

Article

Drone-Assisted Last-Mile Delivery Under Windy Conditions: Zero Pollution Solutions

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Highlights:**What are the main findings?**

- Drone deliveries under windy conditions are viable and lead to improved efficiency and reduced air and noise pollution compared to traditional delivery methods.
- Noise pollution requires further study to incorporate dynamic, spatiotemporal-oriented factors, including meteorological conditions, to better mitigate its impact on urban environments.

What are the implications of the main findings?

- Integrating drones in last-mile delivery can help cities meet zero pollution goals, particularly for reducing air pollution.
- Integrated approaches addressing both environmental and social factors, particularly noise pollution, are essential for sustainable drone delivery ecosystems.

Abstract: As cities expand and the global push for zero pollution intensifies, sustainable last-mile delivery (LMD) systems are essential to minimizing environmental and health impacts. This study addresses the need for more sustainable LMD by examining the integration of wind conditions into drone-assisted deliveries, focusing on their effects on air and noise pollution in urban areas. We extend the flying sidekick traveling salesman problem (FSTSP) by incorporating meteorological factors, specifically wind, to assess drone delivery efficiency in varying conditions. Our results show that while drones significantly reduce greenhouse gas emissions compared to traditional delivery vehicles, their contribution to noise pollution remains a concern. This research highlights the environmental advantages of using drones, particularly in reducing CO₂ emissions, while also emphasizing the need for further investigation into mitigating their noise impact. By evaluating the trade-offs between air and noise pollution, this study provides insights into developing more sustainable, health-conscious delivery models that contribute to smart city initiatives. The findings inform policy, urban planning, and logistics strategies aimed at achieving zero pollution goals and improving urban livability.

Keywords: drone; unmanned aerial vehicle (UAV); last-mile delivery; traveling salesman problem with drone; wind; noise pollution; CO₂ emissions



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1. Introduction

Last-mile delivery (LMD) is crucial in city logistics, representing the final step in delivering goods from distribution centers to consumers. As cities grow and urbanization continues worldwide, increased density leads to higher traffic and demand. Consequently, LMD routes become significant contributors to pollutant emissions and noise, which have immediate health impacts, particularly in densely populated urban environments. This urgency aligns with global efforts to reach net zero pollution, as highlighted by international plans [1,2]. The EU's Zero Pollution Action Plan, for instance, aims for a 55%

cut in premature deaths from air pollution and a 30% reduction in people heavily impacted by transport noise by 2030 [3], emphasizing the role of LMD in these environmental goals.

Greenhouse gas (GHG) emissions from transportation, including LMD operations, significantly contribute to air pollution [4]. The transition towards net zero LMD solutions is essential to mitigate these impacts. Technologies such as electric vehicles and drones powered by renewable energy sources provide promising alternatives by reducing or eliminating emissions [5]. Many companies are seeking new ways to deliver goods rapidly, cost-effectively, and with less polluting technologies in the last mile. Drones are gaining prominence as effective delivery vehicles for LMD due to their speed, flight capabilities, autonomous operation, and reduced energy consumption and emissions [6–8].

Traffic noise is a major cause of noise pollution, with adverse effects on cardiovascular health, mental well-being, and sleep extensively documented [9–11]. Despite the significant contribution of LMD to noise pollution, this area remains under-researched. Studies have shown that delivery vehicles significantly contribute to urban noise levels [12,13]. Electric vehicles have been identified as a viable solution to reduce noise compared to diesel trucks [14,15]. However, there is a scarcity of research directly addressing noise in delivery problems, as indicated by a Scopus search revealing only two relevant studies [16,17]. Addressing noise pollution is crucial for social sustainability, as it directly impacts human health, quality of life, and well-being. Reducing exposure to harmful noise levels allows people to live under better conditions. This gap in research highlights the need for more focused studies on how innovative LMD solutions, like drone deliveries, may mitigate noise pollution. While drone deliveries reduce both road traffic and the noise caused by road vehicles, they introduce new noise sources that require further study and regulation. Current research on drone noise pollution underscores its potential adverse effects on human health [18,19]. Although drones offer operational efficiency, they still add to noise pollution, posing risks to human health and well-being. There is a need to assess whether drone assisted delivery noise is comparable to or less than that of traditional delivery related traffic noise, considering the logarithmic nature of noise propagation.

As the demand for efficient and sustainable delivery solutions grows, drones have emerged as a promising option for LMD, either operating independently or in collaboration with traditional delivery vehicles. The literature on drone routing problems can be primarily classified into two categories [20–23]: synchronized models, where trucks and drones collaborate to perform deliveries, and drone-only models, where drones independently handle deliveries. This study focuses specifically on a synchronized model known as the flying sidekick traveling salesman problem (FSTSP), which is an extension of the traveling salesman problem (TSP) involving the routing of a delivery truck in collaboration with one or more drones to distribute parcels [24,25]. Current reviews in drone delivery studies highlight future research topics considering factors such as weather conditions [7,26–29], environmental impacts [20,21] including noise pollution [7,30], the utilization of real-world data [20,21,26,29], and the adoption of methods yielding precise solutions [20,27]. Following these recommendations, the proposed model in this study aims to consider wind conditions in planning the routes in a one truck one drone real world setting and assess the impact of drone assisted deliveries in terms of air and noise pollution.

Drone-assisted deliveries offer a viable solution for optimizing last-mile delivery routes; however, their widespread adoption depends on effectively addressing the environmental and social impacts they generate. Therefore, drone-assisted delivery models must prioritize strategies aimed at mitigating noise levels and reducing air pollution to align with broader sustainability objectives. This study aims to investigate how drone deliveries affect air and noise pollution even in windy conditions, aiming to advance sustainable last-mile delivery practices. By analyzing the interactions between environmental, social, and economic factors, we aim to offer insights that guide the development of effective drone-assisted delivery models.

The proposed model is applied to the case of urgent pharmacy deliveries and the results are compared to traditional delivery methods in terms of time, cost, energy con-

sumption, and air and noise pollution. Our results indicate that drone-assisted deliveries even in windy conditions significantly reduce delivery times and energy consumption. Additionally, they achieve substantial cost savings and lower CO₂ emissions compared to truck-only methods, highlighting significant environmental benefits. Static noise levels remain similar with and without drone assistance, however drones are reported to contribute to increased perceived annoyance [31]. This research underscores the potential of drone assisted deliveries to improve efficiency, sustainability and noise mitigation, while also addressing the need for more comprehensive noise impact analysis to ensure a balanced approach to sustainability in drone-assisted delivery systems.

