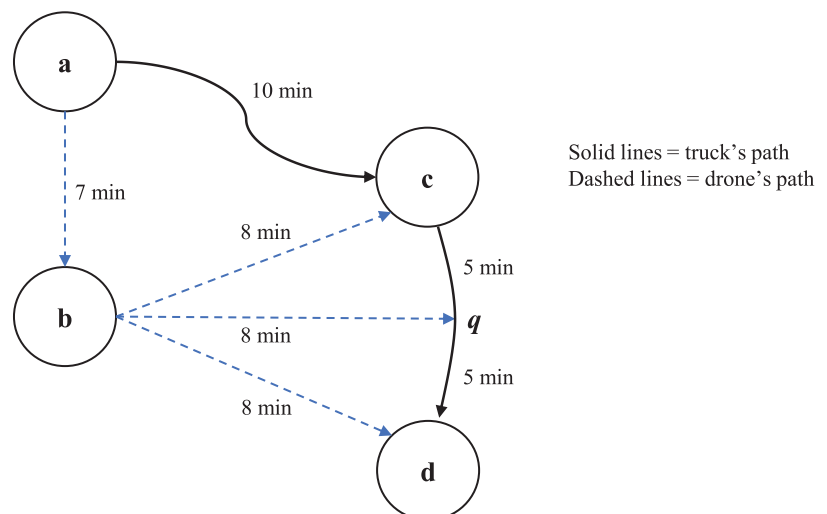
customer nodes, it adds extra time to the delivery completion time. These "extras" include the time to (1) slow down the truck to a stop and accelerate back to the original speed (if a drone can be operated at roadside) and (2) drive extra miles to reach a location suitable for operating a drone (if roadside operation is not permitted).

4.3 | Calculating benefits

The above paragraph suggests that using IPs has both advantages and disadvantages, so that it may not necessarily give positive benefits in all cases. The "net" benefit of using IPs is given by the difference of (1) cost (total delivery time) when using only the customer nodes as DLR points (denoted t_1), and (2) that when using IPs in addition to customer nodes as DLR points (denoted t_2). Let us consider the example shown in Figure 2, in which $\mathbf{q}$ is used as an IP. In this case, we are evaluating the time it takes for a truck, with a drone, to move through nodes a–d. There are two ways to calculate t_1, that is, when using node c as the drone's recovery point and when using node d as the recovery point. There is only one way to calculate t_2 (as there is only one IP).

Let c^T_{ij} and c^D_{ij} be the cost (time) of traveling an arc (i, j) by the truck and that by the drone, respectively. For example, c^T_{ac} is the time it takes for the truck to move the arc connecting nodes a to c, and c^D_{ab} is that for the drone to move the arc connecting nodes a to b, respectively. Moreover, let W^T_i and W^D_i be the waiting times of the truck and that of the drone, respectively, at recovery point i. Note that the waiting time can exist only at recovery points (not at launch points) because a driver is naturally required to have a drone before arriving at a launch point, that is, point i cannot be used as a drone's launch point if the driver does not have the drone on hand when arriving at i.

Ignoring the time needed to service customers a–d, as well as the time needed to launch and recover a drone at the launch and recovery points, respectively (which are identical between t_1 and t_2), t_1-t_2 is given by Equations (1) and (2). Note that Equation (1) gives the net benefit if using node c as the recovery point in calculating t_1, whereas Equation (2) gives that if using node d as the recovery point:

$$\left(c^T_{ac} + W^T_c + c^T_{cd}\right) - \left(c^T_{ac} + c^T_{cd} + S_{LR}\right) = W^T_c - S_{LR} \quad (1)$$

$$\left(c^T_{ac} + c^T_{cd} + W^D_d\right) - \left(c^T_{ac} + c^T_{cd} + S_{LR}\right) = W^D_d - S_{LR} \quad (2)$$

where S_{LR} is the time it takes for a truck to deviate from the route to reach $\mathbf{q}$, plus the time needed to slow down the truck to come to a complete stop at $\mathbf{q}$ and accelerate it back to the original speed.

It is to be noted that although W^T_c of Equation (1) directly affects (increases) the time to go through customers a–d (e.g., if W^T_c increases from 5 to 10 min, the total time will increase by 5 min from 20 to 25 min), W^D_d of Equation (2) does not (e.g., if W^D_d increases from 5 to 10 min, the total time

remains unchanged at 20 min). This implies that we can possibly ignore W^D_d when calculating the net benefit. We, nonetheless, include W^D_d in Equation (2) because it reflects the opportunity cost. To see this point, consider a comparison between the case where d is used as the recovery point and that where $\mathbf{q}$ is used as the recovery point. In the former case, the earliest time the drone can be launched for the next flight would be $\alpha + 20$ min, where α is the time the truck (and drone) departs node a. Although the drone arrives at d at $\alpha + 15$ min, it must wait for 5 min for the truck to arrive at d before it can be launched. In contrast, the earliest time the drone can be launched in the latter case would be $\alpha + 15$ min because it can be launched directly from $\mathbf{q}$ (rather than d), meaning that the launch time of the drone's next flight can be 5 min earlier when using $\mathbf{q}$ as the recovery point than when using d. This means that if the truck must use d as a recovery point, the launch time (and hence the completion time) of the drone's subsequent flight is delayed by 5 min due to the waiting time at d (W^D_d). This, in turn, can delay the truck's return time to the depot with the drone.

