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Optimizing Drone Operations for Middle-mile Deliveries: Are We Ready for Real-World Deployment?

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Abstract

The use of drones for freight delivery has been extensively investigated in the context of last-mile logistics, with existing literature underlining potential benefits across several dimensions, from economic efficiency to reductions in CO_2 emissions. However, it is not clear if these advantages also extend to longer routes and apply to middle-mile delivery (MMD). By relying on real-world data on freight transported between distribution and sorting centers of one of Italy's major freight operators and proposing an optimization model dealing with drone location and flight scheduling, this study evaluates the operational feasibility of using drones for MMD. We consider three different variants of the model —namely, maximization of freight transported, maximization of the ground movements replaced by drones, and minimization of overall CO_2 emissions— to evaluate the applicability of drones based on different objective functions. The results reveal that, while the current technical characteristics of drones are not yet sufficient to fully replace ground-based freight movements, they already offer opportunities for integration in specific segments. By applying the proposed model to a real-world MMD network in Central Italy, we found that drones can handle up to 31.6% of the total daily package demand, contributing to a reduction of up to 3.5% in current emission levels. These findings provide a preliminary instrument for operators and policymakers, highlighting the potential role of drones as a complementary solution within MMD, while also emphasizing the need for continued technological and regulatory advancements to fully realize their potential.

Keywords: Middle-mile; drones; UAV; Urban air mobility

1. Introduction

The use of drones, or unmanned aerial vehicles (UAVs), in logistics has attracted growing interest in recent literature, with several studies highlighting both the challenges and potential impacts of their deployment (e.g., Garg et al., 2023; Jazairy et al., 2024; Masorgo et al., 2024).

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This is particularly verified in the context of last-mile delivery (LMD)–defined as the delivery of packages from a distribution center to the end consumer (Jazairy et al., 2024; Masorgo et al., 2024). Numerous contributions have explored the role of drones in LMD, reporting potential advantages across multiple dimensions. These include (*i*) reduced delivery times (Rejeb et al., 2023; Jazairy et al., 2024; Murray and Chu, 2015; Zhao et al., 2022), (*ii*) cost efficiency (Filiopoulou et al., 2025; Garg et al., 2023; Lemardelé et al., 2021; Rejeb et al., 2023; Jazairy et al., 2024), (*iii*) increased flexibility (Rejeb et al., 2023; Murray and Chu, 2015; Jazairy et al., 2024), (*iv*) improved sustainability—often measured in terms of CO_2 emission reductions (Garg et al., 2023; Rejeb et al., 2023; Jazairy et al., 2024)—and (*v*) enhanced customer accessibility, whether for emergency logistics or deliveries to remote areas (Rejeb et al., 2023; Garg et al., 2023; Jazairy et al., 2024). These findings align with broader global trends and challenges, including the rapid growth of e-commerce, the push for more sustainable logistics solutions, and the pursuit of improved time and cost efficiency (Boysen et al., 2021).

Another important dimension of LMD research involves the characterization of stakeholders. In general, two key actors are identified: senders (e.g., service providers) and receivers (e.g., consumers) (Jazairy et al., 2024; Masorgo et al., 2024). These stakeholders often have overlapping yet distinct objectives: while senders prioritize cost reduction and optimized routing, receivers tend to place greater emphasis on timely deliveries and accessibility (Jazairy et al., 2024).

But what happens when we move beyond LMD to longer routes? Do these dynamics still apply to middle-mile delivery (MMD)? From the standpoint of emerging trends and operational challenges, many similarities exist. However, in terms of stakeholder involvement, MMD implies a transition from a business-to-consumer (B2C) to a business-to-business (B2B) framework, where the sender and receiver are often part of the same organizational system. This shift raises new questions about which objectives should be prioritized. Despite the extensive body of literature on LMD, research on the use of drones in MMD remains relatively scarce. To the best of our knowledge, only a limited number of studies have explored this area (Gunady et al., 2022; Petit and Ribeiro, 2025; Purtell et al., 2025).

Petit and Ribeiro (2025) approach the problem from an operational standpoint, developing a multi-objective optimization model for the placement of vertiports in a drone-based MMD system. The model accounts for capacity constraints, land availability, safety, and noise impacts.