This study's contributions are summarized as follows:

- The study evaluates the impact of drone-assisted deliveries on air and noise pollution, offering insights into environmental as well as social effects.
- The study extends the FSTSP by incorporating wind effects for more realistic delivery modeling.
- The study compares truck-only and truck–drone delivery methods, demonstrating that the truck–drone combination improves efficiency and sustainability even under windy conditions.
- The study addresses the need to consider noise pollution in delivery operations to enhance urban livability and promote sustainable last-mile practices.
- The study identifies research gaps in dynamic noise modeling and the integration of meteorological factors into delivery planning.

The remainder of this article is structured as follows: Section 2 reviews the existing literature on wind-aware drone route planning, identifying research gaps and opportunities in sustainable LMD. Section 3 outlines a model for optimizing delivery time in drone-assisted delivery under windy conditions, with analysis of emissions and noise. Section 4 applies the model to pharmaceutical deliveries. Section 5 presents analysis findings, focusing on noise levels and emissions from drone operations. Finally, Section 6 provides conclusions and recommendations for future research to enhance LMD sustainability in urban environments.

2. Literature Review

There is increasing interest in achieving efficiency and sustainability in LMD operations in the broader effort to promote environmental sustainability and meet zero pollution goals. Among them, routing problems involving drones have garnered substantial attention due to their potential to enhance efficiency and reduce operational costs and carbon footprint. This section delves into research trends associated with drone routing problems, with particular interest in wind conditions.

Drone delivery routing problems can be primarily classified into two categories: synchronized models and drone-only models [20–23]. This study adopts the classification presented by [20], where the traveling salesman problem with drones (TSP-D) and vehicle routing problem with drones (VRP-D) are synchronized models and the delivery problem with drones (DDP) are drone-only models. Following the future research suggestions outlined in the recent literature on drone-assisted deliveries, there is a need to address weather conditions and environmental impacts, including noise pollution, while utilizing methods that yield precise solutions with real-world data [7,20,26–30]. Recent research has begun to address these factors individually, but a comprehensive strategy remains a fertile ground for exploration. This paper aims to contribute to this emerging field by examining the interplay between these factors (i.e., wind, air pollution, and noise pollution) and assessing the efficiency and viability of drone deliveries in diverse environmental conditions.

The review of the literature considering the effect of wind in drone route planning is summarized in Table 1. The majority of research (eight from a total of twelve papers) is on drone-only deliveries (DDP). DDPs are either modeled as a routing problem where the drone leaves the depot with multiple loads and services multiple customers along the route [32–36] or as a pickup and delivery problem in which the drone makes indi-

vidual trips to service customers, departing from and returning to a central depot each time [37–40]. The studies vary in their objective functions: some prioritize minimizing the total travel time [32,33,35–37,40], while others optimize order fulfillment [34,38,39]. Studies on synchronized drone models (TSP-D and VRP-D) considering wind fall into two categories. One category prioritizes minimizing energy consumption and analyzing the impact of various parameters through simulation [41,42]. The other focuses on developing efficient algorithms to minimize total travel time [43,44]. However, all reviewed studies largely neglect the issue of emissions (air pollution), either omitting it entirely or mentioning only potential benefits in passing and none mention noise pollution. Overall, while these studies offer valuable insights into optimizing drone route planning under windy conditions, they fall short in addressing the need to integrate environmental and social considerations into drone routing models to develop more sustainable and efficient solutions.

Table 1. Studies that consider the effect of wind on drone delivery.

Article	Type	Objective Function	Approach	Reduced Emissions (Air and Noise)
[35]	DDP	Minimizing total travel time	Lin–Kerninghan algorithm	Not mentioned
[41]	TSP-D	Minimizing total energy consumption	Simulation	Not mentioned
[37]	DDP	Minimizing total travel time	Genetic algorithm	Not mentioned
[36]	DDP	Minimizing total travel time	Heuristic algorithm	Not mentioned
[42]	TSP-D	Minimizing total energy consumption	Heuristic algorithm and simulation	Assumes that minimizing energy needs would reduce GHG emissions; no direct emission calculation
[38]	DDP	Optimizing the order fulfillment rate within a given time frame	Dynamic programming	Mentions presumed benefits; no concrete analysis
[32]	DDP	Minimizing total travel time	Dynamic programming	Mentions presumed benefits; no concrete analysis
[39]	DDP	Optimizing the order fulfillment rate	Robust optimization	Not mentioned
[43]	TSP-D	Minimizing total travel time	Metaheuristic algorithms	Not mentioned
[34]	DDP	Maximizing total profit: (profit = order fulfillment revenue – energy cost)	Column generation-based and path enumeration algorithms	Not mentioned
[44]	VRP-D	Minimizing total travel time and balancing order fulfillment rates	Hybrid heuristic algorithm	Not mentioned
[33]	DDP	Minimizing total travel time	Integer quadratic programming and integer cubic programming	Not mentioned
[40]	DDP	Minimizing total travel time	Hybrid heuristic algorithm	Mentions presumed benefits; no concrete analysis
This study	TSP-D	Minimizing total travel time	Exact method	Detailed analysis highlighting the potential for drone delivery to reduce costs, GHG emissions, and noise pollution

The aim of this study is to address a gap in drone delivery research by focusing on the environmental and social impacts, particularly air and noise pollution, of time-optimized routes in the FSTSP model. Unlike previous studies that primarily emphasize minimizing travel time, this research introduces a novel approach by integrating wind conditions and then analyzing the associated pollution effects. To the best of our knowledge, no previous study has simultaneously considered air and noise pollution impacts in the analysis of time-minimized routes. By comparing truck-only deliveries with drone-assisted operations, this research offers critical insights into how drone delivery can contribute to reducing air and noise pollution, fostering a more sustainable and responsible delivery ecosystem.

3. TSP-DW: Traveling Salesman Problem Considering Wind

A variant of the FSTSP is introduced in this study: the traveling salesman problem considering wind (TSP-DW). In the FSTSP [24], a truck and a drone collaborate to visit each customer exactly once. They depart from a single depot together or simultaneously, service the customers, and return to the same depot. Some customers are visited by the drone, while others are serviced by the truck, with the drone being carried by the truck while they travel together. The goal of the FSTSP is to minimize the resources (e.g., travel time) required for the truck–drone system to serve all customers and return to the depot considering potential waiting times because of the synchronization of the truck and drone [24].

The TSP-DW builds upon the exact method for the TSP-D presented by [45] but incorporates the additional factor of wind impact on drones. The same model and algorithm are used for both the TSP-DW and TSP-D, with the key difference being the inclusion of wind in the solution procedure. The calculations consider the wind's influence on the direction and speed of the drone, independent of its endurance constraints. After finding the optimal route, air pollution and noise pollution along with costs are evaluated.