Equations (1) and (2) assume implicitly that the IP ($\mathbf{q}$) is located at the "optimal" position such that both the truck and the drone arrive at the IP at exactly the same time, that is, that neither of them needs to wait for the other party at $\mathbf{q}$. In reality, however, it is often difficult to find an IP exactly at the optimal location, as there are only a finite number of suitable IP locations along each arc (as discussed earlier). If this is the case, there will be a waiting time at $\mathbf{q}$ (time either a truck or a drone must wait for the arrival of the other party at $\mathbf{q}$), so that this waiting time (denoted W_q) must also be added to Equations (1) and (2). Because it is intuitive that W_q becomes larger as $\mathbf{q}$'s location gets further from the optimal location $\mathbf{q}^{opt}$ (the recovery location where the waiting time of both parties becomes zero), we can express the waiting time at $\mathbf{q}$ as $W_q = u(|\mathbf{q}-\mathbf{q}^{opt}|)$, where $|\mathbf{q}-\mathbf{q}^{opt}|$ is the absolute value of the distance (or travel time) between $\mathbf{q}$ and $\mathbf{q}^{opt}$ along the arc (c, d), and $u(.)$ is the function that maps $|\mathbf{q}-\mathbf{q}^{opt}|$ onto W_q. After incorporating W_q, Equations (1) and (2) can be rewritten as follows:

$$W^T_c - u\left(|\mathbf{q} - \mathbf{q}^{opt}|\right) - S_{LR} \quad (3)$$

$$W^D_d - u\left(|\mathbf{q} - \mathbf{q}^{opt}|\right) - S_{LR}. \quad (4)$$

5 | THEORETICAL IMPLICATIONS

This section develops a set of implications from Equations (3) and (4), which specify the type of networks that would, or would not, benefit from using IPs. Although Equations (3) and (4) are developed specifically to compute the net IP benefit for the example shown in Figure 2, they can also be used to derive implications for other cases. This is because the implications derived from these formulas would be the same as those derived from the "generic" benefit formulas that apply equally well to all cases (see online Appendix A for details),

so that they can be generalized to other cases. The implications derived in this section will later be tested empirically in computational experiments.

5.1 | Number of IPs per arc

As discussed earlier, adding IPs to the truck-and-drone routing problem cannot worsen the solution value. Thus, it is intuitive that increasing the number of available IPs per arc in a network either reduces or does not change the routing cost in the network, which suggests that for the best results, one should prefer networks with many IPs per arc to those with very few IPs per arc. Equations (3) and (4), however, provide insights that contradict this intuition. They indicate that the closer the location of an IP (**q**) to the theoretical optimum **q**^{opt} (where the waiting time of both truck and drone becomes zero), the higher the benefit of using the IP. This means that having many IPs in an arc may not save cost if their positions are far from the optimal location, whereas having only one IP in the arc may save cost greatly if its location is at or near the optimal location. Thus, from the benefit maximization standpoint, the IP location (where) may be a more important factor than the number of IPs per arc (how many). This implies that merely increasing the number of available IPs per arc in a network may not significantly increase the cost saving realized by parcel carriers.

One may still argue that increasing the number of available IPs per arc is an effective method to maximize benefit because if we increase the number of available IPs in an arc, the probability of finding an IP at or near the optimal location for any drone flight originating from or terminating at this arc increases for all scenarios. In theory, however, this positive relationship between the IP benefit and the number of IPs per arc can be observed only asymptotically, so that when the number of IPs per arc is small (which is usually the case in practice), it is unlikely that we observe this relationship to be significant. This condition suggests that, although the benefit of using IPs is higher in networks that have many IPs per arc than those having very few IPs per arc, the incremental benefit realized by the former network over the latter network may be limited.

5.2 | Customer density

Equations (3) and (4) indicate that the larger the W_c^T and/or W_d^D (waiting time by truck and/or drone at a recovery point under the traditional "no-IP" truck-and-drone routing solutions), the higher the benefit of using IPs. Because the waiting time at a recovery point j is given by the absolute value of the difference between the truck's arrival time and the drone's arrival time to j, it can be expressed as $|g_{ij} - h_{ij}|$, where g_{ij} and h_{ij} are the travel time from the launch point i to the recovery point j by the truck and that by the drone, respectively. Note that under the "no-IP" routing solutions, g_{ij} and h_{ij} represent the summed lengths (traversal times) of all the arcs included in the truck's path and that in the drone's path, respectively,

from i to j, where i and j are customer nodes. This means that if we increase the length between every pair of customer nodes proportionally, both g_{ij} and h_{ij} increase for all (i, j) pairs, which, in turn, increases $|g_{ij} - h_{ij}|$ for all j (because if both g_{ij} and h_{ij} increase by the same percentage Δ, then $|g_{ij} - h_{ij}|$ must also increase by Δ; see online Appendix B).