Purtell et al. (2025) involve 33 industry executives to explore the financial drivers, future prospects, and challenges of drone integration in MMD. They identify two major opportunities: first, drones can address logistical complexities in remote or infrastructure-limited areas; second, MMD drone implementation fosters collaboration between industry, research, and policy, particularly in navigating regulatory challenges and technological limitations. Finally, Gunady et al. (2022) investigate electric Vertical Takeoff and Landing (eVTOL) aircraft as a better alternative to drones for MMD, proposing a methodology to simulate package demand and modal choice in urban air mobility scenarios.

Within this research stream, our study aims to propose an essential and generalized strategic-level optimization model and contributes to the literature by providing evidence on the evolving readiness of drones for real-world deployment in middle-mile logistics. Specifically, we develop three strategic-level optimization variants to assess drone applicability by maximizing: (*i*) freight transported, (*ii*) ground-based movements replaced by drones, and (*iii*) CO_2 emissions avoided. These models are applied to real-world data from a case study in Central Italy to quantify the potential benefits of drone integration into MMD.

The remainder of this work is structured as follows. Section 2 introduces the three model formulations. Section 3 details the empirical setup, including the case study and underlying assumptions. Section 4 presents the main findings, and Section 5 provides some conclusive remarks.

2. Modeling framework

2.1. Problem setting

In this Section, we discuss the model setting and its main assumptions. The model addresses drone location and flight schedule decisions for a single freight operator with the aim of maximizing the use of drones to replace current ground-based MMD operations. In a nutshell, given a defined fleet size w and the set of potential flights $\mathcal{F}$ between different distribution or sorting centers ($d \in \mathcal{D}$), the key decision of the model is represented by variables x_f, representing the number of drones allocated to operate the specific flight f. We include as an additional output of the model the initial location of drones (w_d), indicating the number of drones based at each distribution or sorting center at the beginning of the prototypical day of operation considered. While the model optimizes drone location and flight schedule, it is intended for strategic rather than tactical or operational purposes, aiming to evaluate the suitability of drones for deployment over such distances typical of middle-mile operations.

Different variants of the model can be formulated to investigate the resulting flight configurations based on various objective functions:

- **Maximization of freight transported** ($\mathcal{M}_1$): This objective involves solving the model to maximize the weight of freight transported using drones.
- **Maximization of substituted ground movements** ($\mathcal{M}_2$): This objective involves solving the model to identify the optimal drone use that maximizes the number of ground movements replaced by drone flights.
- **Minimization of CO_2 emissions** ($\mathcal{M}_3$): This entails solving the model under an explicit CO_2 minimization objective, by considering both the CO_2 emissions from recharging drones and the emissions avoided due to the substitution of ground movements.

2.2. Model formulation

From a technical standpoint, the optimization models are formulated as mixed-integer programming problems developed taking into account state-of-the-art developments in the field of airline flight scheduling (e.g., Birolini et al., 2021) and application of eVTOLs and drones for MMD (Gunady et al., 2022). In the following, we formulate the optimization models mathematically.

Maximization of freight transported ($\mathcal{M}_1$)

We first introduce the basic freight-maximization optimization model ($\mathcal{M}_1$).

$$O_1 = \max \sum_{f \in \mathcal{F}} y_f \tag{1}$$

$$\text{s.t.} \quad y_f \le x_f \vartheta_f \qquad \forall f \in \mathcal{F} \tag{2}$$

$$\sum_{f \in \mathcal{F}_{mp}} y_f \le \varphi_{mp} \qquad \forall m \in \mathcal{M}, \forall p \in \mathcal{P} \tag{3}$$

$$\sum_{d \in \mathcal{D}} w_d = \bar{w} \tag{4}$$

$$\sum_{f \in \mathcal{I}_d} x_f = \sum_{f \in \mathcal{O}_d} x_f \qquad \forall d \in \mathcal{D} \tag{5}$$

$$w_d + \sum_{f \in \mathcal{I}_{dt}} x_f \ge \sum_{f \in \mathcal{O}_{dt}} x_f \qquad \forall d \in \mathcal{D}, \forall t \in \mathcal{T} \tag{6}$$

The objective function (1) maximizes the freight transported using drones (y_f). Constraints (2) enforce capacity constraints under which freight transported on each flight does not exceed allocated capacity, in turn depending on the number of drones operating the specific flight (x_f) and the maximum payload for operating f (ϑ_f). Constraints (3) ensure that the freight transported in market m and time period p by drones does not exceed its as-is (observed) package demand. Constraint (4) enforces fleet count, that is, the sum of drones allocated to single distribution/sorting centers at the beginning of the day is equal to the given fleet size ($\bar{w}$). Constraints (5)-(6) are basic network constraints that ensure flow balance and resource availability, respectively. Constraints (5) force the number of outbound flights and inbound flights at any distribution/sorting center to be equal, while constraints (6) ensure the availability of drones at each distribution/sorting center at each event (i.e., drone departure).