The fundamental mathematical model used in this study is presented below. Tables 2 and 3 present the assumptions and definitions of the model.

Table 2. Assumptions of the TSP-DW model.

Assumptions
A single truck equipped with a single drone is available at the depot.
All customers must be served by either the truck, the drone, or a combination of both.
Each customer can be served solely by the truck, solely by the drone, or by both the truck and the drone together.
Traffic congestion is not considered.
The truck's speed remains constant, and instantaneous changes in the truck's speed are not taken into account.
The drone's speed remains constant, and instantaneous changes in the drone's speed are not taken into account.
The drone has a limited capacity and can serve at most one customer alone before returning to the truck to start another service.
The drone can land and take off only at customer locations or the depot and cannot land and take off at the same node.
The drone can land at the combined node while waiting for the truck, so its flight time is equal to its travel time.
The drone's landing and takeoff dynamics (including energy consumption) are ignored.
The drone does not adjust for any elevation changes and moves at a constant altitude, assuming no obstacles.
Changes in the drone's battery charge level are not considered; the drone's battery is sufficient for the entire journey (outbound and return trip).
Fluctuations in drone speed due to the drone's load are ignored.
The weather forecast is known with sufficient accuracy, and constant weather conditions exist in terms of the speed and direction of the wind within the planned routing time frame.
Wind speed and direction affect the ground speed of the drone but have no effect on the truck.

Table 3. Notations for the TSP-DW model.

Notations	Description
Sets	
G	$G = (V, A)$: A complete directed graph defined by the sets V and A .
V	$V = \{0, 0'\} \cup N$: Set of vertices (nodes). Both 0 and 0' represent a single depot and N represents the set of n customers to be served.
A	$A = \{(0, j) \mid j \in N\} \cup \{(i, j) \mid i, j \in N: i \neq j\} \cup \{(i, 0') \mid i \in N\}$: Set of arcs, including: $\{(0, j) \mid j \in N\}$: Arcs from the depot (0) to each customer (j), $\{(i, j) \mid i, j \in N: i \neq j\}$: Arcs between customers (i and j), where $i \neq j$, $\{(i, 0') \mid i \in N\}$: Arcs from each customer (i) to the depot (0').
Parameters	
t_{ij}^T	Travel time of the truck from node i to node j (time to travel arc (i, j))
t_{ij}^D	Travel time of the drone from node i to node j (time to travel arc (i, j))
d_{ij}^T	Road distance between node i and node j for truck
d_{ij}^D	Air-flight distance between node i and node j for drone
$v_{g,ij}$	Ground speed of the drone between node i and node j
v_T	Speed of the truck
Variables	
$x_{ij}^T \in \{0, 1\}$	1 if the truck travels arc (i, j) , 0 otherwise
$x_{ij}^D \in \{0, 1\}$	1 if the drone travels arc (i, j) , 0 otherwise
$y_i^T \in \{0, 1\}$	1 if customer i is a truck customer, 0 otherwise
$y_i^D \in \{0, 1\}$	1 if customer i is a drone customer, 0 otherwise
$y_i^C \in \{0, 1\}$	1 if customer i is a combined customer, 0 otherwise.
$a_i \in \mathbf{R}^+$	Arrival time of the truck or drone or both at node i .

$$t^* = \min a_0 \quad (1a)$$

$$\sum_{(i,j) \in A} x_{ij}^T = \sum_{(j,i) \in A} x_{ji}^T \quad i \in N \quad (1b)$$

$$\sum_{(i,j) \in A} x_{ij}^T = y_i^T + y_i^C \quad i \in N \quad (1c)$$

$$\sum_{(0,j) \in A} x_{0j}^T = \sum_{(i,0) \in A} x_{i0}^T = 1 \quad (1d)$$

$$\sum_{(i,j) \in A} x_{ij}^D = \sum_{(j,i) \in A} x_{ji}^D \quad i \in N \quad (1e)$$

$$\sum_{(i,j) \in A} x_{ij}^D = y_i^D + y_i^C \quad i \in N \quad (1f)$$

$$\sum_{(0,j) \in A} x_{0j}^D = \sum_{(i,0) \in A} x_{i0}^D = 1 \quad (1g)$$

$$y_i^T + y_i^D + y_i^C = 1 \quad i \in N \quad (1h)$$

$$a_i + t_{ij}^T \leq a_j + M(1 - x_{ij}^T) \quad (i, j) \in A \quad (1i)$$

$$a_i + t_{ij}^D \leq a_j + M(1 - x_{ij}^D) \quad (i, j) \in A \quad (1j)$$

$$x_{ij}^D + x_{ji}^D \leq y_i^C + y_j^C \quad i, j \in N : i < j \quad (1k)$$

$$x_{0i}^D + x_{i0}^D \leq 1 \quad i \in N \quad (1l)$$

$$x_{ij}^T, x_{ij}^D \in \{0, 1\} \quad (i, j) \in A \quad (1m)$$

$$y_i^T, y_i^D, y_i^C \in \{0, 1\} \quad i \in N \quad (1n)$$

$$a_i \in \mathbf{R}^+ \quad i \in V \quad (1o)$$

$$\sum_{(i,j) \in A} t_{ij}^T x_{ij}^T \leq a_0 \quad (1p)$$

$$\sum_{(i,j) \in A} t_{ij}^D x_{ij}^D \leq a_0 \quad (1q)$$

The objective function (1a) aims to minimize the total tour duration required to serve all customers. Constraint (1b) is the flow conservation constraint for the truck. Constraint (1c) links the truck arc variable to the truck customer variable. Constraint (1d) ensures that the truck departs from and returns to the depot exactly once. Constraint (1e) is the flow

conservation constraint for the drone. Constraint (1f) links the drone arc variable to the drone customer variable. Constraint (1g) ensures that the drone departs from and returns to the depot exactly once. Constraint (1h) ensures that each customer is visited at least once. Constraints (1i) and (1j) are subtour elimination constraints and also represent the arrival time of the truck or drone at each node. Constraint (1k) ensures that if the truck visits customers i and j , then the drone can move from customer i to customer j , and ensures that there is at most one drone customer between any pair of truck customers. Constraint (1l) prevents the drone from creating a cycle starting and ending at the same customer after departing from the depot. Constraints (1m)–(1o) model the non-negativity constraints (the range of the decision variables). The computational time to solve a TSP-DW can be significantly decreased by adding constraints (1p) and (1q) that limit tour duration by the maximum travel times of truck and drone separately.