The above paragraph suggests that increasing the average arc length in a network (where an arc refers to the link between customer nodes) generally increases the benefit of using IPs in the network. Because it is known that the average arc length of a network increases when (1) the service area becomes large while holding the number of customers fixed, and/or (2) the number of customers becomes small while holding the size of service area fixed (Suzuki & Lan, 2023), the IP benefit is likely to be affected by *customer density*, which is defined as the ratio of the number of customers to the service area size. Specifically, the benefit of using IPs should be an increasing function of the service area size and a decreasing function of the number of customers, so that it should be a decreasing function of the customer density. This suggests that the benefit of using IPs may be higher for networks having low customer density than those having high customer density.

5.3 | Time windows

This third implication stems from the second implication above. According to the second implication, increasing the average arc length in a network generally increases the benefit of using IPs in the network. This means that any change in a network's characteristic, other than customer density, which triggers the growth of average arc length in the network, can also increase the benefit of using IPs. One such change may come from the imposition of delivery time-window constraints.

It is known that imposing time-window constraints on vehicle-routing problems generally worsens the solution quality by increasing the travel time and distance of the optimal solution (e.g., Taş et al., 2014). This means that, generally, the optimal TSP-D solution for a given instance (network) with time windows would have longer average arc length (traversal time) than that without time windows, which suggests that imposing the time-window constraints generally increases both g_{ij} and h_{ij} of TSP-D solutions. Then, using the same logic as before (same as that used to derive the second theoretical implication above, i.e., the larger the g_{ij} and h_{ij}, the higher the benefit of using IPs), we may argue that the benefit of using IPs would be higher in networks that have many time-constrained deliveries than in networks that have no such deliveries.

5.4 | Extra stopping time

Equations (3) and (4) indicate that the smaller the value of S_{LR} (extra time needed to reach an IP), the larger the benefit of using IPs. This implies that we should avoid using IPs

that require trucks to deviate excessively from their assigned routes, which is intuitive. This also implies that networks with many such "costly" IPs can realize less benefit than those with very few such IPs.

It should be noted, however, that this fourth implication has a trivial meaning in this study as well as in the field. This is because the practitioners we interviewed stated that they do not use IPs that require a truck to deviate excessively from the assigned route, so that S_{LR}, for all IPs, includes only the time to travel a short "out of route" distance (often 3–5 m, see UPS (2017) and online Appendix C) and the time to slow down and accelerate the truck. This means that the value of S_{LR} generally does not vary across IPs within the same instance or across instances, that is, S_{LR} represents a constant that cannot explain the variance of benefits that exist across different networks. For this reason, we do not test this fourth implication in our computational experiments.

6 | METHODOLOGY

Although Equations (3) and (4) are derived from graph-theoretic analyses, the implications that stem from these equations merely represent "desk theories" unless they are shown to be consistent with empirical results. This suggests that the theoretical implications obtained in the previous section need to be tested empirically. This section discusses the methodology used in our empirical testing. It is worth noting that, during our practitioner interviews, we found that some practitioners viewed our theoretical implications as counter-intuitive, as they did not believe that the benefit of IPs would be affected by the network characteristics such as customer density and presence of time windows. This reinforces the importance of empirically testing the theoretical implications, which allows us to give correct knowledge to parcel delivery practitioners on when and where to use IPs.

6.1 | Basic approach

We investigate the economic benefits of using IPs by conducting a series of computational experiments. Although (ideally) the actual drone operating data obtained from the industry should be used to investigate the benefits, this was not possible because the use of autonomous drones is still in its experimental phase, and the actual field data are (to our best knowledge) not yet available.

Computational experiments are similar to empirical laboratory experiments, which attempt to cleanly isolate the relationship between variables, which is often difficult to do in real-world settings (Winecoff et al., 2021). It is often claimed that when actual data are not available or when field experiments cannot be conducted, computational experiments are appropriate for empirical studies (Castillo et al., 2022; Kelton, 2016; Muir et al., 2019). For this reason, computational experiments are widely used in empirical studies that test the concepts and technologies that are still in experimental phases, for which the data are not available yet (e.g.,

Agatz et al., 2018; Castillo et al., 2022; Dorling et al., 2016; Kuby & Lim, 2005; Murray & Chu, 2015; Suzuki & Dai, 2013; Suzuki et al., 2023; Wang & Lin, 2009).