Maximization of substituted ground movements ($\mathcal{M}_2$)

After introducing the basic model maximizing freight transported by drones, we next formulate its variant focused on maximizing the number of ground movements replaced. The formulation of $\mathcal{M}_2$ requires a set of additional variables (z_g), assuming value 1 if the ground movement g has been replaced by drones, and 0 otherwise.

Considering these variables, the model maximizes the number of as-is ground movements replaced through expression 7. Besides constraints included in $\mathcal{M}_1$ (constraints 2-6), $\mathcal{M}_2$ also requires constraints 9 that ensure that only ground movements whose freight is transported by drones are considered as replaced. The model $\mathcal{M}_2$ can be formulated mathematically as follows:

$$O_2 = \max \sum_{g \in \mathcal{G}} z_g \tag{7}$$

$$\text{s.t.} \quad \text{Constraints (2)-(6)} \tag{8}$$

$$\sum_{f \in \mathcal{F}_{mp}} y_f \geq \sum_{g \in \mathcal{G}_{mp}} z_g q_g \qquad \forall m \in \mathcal{M}, \forall p \in \mathcal{P} \tag{9}$$

Minimization of CO_2 emissions ($\mathcal{M}_3$)

Model $\mathcal{M}_3$ solves the problem considering an explicit CO_2 minimization objective. To do so, two additional sets of parameters are required: the CO_2 emissions generated to operate each ground movement (ψ_g) and those from operating flight f using a drone. Since drones do not emit CO_2 emissions during operation, we consider emissions required to generate the electricity consumed by drones to operate each flight (ψ_f). Considering these parameters, $\mathcal{M}_3$ assumes the following formulation:

$$O_3 = \min \sum_{g \in \mathcal{G}} (1 - z_g)\psi_g + \sum_{f \in \mathcal{F}} x_f \psi_f \tag{10}$$

$$\text{s.t.} \quad \text{Constraints (2)-(6)} \tag{11}$$

$$\text{Constraints (9)} \tag{12}$$

3. Experimental setup

3.1. Application

The proposed models are applied to a real-world case study based on the network in Central Italy operated by one of the largest middle-mile logistics providers. The analysis is based on freight movement data from a prototypical weekday in March 2023, selected to reflect typical operations and average daily package volumes.[1] According to the actual operating model of the freight operator considered, we divided the day into two time slots for freight delivery: morning deliveries (to be completed by 1 p.m.) and afternoon deliveries (scheduled after 1 p.m.). The network layout is shown in Figure 1 and related summary statistics are reported in Table 1.

The network consists of 3 sorting centers and 60 distribution centers, generating a total of 257 daily ground movements. Its structure resembles a hub-and-spoke model, with sorting centers acting as hubs and distribution centers as spokes. This is reflected in the flow patterns (see Table 1): the majority of movements (52.6%) are from sorting to distribution centers, accounting for an average of 373 kg per trip over an average great-circle-distance of 42 km, and representing about 65% (approximately 50 tons) of the total daily volume. In contrast, return flows are limited,

[1] While this deterministic demand does not capture the stochastic demand variability inherent in middle-mile operations, we argue that such an approach is appropriate given the strategic purpose of the model, which is designed to evaluate the potential applicability of drones to a middle-mile setting rather than investigating specific operational conditions.

accounting only for 16.7% of movements and 6.6% of total volume. The overall average distance and weight —43 km and 303 kg, respectively— are relatively high and in line with MMD standards. These values have to be compared with the technical specifications of the utilized drones, described in the following subsection.