3.1. Consideration of the Wind Factor

Similar to the reviewed studies on drone-assisted deliveries considering wind, we incorporated the impact of wind on drone movement, where the drone's ground speed varies based on both wind direction and magnitude [34,36,44]. The calculations consider the drone's air speed, the orientation of the drone in the arc (i, j) , wind direction, and wind speed (magnitude) but exclude any movement perpendicular to the ground. Wind directions in this study are based on data from the Turkish State Meteorological Service (TSMS), where wind angles blowing from south, west, north, and east correspond to 0° , 90° , 180° , and 270° , respectively. Figure 1 shows the change in the ground speed of the drone due to wind.

The following formulation is employed to compute the drone's ground speed (v_g).

$\vec{v}_a$: The air speed vector, the speed and orientation of the drone in the air, is known.

$\vec{v}_w$: The wind speed vector, the distance the wind travels per unit time with respect to the ground, with the wind angle, is known.

$\vec{v}_g$: The ground speed vector is the velocity of the projection of the drone on the Earth under the effect of the wind during flight.

α : The angle from the north to the ground speed vector.

β : The angle between the wind speed vector and the vertical axis is known; e.g., for northerly wind $\beta = 180^\circ$.

φ : The angle from the north to the air speed vector. Calculated using the formula $\Phi = \alpha + \theta$.

δ : The angle between the wind speed vector and the ground speed vector. Calculated using the formula $\delta = \alpha - (180 + \beta)$.

θ : The wind correction angle; it is the angle between the ground speed vector and the air speed vector (calculated using the formula $\theta = \arcsin((\vec{v}_w/\vec{v}_a) \times \sin \delta)$).

When wind direction and wind speed are known and constant and the air speed of the drone is known, the ground speed, v_g , can be calculated as follows:

$$v_g = \sqrt{\left(\left(\vec{v}_a\right)^2 + \left(\vec{v}_w\right)^2 - \left(2\vec{v}_a\vec{v}_w\cos(\varphi - \beta)\right)\right)} \quad (2)$$

For all arcs (i, j) , the ground speed $v_{g,ij}$ of the drone is calculated for any given wind direction and wind speed using Equation (2). The direct air-flight distance between nodes i and j is divided by its corresponding ground speed value to obtain the travel time of the drone from node i to node j using Equation (3):

$$t_{ij}^D = d_{ij}^D / v_{g,ij} \quad (3)$$

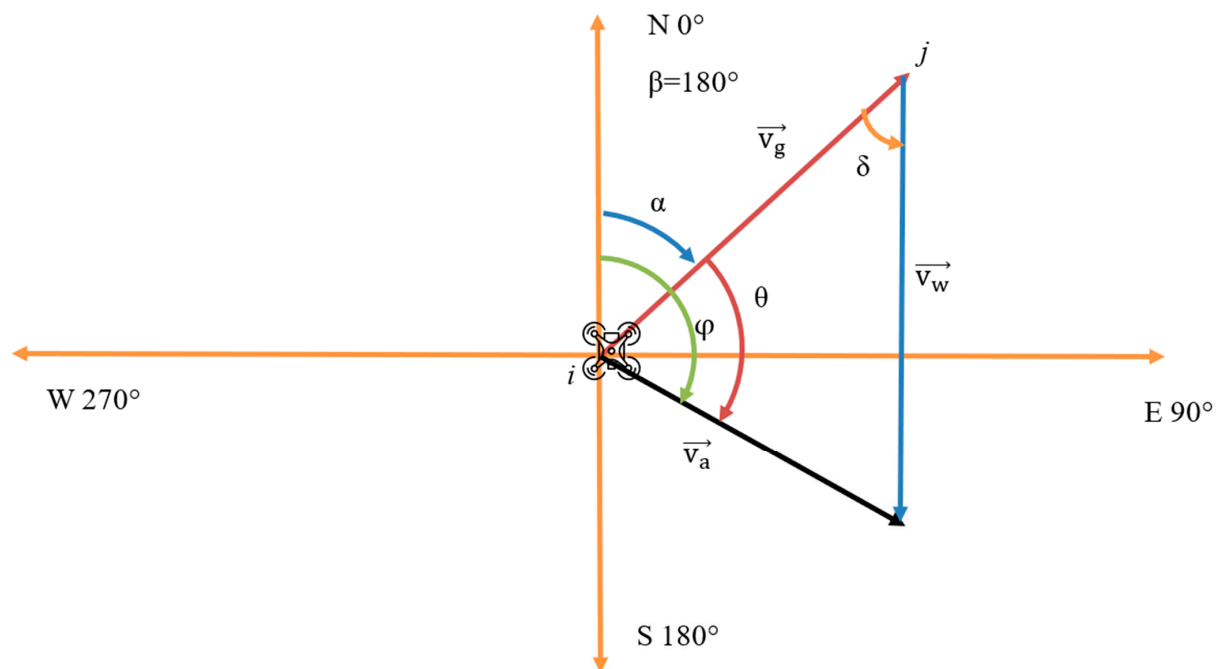


Figure 1. The relationship between air speed, ground speed, and wind speed while the drone travels to the arc (i, j) and the wind blowing from the north.

According to the Beaufort wind scale (Table 4), wind intensities equal to or smaller than 5 were considered. The reason for limiting the scale to these values is that wind speeds greater than Scale 5 do not provide suitable weather conditions for drone operations. The impact of Scale 0 on drone speed is negligible for $\vec{v}_g = \vec{v}_a$.

Table 4. Winds on the Beaufort scale; data from the TSMS [46].