6.2 | Overview of experiments

We carefully designed the experiments by soliciting expert opinions from practitioners. This approach not only allows us to obtain realistic results and implications but also increases the validity and credibility of research results (Castillo et al., 2022; Chandrasekaran et al., 2018; Gray et al., 2017). Our experiments generate many truck-and-drone routing instances randomly under a variety of conditions and compute two solutions for each instance, namely, the solution that uses IPs (new approach tested in this article) and the solution that does not use IPs (existing TSP-D approach). We then contrast the cost (total delivery time) of the two solutions across different instances to find out the conditions under which the use of IPs results in cost savings. This allows us to (1) understand if, when, where, and to what extent the use of IPs is beneficial for truck-and-drone operations (thereby answering our research questions empirically) and (2) judge whether the theoretical implications derived in the previous section would agree with our empirical results (thereby testing the consistency between theoretical and empirical results, which is important to establish the generalizability of our study findings).

Because our experiment requires solving the TSP-D with IPs, which currently does not exist in the literature, we developed such a model by creating a variant of the TSP with time windows, which we call the *traveling salesman problem with time windows, a drone, and intermediate points* (TSPTWD-IP). Given the difficulty involved in solving the TSPTWD-ID (it is an extension of the standard TSP, which is already NP-hard), we also developed a metaheuristic algorithm, a variant of the simulated annealing (SA), for this problem. Our algorithm can solve the TSPTWD-IP with up to 100 customers in reasonable CPU time (although an exact method based on the simplex algorithm and branch-and-bound method can also be used to solve the TSPTWD-IP, it requires long solution times except for small instances). We chose SA over other metaheuristics because SA is also used in practice (e.g., UPS) to solve parcel routing problems (UPS, 2017). Details of the TSPTWD-IP, along with those of our SA algorithm, are provided in online Appendices D and E. The two solutions that must be generated for each instance (with and without IPs) are obtained by applying this same model and algorithm, except that the number of IPs per arc is set at (or above) 1 when generating the former solution, whereas it is set at 0 when generating the latter solution.

6.3 | Experimental design

Experimental factors, the values of which define the operating environment under which a truck and a drone must operate, were carefully chosen. Specifically, we chose them vigilantly

TABLE 2 Factors and selected parameters of computational experiments.

Category	Values or ranges	Data source
Experimental factors		
Length of side (of a squared area)	[1.5, 5, 8] miles	A
Number of customers	[60, 80, 100]	B, interview
Number of intermediate points per arc	[0, 1, 2, 3]	Interview
Presence or absence of time windows	0 or 1	–
TSPTWD-IP parameters		
Percentage of customers eligible for drone delivery	80%	C
Percentage of customers in drone-restricted locations	10%	Interview
Percent of customers with time windows (if TW is present)	4%	B, interview
Ratio of time windows to total delivery time (if TW is present)	[20%–65%]	B
Distances traveled by truck	Manhattan distance	D
Distances traveled by drone	Euclidean distance	Interview
Average truck speed (serving time included)	12 mph	A, B
Average drone speed	40 mph	E
Time to launch or receive a drone	1 min	D
Maximum flying time of a drone	30 min	E
Time of a truck traversing out-of-route to operate a drone	0.1466 min	G, interview
Simulated annealing parameters		
Operator	2-opt	F
Initial temperature	Varies by instance	F
Cooling ratio	0.99	F
Ending temperature	1.0	SA test run
Level loop (iterations per temperature)	1000	SA test run
Penalty weight of time windows	1.0	SA test run
Penalty weight of maximum flying time	6.0	SA test run
Number of algorithm runs per instance	10	SA test run

Note: data source—A, Lammert and Walkowicz (2012); B, Don (2013); C, Guglielmo (2017); D, Murray and Chu (2015); E, Perez and Kolodny (2017); F, Xiao et al. (2012); G, Appendix C.

Abbreviations: SA, simulated annealing; TSPTWD-IP, traveling salesman problem with time windows, a drone, and intermediate points.

to ensure that, by adjusting them systematically during experiments, we can generate the types of networks that were described in our theoretical implications as those that would (or would not) benefit from using IPs. This allows us to empirically test our theoretical implications by examining if the networks for which IP cost savings are expected theoretically would actually generate cost savings in our experiments. We use a full factorial design of the following four factors (also see Table 2).

First is the service area size (length of the sides of a square area). Because the literature suggests that a parcel delivery service area typically ranges between 1.5 × 1.5 and 8 × 8 mi^2 (e.g., Lammert & Walkowicz, 2012), we vary the service area size in three levels within this range. Second is the number of customers. We vary this factor in three levels between 60 and 100, inclusive (this factor is capped at 100, following Don (2013)). Note that although the problem size with 100 customer nodes may not seem large, it indeed is quite large because in most networks certain nodes represent common delivery points of multiple customers (e.g., mail room of

an apartment complex or office building), so that an instance with 100 customer nodes can frequently involve over 150 package deliveries (Cortes & Suzuki, 2022). Our algorithm can also solve problems as large as 150 nodes, albeit with longer solution times. Third is the number of available IPs per arc. We vary this factor between 1 and 3, inclusive, based on the inputs obtained from practitioners. Fourth is the time-window constraint. This factor takes a 0/1 binary value such that it is 1 if the customers requesting delivery time windows are present, whereas it is 0 if such customers are absent (in the former case, we assume that about 4% of customers require time windows—see Table 2).