Based on the current network structure and package flow pattern, we define the potential set of flights ($\mathcal{F}$). In this study, we restrict $\mathcal{F}$ to include all pairs of sorting and distribution centers for which package demand is observed on the prototypical day under consideration.[2]

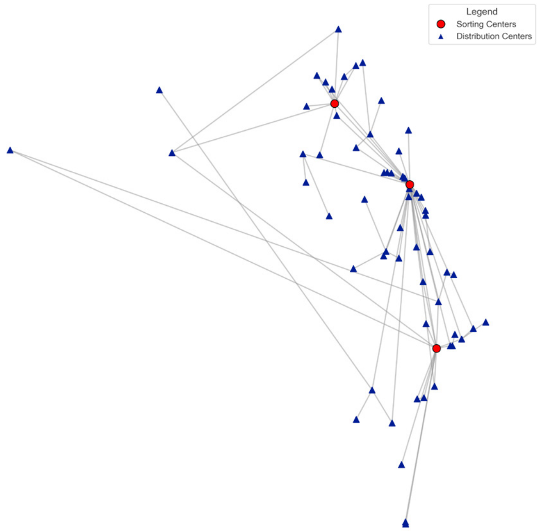


Fig. 1: Middle-mile delivery network

Total movements (% over total)			
From / To	Sorting Center	Distribution Center	Total
Sorting Center	19 (7.4%)	135 (52.6%)	154 (59.9%)
Distribution Center	43 (16.7%)	60 (23.3%)	103 (40.1%)
Total	62 (24.1%)	195 (75.9%)	257 (100.0%)
Daily cumulative great-circle-distance covered in km (per movement)			
From / To	Sorting Center	Distribution Center	Total
Sorting Center	1,932 (101.7)	5,617 (41.6)	7,549 (49.0)
Distribution Center	2,259 (52.5)	1,181 (19.7)	3,440 (33.4)
Total	4,191 (67.6)	6,798 (34.9)	10,989 (42.8)
Daily freight volume in kg (per movement)			
From / To	Sorting Center	Distribution Center	Total
Sorting Center	8,995 (473.4)	50,307 (372.6)	59,302 (385.1)
Distribution Center	5,155 (119.9)	13,389 (223.1)	18,543 (180.0)
Total	14,150 (228.2)	63,696 (326.6)	77,845 (302.9)

Table 1: Descriptive statistics on nr. of movements, distance covered, and volume by node type

3.2. Assumptions

To practically implement the proposed optimization models, besides data on the middle-mile network and daily package demand, specific assumptions and data are required. These primarily include technical characteristics of drones and their operational procedures and regulations. For the experimental setup, technical characteristics are based on the Flying Basket FB3 drone, an unmanned multicopter with 8 rotors powered by rechargeable batteries, which has an operating range of 25 km, a maximum payload of 100 kg, and a maximum operating speed of 25 m/s. We consider this drone as it is a readily available solution and, despite the limited performance in terms of flight range with respect to other models, has a relatively high payload capacity, which makes it optimal to be used for MMD. Naturally, as the weight transported increases, the drone operating range decreases. Accordingly, to feed our optimization model, we calibrated an empirical function estimating the maximum payload for any flight (ϑ_f) as a sole function of the distance to cover (d_f). The resulting function, estimated based on data available on the FB3 technical factsheet, is as follows: $\vartheta_f = max(0, 103.63 - 3.8986 d_f)$.

In addition to the clear operational limitations imposed by drone technology being in its infancy, the current regulation further constrains the performance of cargo drones. Specifically, the Italian regulation mandates that the drone must be able to return to its origin and land safely if it is unable to land at its destination, for example, due to adverse weather conditions. This stringent requirement *de facto* halves the operational performance of drones by imposing that only half of the available battery capacity can be used for each flight. We consider such regulation by modifying the maximum operating distance and adjusting the payload empirical function accordingly.

[2] While a more distributed network with (partially) point-to-point connections or fragmented links involving intermediate steps could increase the applicability of drones, such configurations would also introduce greater complexity in managing drone corridors and could lead to a less efficient use of the drone fleet. For these reasons, we prefer to stick to the current network configuration. Nevertheless, exploring the potential impacts of network restructuring remains a promising direction for future research.

Table 2: Summary of the results for the different optimization models and various fleet sizes (number of drones).