Scale	Wind Speed (m/s)	Description
0	0.0–0.2	Calm—No wind
1	0.3–1.5	Light Air
2	1.6–3.3	Light Breeze
3	3.4–5.4	Gentle Breeze
4	5.5–7.9	Moderate Breeze
5	8.0–10.7	Fresh Breeze
6	10.8–13.8	Strong Breeze—Not suitable for drone operations

3.2. Consideration of the Air Pollution Factor

When incorporating air pollution into our analysis, we used GHG emissions as a proxy. GHG emission factors are integrated into the evaluation of the optimized results, with the assumption that energy consumption and emissions are proportional to the distance traveled. The GHG emissions of a route taken by electrical vehicles (i.e., electrical vans and drones) also depend on the emissions intensity of the regional electricity grid. For each vehicle type (e.g., diesel van, electric van, and drone), the energy consumed (E_{route}), emissions emitted (GHG_{route}), and energy-relevant costs (C_{route}) are calculated using Equations (4)–(6).

$$E_{route} = E_T \sum_{(i,j) \in A} d_{ij}^T x_{ij}^T + E_D \sum_{(i,j) \in A} d_{ij}^D x_{ij}^D \quad (4)$$

$$GHG_{route} = GHG_T \sum_{(i,j) \in A} d_{ij}^T x_{ij}^T + GHG_D \sum_{(i,j) \in A} d_{ij}^D x_{ij}^D \quad (5)$$

$$C_{route} = C_T \sum_{(i,j) \in A} d_{ij}^T x_{ij}^T + C_D \sum_{(i,j) \in A} d_{ij}^D x_{ij}^D \quad (6)$$

E_{route} is the total energy consumption (MJ) of the route where E_T and E_D are the truck and drone energy consumption constants (MJ/km), respectively. Similarly, GHG_{route} is the total emissions (g) of the route and GHG_T and GHG_D are the emission constants (g/km) of the truck and drone, respectively. In the same manner, the cost of the route, C_{route} , is calculated using the cost per km for the truck, C_T , and the drone, C_D .

3.3. Consideration of the Noise Pollution Factor

To evaluate and predict noise pollution, we employed traffic noise models, which assess noise levels based on vehicle, traffic, and road characteristics. Road noise prediction models are widely employed to evaluate noise levels and implement control measures or pinpoint problem areas in various urban zones [12,47,48]. There are numerous established models for road vehicles, such as FHWA for the United States, CNOSSOS-EU for the European Union, and CoRTN for the United Kingdom. However, there is a lack of standardized regulations for measuring and evaluating drone noise emissions globally. While the FAA sets individual standards for drone models [49], EU regulations seek to harmonize noise considerations within the EU [50]. As of now, there is no explicit extension of the EU Environmental Noise Directive [51] to encompass drones, despite its primary focus on addressing noise pollution from road, rail, and airport traffic, as well as large industrial installations, with the aim of safeguarding public health.

While existing studies on noise pollution have primarily focused on road vehicles or drones separately, this research presents a novel approach by considering the combined noise emissions from both vehicle types in a truck–drone delivery system. To incorporate noise pollution factors into the analysis, we employed the CNOSSOS-EU framework for road vehicles [52,53] and studies on drone noise emissions [18,54,55] and EU regulations [50] for drones as a basis. We calculated the combined noise level from both road and drone traffic using the energetic sum of the van and drone noise levels. This approach is supported by [31], who found that although drone noise increases annoyance, its overall impact is limited when road traffic noise is also present.

For the road vehicle, CNOSSOS-EU considers two main noise sources, rolling noise due to tyre–road interaction and the propulsion noise produced by the driveline (engine, exhaust, etc.) of the vehicle. For light, medium and heavy motor vehicles, the sound power level ($L_{W,i,m}(v_m)$), corresponds to the energetic summation of the rolling ($L_{WR,i,m}$) and propulsion ($L_{WP,i,m}$) noise given in Equations (7)–(9). Coefficients A and B are dependent on vehicle category m and frequency band i . The CNOSSOS-EU model [53] does not define the coefficients for electric vehicle noise emission; thus, the coefficients for category $m = 5$ of CNOSSOS-EU defined by [56] were used. These equations and coefficients are valid under reference conditions in terms of meteorology and traffic. In our calculations, these reference conditions are accepted as is, with correction terms ΔL set to 0. The reference speed v_{ref} is 70 km/h. For detailed explanation of the calculations, the reader is referred to [52]. The A-weighted sound level, ($L_{Aeq,m}$) given in Equation (10) in decibels A (dBA), is obtained by summing levels in each frequency band i [57].

$$L_{W,i,m}(v_m) = 10 \times \lg \left(10^{\frac{L_{WR,i,m}(v_m)}{10}} + 10^{\frac{L_{WP,i,m}(v_m)}{10}} \right) \quad (7)$$

$$L_{WR,i,m} = A_{R,i,m} + B_{R,i,m} \times \lg \left(\frac{v_m}{v_{ref}} \right) + \Delta L_{WR,i,m}(v_m) \quad (8)$$

$$L_{WP,i,m} = A_{P,i,m} + B_{P,i,m} \times \lg \left(\frac{v_m - v_{ref}}{v_{ref}} \right) + \Delta L_{WP,i,m}(v_m) \quad (9)$$

$$L_{Aeq,m} = 10 \times \lg \sum_i 10^{L_{W,i,m}(v_m)} \quad (10)$$

For the drone, the sound power level is assumed to correspond to the maximum allowable noise level (MNL) of the drone, which is calculated based on the maximum take-off weight (MTOM) as specified in Equation (11) [50]. Notably, this calculated value exceeds the observed levels of drone noise reported in recent studies [18,54,55]. Given the absence of a universally accepted metric for noise emission modeling, we opted to use the higher calculated value to ensure a conservative approach in our assessments. Since the drone acts as a point source and flies at an altitude of r_2 while the observer is located at point r_1 , the sound pressure level of the drone varies inversely with the square of the distance between the drone and the observer [57]. Consequently, the sound level of the drone at the street level, L_D , is determined by the relationship outlined in Equation (12).

$$MNL = 85 + 18.5 \times \lg\left(\frac{MTOM}{0.9}\right) \quad (11)$$

$$L_D = MNL - 10 \times \lg\left(\frac{r_2}{r_1}\right)^2 \quad (12)$$

The combined noise level from both road and drone traffic is calculated using the energetic sum of the van and drone noise levels.

The noise levels considered in this study are based on a source-centric model, focusing on noise directly generated by delivery vehicles. However, optimizing delivery routes with a focus on noise impact would benefit from a more comprehensive analysis that spans both spatial and temporal dimensions [17,58]. For example, in urban areas where delivery routes pass through, affected population density, building façades, exact path taken, and duration of the route, as well as meteorological factors such as temperature and the wind, significantly influence the overall noise impact. Although these variables were not incorporated into the current analysis, future research could extend this work by adopting a spatiotemporal approach to better capture the dynamic nature of combined noise impact.