The above experimental design requires creating 3 × 3 × 3 × 2 = 54 different combinations of factor values (each such combination is denoted as a scenario). For each scenario, we generate and solve five instances. Characteristics of the instances, such as the locations of IPs in each arc, are determined randomly. Each instance is solved twice to obtain both the no-IP (standard TSP-D) and the TSPTWD-IP solution values, the ratio of which defines the benefit (cost saving)

of using IPs for the instance. Because our algorithm uses a stochastic search technique, we determine the cost of each solution by running the algorithm 10 times and calculating the average cost of feasible solutions. This means that in total, we generate $54 \times 5 = 270$ instances and perform $270 \times 2 \times 10 = 5400$ SA runs in our testing. We ran the experiments by using Julia (Bezanson et al., 2017) on a desktop PC with 32 GB of memory (Core i7 2.4 GHz quad-core).

6.4 | Parameters

Values of the parameters used in our experiments are reported in Table 2. Most parameter values are taken from the literature. In particular, we relied heavily on the following two sources: (1) the National Renewable Energy Laboratory (NREL) report, which was developed from an 18-month field testing of UPS delivery vans (Lammert & Walkowicz, 2012), and (2) Don (2013), which also reports the real field experiences of UPS deliveries. The parameters determined in this way include the percentage of customers with time-window constraints, the width of time windows, and the proportion of parcels suitable for drone deliveries (<5 lbs.). Other parameter values are derived from expert (practitioner) inputs. The parameters determined in this way include S_{LR} and the proportion of customers that cannot be served by a drone (located within zones where drone operations are forbidden). Most SA parameters are taken from the literature, although some SA parameters are determined based on the results of our test SA runs (see Table 2 for more details).

7 | RESULTS AND FINDINGS

7.1 | Validating solution method

Before presenting the experimental results, we first discuss the process we used to validate the TSPTWD-IP solution method. Because we use a metaheuristic (SA) to solve the problems generated in our experiments, it is crucial that we understand the degree of suboptimality induced by the use of our method (i.e., how the use of our method affects the quality of solutions). To this end, we performed a separate small-scale experiment in which the problem instances that were small enough to obtain optimal solutions within reasonable CPU time were generated and solved to compute the optimality gap. Following Lim et al. (2023), we generated 40 random instances (10 instances with 3–6 customer nodes) and solved each of them twice, once to optimality using a commercial simplex solver (Gurobi 8.1.1) and once to near-optimality using our algorithm.

Optimality gaps of our SA algorithm are reported in Table 3. The table shows that the gap ranges between 0% and 8.35%, with an overall average of 2.16%. These values are comparable to those reported in other TSP-D studies, which range between 0% and 14.07% (see the studies cited in our literature review). For completeness, we also performed the

t-test that compares the optimal and heuristic solutions (this test was performed for each problem size ranging from 3 to 6 customer nodes). Results showed that, in every test, the difference between the two methods was statistically insignificant (p-values ranged from 0.287 to 0.476), implying that the two methods are statistically indistinguishable. Given these results, the performance of our algorithm was deemed reasonable.

7.2 | Experimental results

Results of the experiments are summarized in Tables 4 and 5 and in Figure 3a–c. All results are reported in cost (delivery time) savings achieved by the TSPTWD-IP solutions over the "no-IP" (traditional TSP-D) solutions. Table 4 reports the time saving (in minutes) separately for each value of available IPs per arc (1, 2, 3), whereas Table 5 reports the time saving (in percentages) for each scenario tested in our experiments. Figure 3a–c reports the sensitivity of experimental results to the changes in the values of experimental factors. The most important findings are as follows.
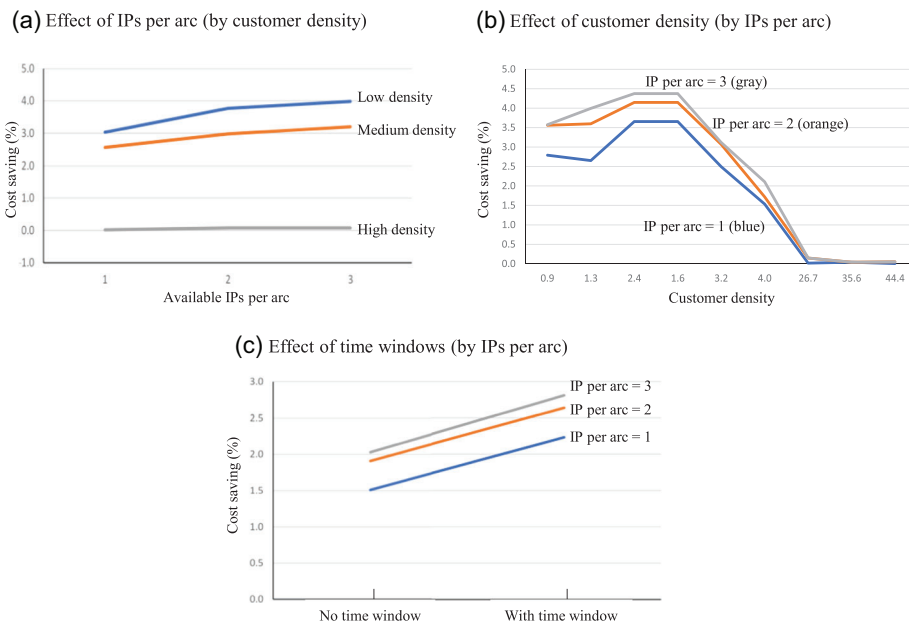
First, Table 4 shows that the cost saving attained by the TSPTWD-IP solutions over the traditional TSP-D solutions is significantly higher than zero for all values of available IPs per arc (with 99% statistical confidence). This means that the solutions that utilize IPs provide significant cost savings over the conventional no-IP solutions, regardless of the number of available IPs per arc. As such, our results suggest that when using a delivery truck and a drone jointly, utilizing IPs is generally beneficial for saving the time needed to complete a given set of parcel delivery tasks.