Nr. drones	Freight diverted (kg)			Ground movements replaced			Saved CO_2 emissions		
	$\mathcal{M}_1$	$\mathcal{M}_2$	$\mathcal{M}_3$	$\mathcal{M}_1$	$\mathcal{M}_2$	$\mathcal{M}_3$	$\mathcal{M}_1$	$\mathcal{M}_2$	$\mathcal{M}_3$
10	10.1%	6.4%	6.5%	6.2%	12.8%	12.8%	0.7%	1.8%	1.9%
50	26.8%	22.6%	18.6%	17.1%	20.2%	18.3%	2.3%	2.8%	2.9%
90	31.5%	30.3%	31.2%	21.8%	23.3%	22.6%	3.2%	3.4%	3.4%
110	31.6%	31.6%	31.6%	22.6%	23.3%	23.3%	3.4%	3.5%	3.5%
150	31.6%	31.6%	31.2%	23.3%	23.3%	23.0%	3.5%	3.5%	3.5%
Maximum achievable		31.6%			23.3%			3.5%	

The last assumption needed concerns the turnaround time of a drone landing at a vertiport for dropping off its payload and recharging or swapping batteries. Given that only half of the battery's capacity can be used for each flight (due to the current regulation), we assume a fixed turnaround time of 30 min.

4. Results

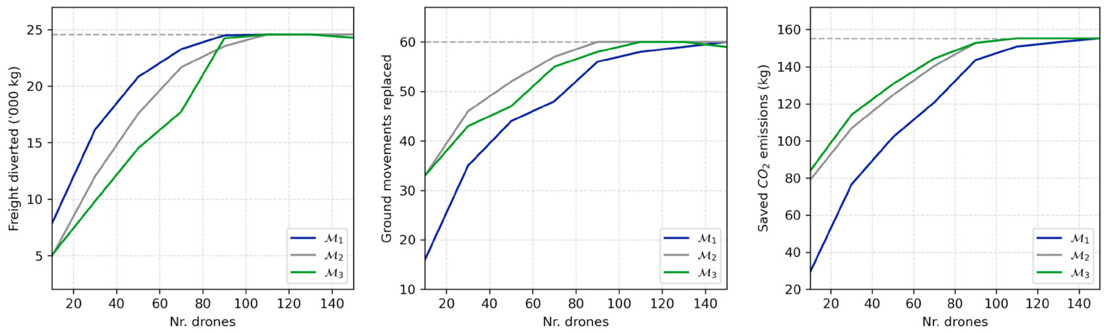
This Section presents the results obtained by applying the proposed operational model to the real-world case study on the Central Italy middle-mile network. Due to the relatively simple structure of the network, which reflects current technological constraints on drone range and payload capacity, all instances reach small optimality gaps (i.e., below 0.5%) with low computational time (i.e., lower than 60 seconds). Table 2 details the outcomes of the optimization models under various objectives ($\mathcal{M}_1$, $\mathcal{M}_2$, and $\mathcal{M}_3$) and by considering different fleet sizes, ranging from 10 to 150 drones. The table reports a set of KPIs describing the solutions returned by the models: the volume of freight transported by drones (kg), the number of ground movements replaced, and the reduction in CO_2 emissions. All values are expressed as percentages relative to the total values of the modeled network. Figure 2 illustrates the trends of these KPIs (in absolute terms) as fleet size increases.

Looking at the base model $\mathcal{M}_1$, we observe that the volume of freight transported by drones increases with fleet size, ranging from 7,852 kg (10.1% of the total) with 10 drones to approximately 24,598 kg (31.6%) with a fleet of 150. By considering $\mathcal{M}_2$, consistent with the model's objective, we observe a prioritization of substituting ground movements over the overall amount of freight transported by drones. Specifically, 12.8% of the ground movements are replaced in $\mathcal{M}_2$ (vs. 6.2% in $\mathcal{M}_1$), albeit with a lower amount of freight transported (6.4% vs. 10.1%). Lastly, model $\mathcal{M}_3$ prioritizes the reduction of CO_2 emissions over the number of ground movements replaced, thus considering both the distance avoided and the amount of freight diverted. This approach likely favors replacing trips operated by older, more polluting vehicles, which typically transport heavier payloads. Under this objective, current emissions can be reduced by approximately 1.9% with a fleet of 10 drones, increasing to 3.5% with 110 drones. While the various models yield different outcomes at smaller fleet sizes—each aligned with its respective objective—their results tend to converge as the fleet size increases (see Figure 2).

Table 2 also reports the upper bound of the KPIs that can be achieved by considering the analyzed network and current technical performance of drones. Notably, around 32% of the total daily package demand can be transported by drones, and approximately 23% of current ground movements can be fully replaced. These results indicate that, while drones can already serve a relevant share of the MMD network, a substantial portion remains challenging to reach due to current technical and regulatory constraints. As a result, the potential reduction in CO_2 emissions is limited to a maximum of 3.5% of the total. These findings are consistent with previous studies that highlight both the opportunities and the current limitations of drone integration in MMD (Petit and Ribeiro, 2025).