4. Pharmaceutical Delivery Case

The application addresses the daily urgent pharmaceutical deliveries from a central warehouse to local pharmacies. In the dynamic environment of pharmaceutical distribution, the ability to handle urgent deliveries efficiently and sustainably is critical, particularly in densely populated urban areas such as the Ümraniye district of Istanbul. Given the unpredictable nature of urgent pharmaceutical needs, our application model accommodates multiple pharmacies requiring immediate attention within a specified time window. The delivery process is divided into four distinct time windows throughout the day, with each window allowing the delivery vehicle approximately two hours to complete its route and return to the warehouse for the next cycle. Each delivery operation, termed a drop-off cycle, encompasses the time from when the delivery vehicle stops and parcels are retrieved and delivered to pharmacies to when the vehicle resumes its route. This cycle is estimated to take an average of 6 min and is considered constant for all delivery operations. The remaining time of the delivery, defined as the distribution time, is the total travel time of the route by the vehicle, which can accommodate up to 13 pharmacies. Thus, our focus lies in optimizing the distribution time across the 13 randomly selected pharmacies using the TSP-DW. Our model incorporates wind data to enhance route optimization. The instances use combinations of 13 randomly selected pharmacies from the 160 pharmacies in Ümraniye district. Since the pharmacies are relatively close to each other, the distribution process involves short-range trips between locations; which justifies the infinite drone endurance assumption. A sample set of the warehouse and pharmacy locations can be seen in Figure 2.

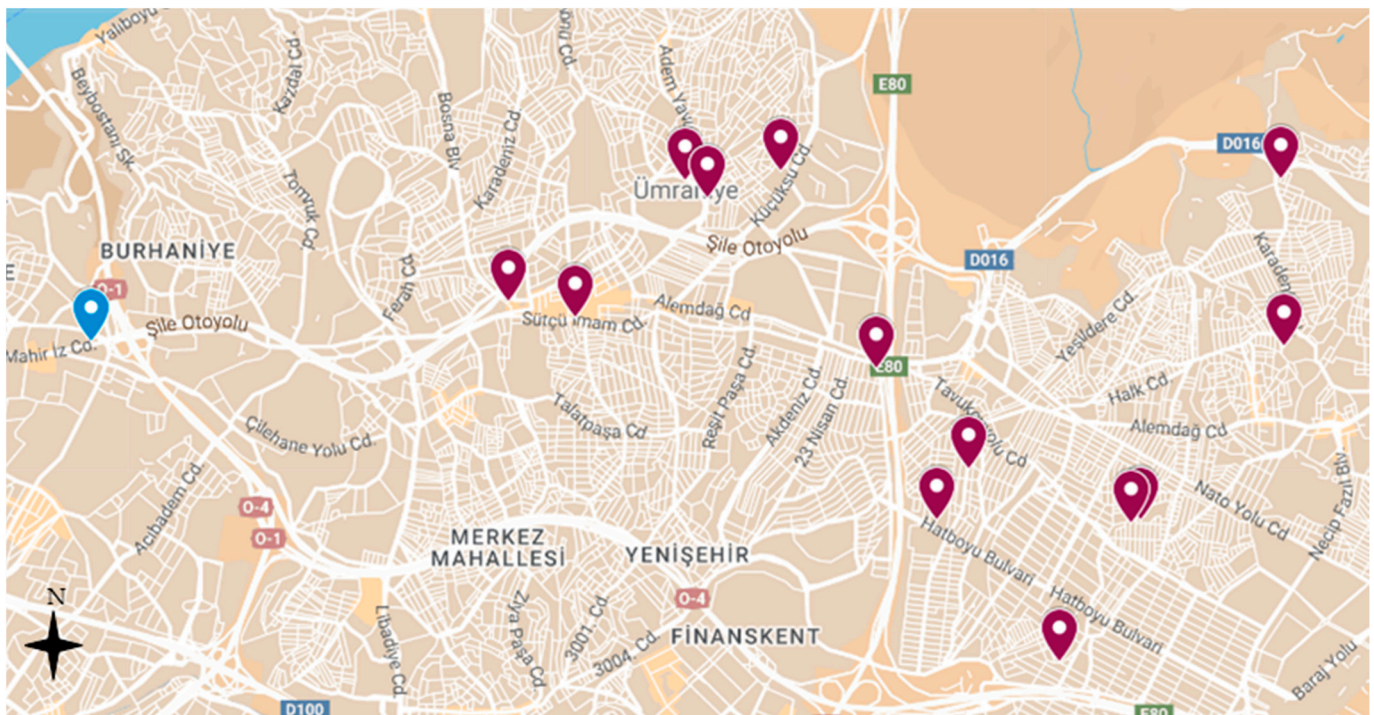


Figure 2. Locations of the warehouse (in blue) and sample pharmacies (in red).

Road distances for trucks (d_{ij}^T) were derived from data provided by Google Maps, while air-flight distances for the drone (d_{ij}^D) were calculated using the Haversine formula based on geographical coordinates from Google Maps. Consistent with prior work and commercial drone specifications, the truck's average speed (v_T) is assumed to be 40 km/h, and the drone's average air speed (v_a) is assumed to be 60 km/h. The wind is factored into the calculation of the ground speed of the drone ($v_{g,ij}$). Using these distance and speed values, travel times for the truck (t_{ij}^T) and the drone (t_{ij}^D) for all arcs are computed and used as input values for the model.

Istanbul experiences near-constant winds, with wind present 85% of the time at or above Scale 1, according to long-term data from the TSMS [59]. Table 5 summarizes the annual distribution of wind speeds and directions in Istanbul as a percentage of time throughout the year. To capture realistic wind scenarios, we considered the wind directions and speeds that are consistently high and observed at least 25% of the time, as indicated in bold in Table 5. Based on these prevailing wind conditions, we calculated the respective ground speed of the drone ($v_{g,ij}$) using Equation (2). In our calculations, we assumed the upper limits of each Beaufort Scale category (e.g., for Scale 4, we used 7.9 m/s to represent the range of 5.5–7.9 m/s).

When generating problem instances, pharmacy locations are sampled from all pharmacies in the district. All model assumptions are also applicable to the application. For all 30 instances, the proposed TSP-DW is solved using CPLEX version 22.1.1. via IBM ILOG CPLEX Optimization Studio. The hardware platform is a notebook with an Intel(R) Core(TM) i5-8250U CPU @ 1.60 GHz, 8.00 GB RAM running Windows 10 Operating System.

To facilitate a comprehensive comparison, each instance is solved using three models: (1) truck-only delivery (TSP); (2) a truck–drone combination without wind (TSP-D); and (3) a truck–drone combination with wind (TSP-DW). In analyzing the experimental results, we consider two types of vehicles—diesel and electric small vans—and a small quadrotor (C2) drone. The base energy consumption and GHG emissions for these vehicles, assuming an equal grid mix, as reported by [8], are given in Table 6. Costs in Table 6 are calculated based on manufacturer-specified consumption of the vehicles with diesel fuel prices ob-

tained from [60] and electric vehicle energy prices obtained from the ZES electric vehicle tariff [61]. Using Equations (4)–(6), the cumulative consumption, costs, and emission per delivery route are calculated for all instances.