Second, Table 5 shows that, although the TSPTWD-IP solutions provide non-negative cost savings over the TSP-D solutions in all the 54 scenarios tested in our experiment, there are some cases where the cost savings were zeros. We see from the table that the use of IPs can save between 0% and 4.769% in total delivery time, with an overall average of 2.189%. This suggests that when operating a truck and a drone jointly, utilizing IPs may not always cut the time needed to complete a given set of delivery tasks. This finding is in line with our theoretical arguments made earlier that IPs have both advantages and disadvantages, so that they may not always give positive benefits.

Third, Figure 3a, which depicts the relationship between the cost saving and the number of available IPs per arc (by customer density), shows mixed results (note: although there are nine levels of customer density, we grouped them into three categories in this figure, namely, "low density," "medium density," and "high density"). The figure shows that: (1) For low and medium density areas, the cost saving increases slightly with the increase in the number of IPs per arc, which weakly suggests that the IP benefit may be an increasing function of the number of IPs per arc, but (2) for high density areas, the increase in the number of IPs per arc seems to have no impact on cost savings. Results of the statistical test, which assessed the impact that the number of

TABLE 3 Optimality gaps of the heuristic for small instances.

Customer nodes	Optimal sol. (min)	% Gap optimal vs. heuristic				
		Min (%)	25th (%)	Mean (%)	75th (%)	Max (%)
3	28.59	0.00	0.00	1.06	1.03	7.35
4	35.87	0.00	0.00	2.31	5.70	8.35
5	35.12	0.00	0.00	3.76	6.90	8.16
6	50.86	0.00	0.00	1.51	3.51	6.83
Average	37.61	0.00	0.00	2.16	4.29	7.67

(a) Effect of IPs per arc (by customer density)

(b) Effect of customer density (by IPs per arc)

(c) Effect of time windows (by IPs per arc)

FIGURE 3 Effect of experimental factors on cost saving (benefit).

TABLE 4 Delivery time (minutes) of traveling salesman problem with drones (TSP-D) versus *TSP with time windows, a drone, and intermediate points* (TSPTWD-IP).

	Difference (TSP-D less TSPTWD-IP)		
	Num. of IP = 1	Num. of IP = 2	Num. of IP = 3
Mean	5.652	6.822	7.316
Variance	41.048	58.366	66.868
Observations	90	90	90
t-Statistic	8.369	8.471	8.488
p-Value	0.000***	0.000***	0.000***

Note: statistical results indicate the results of matched-pair *t*-tests.
***Statistically significant at the 99% confidence level.

IPs has on cost savings, showed insignificant results (significant at the 95%, but not at the 99%, confidence level; details of this test are available in online Appendix F). This implies that, although increasing the number of IPs from 0 to 1 is generally beneficial (Table 4), increasing the available IPs further (beyond 1) may not bring additional benefits. This finding supports the first theoretical implication discussed earlier that while the benefit of IPs is higher in networks with many IPs per arc than those with few IPs per arc, the incremental benefit attained by the former over the latter is limited.

Fourth, Figure 3b shows that the customer density negatively affects the cost saving. The figure, which displays the relationship between the cost saving and the customer density, indicates that the benefit of using IPs decreases substantially as the density increases from 0.94 to 44.44 customers per square mile, regardless of the available IPs per arc. The figure shows that although the benefit (cost saving) may be unaffected by the growth of customer density when the growth is rather mild (from 0.9 to about 1.6), it decreases considerably after the density goes beyond 1.6, moving rapidly toward the near-zero saving once the density exceeds roughly 26 customers per square mile. Statistical test results, which assessed the impact that the customer density has on cost savings (online Appendix F), showed significant results (significant at the 99% confidence level). This finding, which agrees with the second theoretical implication derived earlier,

TABLE 5 Delivery time saving (%) of *traveling salesman problem with time windows, a drone, and intermediate points* (TSPTWD-IP) over TSP with drones (TSP-D).