5. Conclusions

Based on the application of the proposed operational models to the network in Central Italy operated by one of the largest middle-mile logistics providers, we derived some insights regarding the potential applicability of cargo drones in MMD. First, we observe that the current technological and regulatory constraints limit the portion of middle-mile



(a) Freight transported (b) Ground movements replaced (c) Saved CO_2 emissions

Fig. 2: KPI for the different optimization models for various fleet sizes (number of drones).

freight flows that can be handled by drones. In the analyzed network, about one-third of the total daily package demand can be transported by drones, with a maximum substitution of ground movements reaching 23.3%. Additionally, the environmental benefits —measured by potential CO_2 emission reductions— remain modest, reaching 3.5% of current emission levels. Second, despite some peculiarities, the application of the operational model with different objectives yields consistent results and similar trends. For instance, model $\mathcal{M}_3$ prioritizes the replacement of movements currently operated by older and more polluting vehicles. Conversely, model $\mathcal{M}_2$ focuses on maximizing the number of trips substituted, regardless of the associated emissions or the volume of cargo transported by drones. As fleet size increases, so do the benefits in terms of freight volume, ground movements replaced, and saved emissions. However, beyond 50 to 70 drones, the marginal benefits sharply decrease. This remarks that technical constraints (primarily limited operating range) and regulatory barriers are the key factors that challenge the scalability of drone deployment in middle-mile logistics.

Given the characteristics of MMD networks compared to LMD —namely, longer distances, but also larger and more stable volumes, and the use of standardized corridors between routing and distribution centers— this paper provides a valuable tool to evaluate the potential of utilizing drones in MMD, demonstrating its applicability through a real-world case study. Different stakeholders can benefit from our model and the derived results. First, freight operators can use it as a foundation to evaluate the trade-offs between the costs of implementing drone technology and the potential savings associated with the proportion of ground movements replaced. At the same time, regulators can rely on this model to quantify the impact of easing existing requirements—such as reserve battery provisions—that currently limit drones' operational range and, consequently, their wider applicability. From a welfare perspective, the model also enables the examination of broader trade-offs, balancing the benefits to freight operators with potential reductions in CO_2 emissions.

This work is not without limitations, which open avenues for future research. First, we modeled the network structure to be operated by drones based on the current hub-and-spoke structure. Future studies could explore the potential to redesign the existing network, possibly incorporating a point-to-point configuration with intermediate stops that may better align with drones' technical capabilities. Second, while we evaluated the readiness for real-world deployment of drones from an operational and technical standpoint, future research endeavors could extend the analysis to include economic aspects, such as operating costs.

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Nomenclature

Sets and parameters.

$\mathcal{D}$: set of distribution or sorting centers indexed by d
$\mathcal{F}$: set of flight arcs indexed by f
$\mathcal{G}$: set of as-is ground movements indexed by g
$\mathcal{M}$: set of markets (distribution/sorting center pairs) indexed by m
$\mathcal{P}$: set of time periods indexed by p
$\mathcal{F}_{mp}$: set of flights serving market m in time period p
$\mathcal{G}_{mp}$: set of as-is ground movements serving market m in time period p
$\mathcal{T}$: set of time events (i.e., drone arrivals and departures)
$\mathcal{O}_d$: set of outbound flights from distribution/sorting center d
$\mathcal{O}_{dt}$: set of outbound flights from distribution/sorting center d before time t
$\mathcal{I}_d$: set of inbound flights from distribution/sorting center d
$\mathcal{I}_{dt}$: set of inbound flights from distribution/sorting center d before time t
ϑ_f : maximum payload of flight f
q_g : freight transported on as-is ground movement g
$\varphi_{mp} = \sum_{g \in \mathcal{G}_{mp}} q_g$: total demand on market m and time period p
ψ_g : CO_2 emissions generated to operate ground movement g
ψ_f : CO_2 emissions generated to operate flight f using a drone
$\bar{w}$: maximum number of drones (fleet size)

Variables.

$x_f \in \mathbb{N}^+$: number of drones assigned to operate flight f
$y_f \in \mathbb{R}_0^+$: freight transported by drones operating flight f
$z_g \in \{0, 1\}$: assuming value 1 if the ground movement g is replaced by drones, and 0 otherwise
$w_d \in \mathbb{N}^+$: number of drones available at distribution/sorting center d at the beginning of the day