Table 5. Frequency of wind speeds by direction in Istanbul (% h/year), data from [59].

Beaufort Scale	Wind Direction							
	N	NE	E	SE	S	SW	W	NW
Scale 1	1.16%	0.87%	0.71%	0.92%	0.86%	0.61%	0.84%	0.82%
Scale 2	4.46%	3.77%	1.89%	1.82%	3.39%	3.06%	1.32%	1.59%
Scale 3	7.43%	6.27%	2.55%	0.63%	1.97%	3.47%	1.04%	1.58%
Scale 4	7.24%	6.87%	1.75%	0.10%	0.53%	3.39%	0.94%	0.99%
Scale 5	3.84%	3.18%	0.00%	0.00%	0.17%	1.28%	0.16%	0.19%
≥Scale 6	0.67%	0.49%	0.00%	0.00%	0.00%	0.26%	0.00%	0.00%

Table 6. The base energy consumption, GHG emissions, and costs per km used in calculations, data from [8,60,61].

Vehicle Type	Energy (MJ/km)	GHG (g CO ₂ /km)	Cost (MU/km)
Small diesel van (<i>T</i>)	4.90	339.8	2.361
Small electric van (<i>T</i>)	1.65	293.0	1.304
C2-type drone (<i>D</i>)	0.08	14.4	0.144

The noise calculations use Equations (7)–(12). The coefficients for diesel van category $m = 1$ [53] and electric van category $m = 5$ [56] are used in calculating the noise levels of the vans. The drone is a C2-type drone and its MTOM is approximately 4 kg; it flies at an altitude of 30 m (r_2) while the observer is assumed to be at 2 m (r_1). For the combined noise level, we used the energetic sum of drone and van noises.

5. Results and Discussion

In this section, we present and analyze the case-specific results obtained from different scenarios of delivery method (TSP, TSP-D, and TSP-DW) and vehicle (diesel and electric small vans) combinations and wind conditions. TSP-DW is applied to highly frequent wind speeds and directions in Istanbul (see Table 5). We evaluate each scenario's delivery times, energy consumption, costs, and the impacts on air and noise pollution.

The truck-only method (TSP) has the highest delivery time with a median of 3425 s. In contrast, the truck-drone combination in the absence of wind (TSP-D) significantly reduces the delivery time, showcasing a median of 2183 s (36% less than TSP). These findings align with other drone delivery studies beginning with [24], which report that integrating drones with trucks can substantially decrease delivery times due to parallel deliveries and by allowing drones to bypass ground traffic congestion, particularly in urban areas with high traffic density. When wind is present (TSP-DW), the median time changes slightly, as seen in Figure 3. When the wind direction is favorable (in this case NE for the overall route), it effectively shortens the drone's tour by boosting ground speed along the track, while an adverse wind (in this case N for the overall route) increases the tour time by reducing ground speed. Winds blowing from south (S) and southwest (SW) have a slight but favorable effect. However, it is important to note that these wind effects are case-specific and can vary depending on the location of the districts and nodes involved. Overall, even under adverse windy conditions, drone assistance remains more efficient than the truck-only method, consistent with the findings of [32].

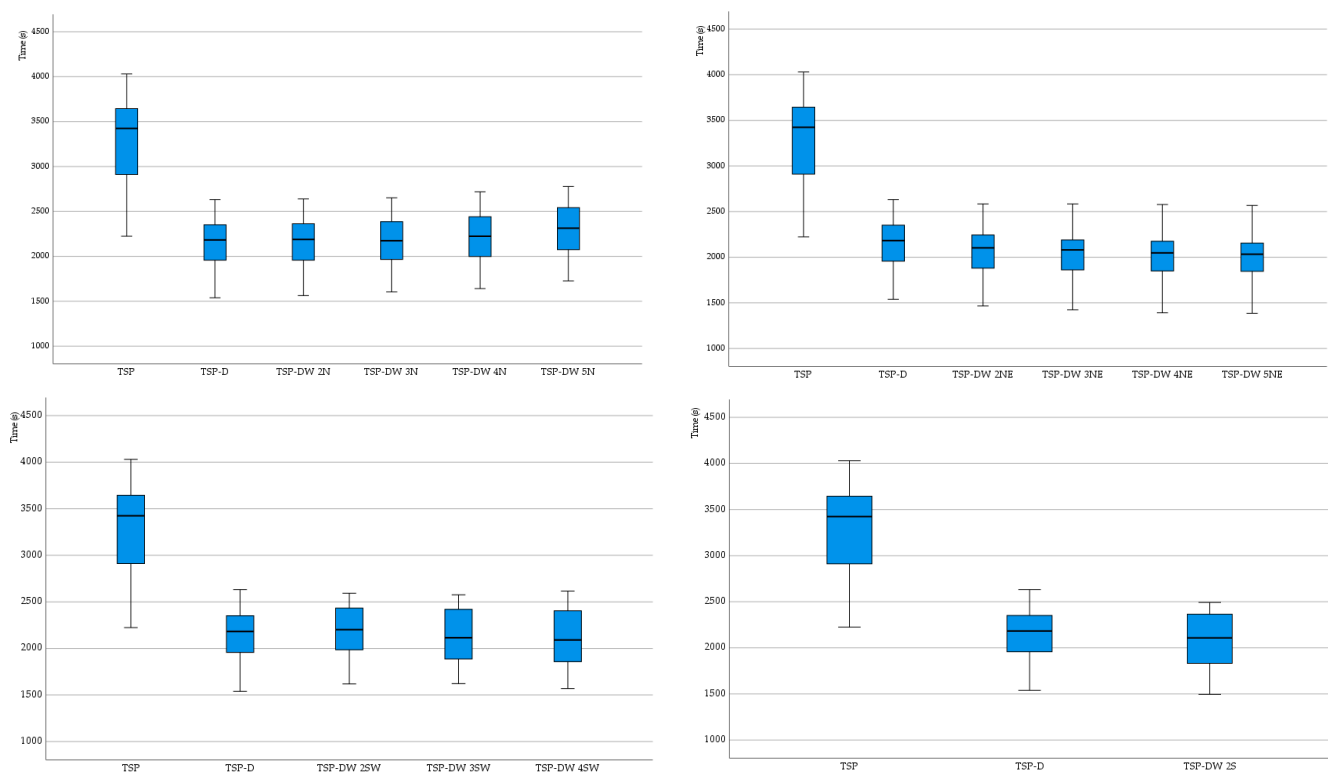


Figure 3. Delivery time comparison across delivery scenarios: under northerly (N), northwesterly (NW), southwesterly (SW), and southerly (S) wind across Beaufort scales 2 to 5.