	Number of customers	Side length	Customer density	Intermediate points per arc		
				IP = 1	IP = 2	IP = 3
No time windows	60	1.5	26.67	0.030	0.297	0.297
	60	5	2.40	3.166	3.611	4.008
	60	8	0.94	2.785	4.327	4.348
	80	1.5	35.56	0.000	0.000	0.000
	80	5	3.20	1.973	2.374	2.374
	80	8	1.25	2.476	2.964	3.220
	100	1.5	44.44	0.000	0.000	0.000
	100	5	4.00	0.000	0.000	0.007
	100	8	1.56	3.166	3.611	4.008
With time windows	60	1.5	26.67	0.000	0.000	0.000
	60	5	2.40	4.145	4.684	4.741
	60	8	0.94	2.794	2.794	2.802
	80	1.5	35.56	0.078	0.078	0.078
	80	5	3.20	3.014	3.764	3.864
	80	8	1.25	2.830	4.230	4.769
	100	1.5	44.44	0.010	0.100	0.100
	100	5	4.00	3.066	3.434	4.205
	100	8	1.56	4.145	4.684	4.741

Note: Customer density = (number of customers)/(side length)^2.

suggests that when customer nodes are close to each other, there is little merit of using IPs because, in such cases, we can always find a customer node that is reasonably close to the optimal DLR location.

Fifth, Figure 3c shows that the presence of time-window constraints positively affects the benefit of using IPs. The figure, which depicts the relationship between the cost saving and the imposition of time-window constraints, displays a strong relationship between the two factors, indicating that the cost saving is noticeably higher in areas where some packages require deliveries within specific time windows than in areas where no such packages exist, regardless of the number of available IPs per arc. Statistical test results, which assessed the impact that the time-window constraints have on cost savings (online Appendix F), showed significant results (significant at the 99% confidence level). This finding agrees with the third theoretical implication derived earlier.

8 | IMPLICATIONS

This study provides several normative implications that can help both researchers and practitioners understand the conditions under which the use of IPs is warranted, and the impacts that the use of IPs can have on the efficiency of truck-and-drone package delivery operations.

First, having more than one IP per arc may not improve operating efficiencies. Both our theoretical and empirical results suggest that, although having one IP per arc is beneficial, increasing the number of IPs further (beyond one) would not increase benefits significantly. This means that having many IPs per arc is not only unnecessary but also undesirable because adding more IPs to a problem would merely increase the problem complexity without adding much benefit. Because our theoretical analyses imply that the location of an IP(s) (where) is more important than the number of IPs per arc (how many), it is perhaps best to use only one IP in each arc that is located at the optimal position. In reality, however, finding the optimal IP location for each arc is difficult because, in each arc, there is no "generic" IP location that works best for every possible scenario. As such, it may be most practical to use only one IP per arc, the position of which is chosen at random. Our computational results suggest that using IPs in this way gives significant cost savings. Alternatively, if a carrier has an idea of where the optimal IP location might be for some arcs based on past experiences, they may wish to establish IPs at or near such (well-thought-out) locations.

Second, the benefit of using IPs may be higher in areas with low customer density than in areas with high customer density. Our results showed that when the customer density is low (i.e., the average arc length is large), creating an IP(s) in each of the long arcs gives considerable benefits. This

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implies that the merit of IPs is higher in low customer-density areas such as rural areas than in high customer-density areas such as urban areas. It also implies that the merit of IPs may be higher for carriers that are serving high customer-density areas but with a limited number of clients (e.g., a regional carrier serving urban regions with a small customer base) than those serving urban or non-urban areas with a large number of clients. Furthermore, it implies that during off-peak seasons when the number of packages delivered becomes small in each area (thereby reducing customer density), the merit of using IPs may become higher. Likewise, it implies that during rush hours, when the length (traversal time) of each arc becomes longer in some urban areas (thereby increasing the average arc length), the merit of using IPs may become higher. Practitioners may wish to start using IPs under these settings to ensure that they receive positive benefit from IPs.

Third, the benefit of using IPs may be affected positively by the presence of operational restrictions that forbid the implementation of the optimal (minimal delivery time) routes. Our results indicate that the imposition of time-window constraints, which often forbids the use of the optimal route (best route in the absence of time windows), would increase the benefit of using IPs. This means that carriers that handle many time-sensitive packages (e.g., mainly serving business customers) may benefit more from using IPs than those that do not handle such packages (mainly serving residential customers). From this finding, we may also conjecture that when a truck (or a drone) is required to perform both deliveries and pickups, it may increase the benefit of using IPs because this constraint often forces a vehicle to first deliver some packages before it performs pickups (to ensure that the vehicle is not overloaded), which may require the use of sub-optimal routes. Other types of operational constraints may also exist that increase the benefit of using IPs. It should be noted, however, that this does not mean the cost becomes lower in the presence of these constraints. Rather, it means that the *cost saving* becomes higher in the presence of such constraints.

9 | CONCLUSIONS AND FUTURE RESEARCH

Autonomous drone technology is no longer science fiction but is becoming reality. It is likely that this technology will be used by parcel carriers to improve operational efficiencies in the near future. Given this outlook, now is the time for parcel carriers to learn how this technology can be utilized in the most effective way to meet the rapidly increasing home delivery needs. This study offers a valuable foundation for future research on this topic by introducing the concept of intermediate points (IPs) as drones' launch/recovery points, and studying if, when, where, and to what extent the use of IPs can be beneficial for drone operations both theoretically and empirically.

This study showed that the use of IPs can be an effective concept for parcel carriers that operate an autonomous drone in conjunction with a delivery truck. Our results suggest that

if using the proposed model (that uses IPs) in lieu of the existing model (that does not use IPs), the cost (delivery time) of package deliveries can be reduced by up to 4.769%, with an average reduction of 2.189%. Because it is known that a reduction of 1 mi per truck per day (roughly equivalent to 1%–2% saving in delivery time) for large parcel carriers such as UPS leads to an annual saving of about $50 million (UPS, 2016), the use of IPs may save tens of millions of dollars for such carriers.

Our results, however, also indicated that IPs have both advantages and disadvantages, so that they do not always provide positive cost savings, and that the amount of attainable cost saving can vary considerably among carriers depending on their network characteristics. Our results, for example, showed that the benefit of IPs becomes zero when a network possesses certain characteristics. This finding is in line with the notion already known in the logistics literature that the cost of operating vehicles in a network is highly dependent on network characteristics (e.g., Ballou & Agarwal, 1988; Bell & Griffis, 2010). This means that parcel carriers need to be careful when deciding when and where to use IPs, as using IPs in improper operating conditions may generate trivial or no cost savings at all. Carriers may wish to use the results and implications reported in this article as a set of practical guidelines when determining if, when, and where to utilize IPs.

This study has its limitations. First, the mathematical model developed for this study (TSPTWD-IP) is complex and difficult to solve. For this reason, we had to use a metaheuristic (SA) to solve the problem, which was perhaps a reasonable approach given the goal of this article (understanding economic benefits of using IPs). However, because it has now been shown that using IPs can be a useful concept, a better (simpler) way(s) of formulating and solving the TSPTWD-IP may be needed that can serve as a practical decision tool. Future studies may explore this issue.

Second, our theoretical implications are derived given the assumptions specified in Table 1, which means that they are only as good as the assumptions we made. Although we believe that our assumptions are reasonable, as they are verified by practitioners, one or more of them could be violated in certain cases, which may invalidate some implications. Future research may wish to investigate the robustness of our theoretical implications to the violation(s) of these assumptions.

Third, our study findings are obtained by conducting computational experiments, not by analyzing real-world data. Although we believe that the use of computational experiments was appropriate for this study given the lack of actual data, future research may nevertheless wish to examine the robustness of our study findings by either (1) repeating the study using the real-world industry data (should such data become available) or (2) applying the TSPTWD-IP model in the field (if possible). This should improve the generalizability of the findings reported in this article.

Fourth, our TSPTWD-IP minimized the return time of a truck, with a drone, to the depot. Although this is the standard objective function used in the literature, an alternative

approach may also be used that minimizes the cost of operating both a truck and a drone. Because it is interesting to examine if and when the solution obtained by minimizing the operating cost differs from that obtained by minimizing the return time (traditional approach), future studies may wish to explore this issue by developing and solving a TSPTWD-IP variant that minimizes the operating cost.

Fifth, we assumed that a truck can carry only one drone with (1) a relatively short range (30 min at 40 mph) and (2) a relatively small capacity (one package weighing 5 lbs. or less). With the rapid advancements in drone technologies observed lately, these assumptions, which are similar to those adapted by many other drone studies, may need to be relaxed in the near future. If we assume that multiple drones can be carried by a truck, multiple packages can be delivered by a drone at a time, and/or longer distance can be flown by a drone per flight, we would have larger feasible regions, which may help improve the solution quality. Though relaxing these assumptions requires formulating a new and more complex problem, developing and solving such a problem would be an interesting extension of this study and a promising direction for future research.

Sixth, we studied a single route (truck-and-drone joint route) problem by using a variant of the TSP formulation. That is, we studied the problem in which the assignment of packages to a truck, with a drone, is already determined. Although we believe that this was a proper focus, given that this was the first study to consider IPs within the context of TSP-D, it is certainly an interesting extension of this study to consider the problem of assigning packages to trucks. This approach, however, requires solving the assignment and routing problems jointly (as we must consider the impact that the assignment solution would have on the quality of routing solutions), which means that we must employ the VRP, rather than the TSP, framework. Although this approach increases the problem's complexity, it may also give significant practical values. Thus, future studies may wish to consider formulating and solving the VRP version of the TSPTWD-IP introduced in this article.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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