The energy consumption of the optimized routes for the 30 instances is summarized in Figure 4. For the truck-only delivery (TSP), the median energy consumption for diesel vans is around 186 MJ, compared to around 63 MJ for electric vans. The truck–drone pairing without wind (TSP-D) reduces the median energy consumption for the diesel van and drone combination to about 119 MJ (36% less than diesel TSP) and for the electric van pairing to approximately 42 MJ (79% less than diesel TSP). When adverse wind (N) is present (TSP-DW), energy consumption slightly increases, with the diesel combination consuming around 127 MJ (33% less than diesel TSP) and the electric combination consuming around 45 MJ (78% less than diesel TSP). With favorable winds, energy consumption further decreases. These results align with previous research which shows that electric vehicles are more energy-efficient compared to diesel vehicles and that integrating drones can reduce energy consumption in delivery systems by optimizing route planning and reducing vehicle travel distances [6–8]. Considering the effect of wind in drone-assisted delivery is more realistic, as wind can influence the energy required for drone operations and thus impact the overall efficiency of the delivery system. Accounting for wind ensures more accurate energy consumption predictions and better energy-saving potential in real-world delivery scenarios.

Cost analysis also favors the use of electric vehicles combined with trucks, as depicted in Figure 5. The truck-only method (TSP) incurs a median cost of about 90 MU for diesel vehicles per route and 50 MU for electric vehicles. Implementing the truck–drone combination in the absence of wind (TSP-D) reduces the median cost to roughly 61 MU (33% less than diesel TSP) for diesel vans and 36 MU for electric vans (60% less than diesel TSP). Even with adverse wind (TSP-DW), costs increase slightly to 65 MU for diesel vans (28% less than diesel TSP) and 38 MU for electric vans (58% less than diesel TSP). When wind is favorable for a given route, costs decrease further. Recent studies [62,63] corroborate these results, underscoring the economic advantage of drone integration in LMD systems, which promises substantial savings in delivery costs. These savings are significant enough

to counterbalance the initial investment in drone technology, particularly when using electric vehicles.

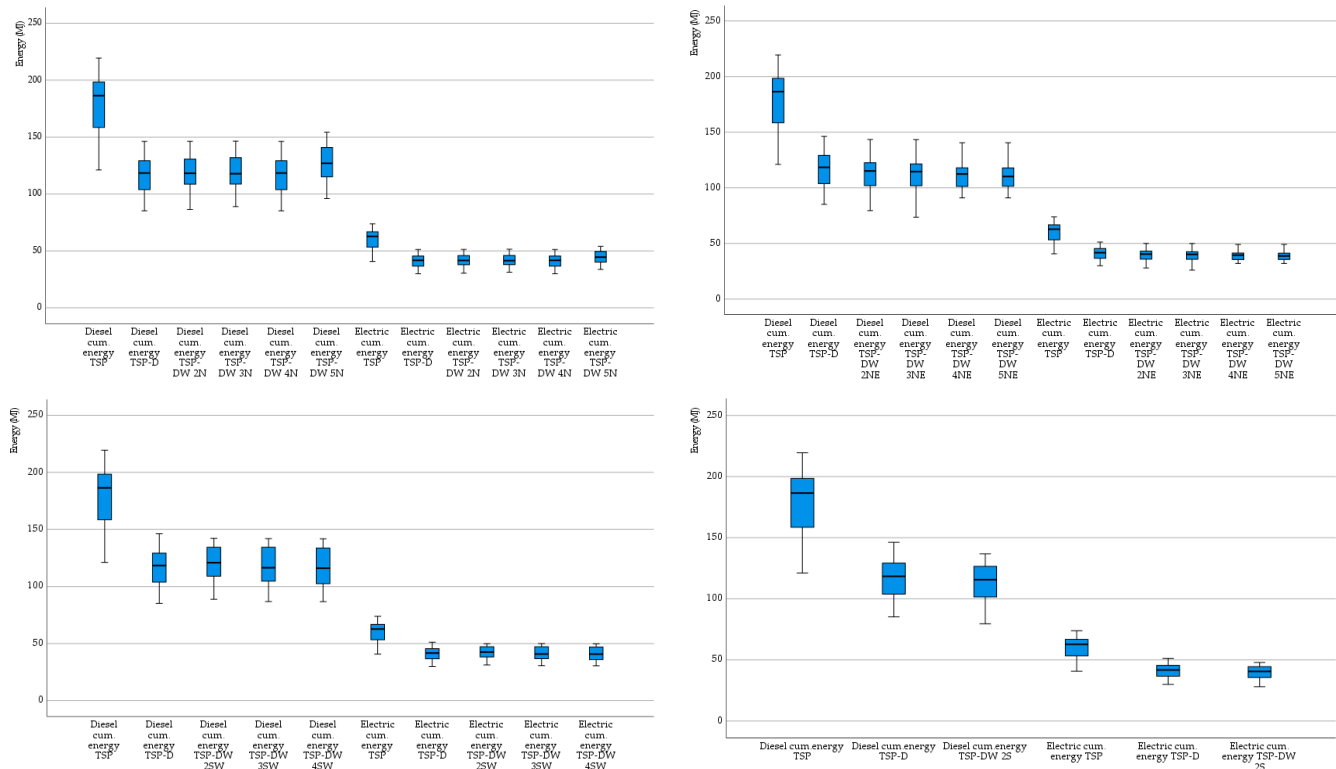


Figure 4. Comparison of cumulative energy consumption for diesel and electric vehicles across delivery scenarios.

Figure 6 shows that electric vehicles consistently generate less CO₂ compared to their diesel counterparts, resulting in reduced air pollution. For the truck-only method (TSP), the diesel option emits approximately 12,933 g of CO₂, while electric trucks emit around 11,152 g. Moving to the truck–drone pairing in the absence of wind (TSP-D), emissions are further reduced to 8527 g for diesel (34% less than diesel TSP) and 7422 g for electric (43% less than diesel TSP). With favorable winds, emissions decrease as drones maintain a shorter ground track, while adverse winds increase emissions slightly due to extended flight times. Under strong adverse winds (5N), emissions rise slightly but remain lower than the truck-only scenario, 8614 g for diesel and 7428 g for electric. Overall, using drones alongside trucks proves to be advantageous, reducing emissions compared to truck-only methods. These findings are consistent with the literature [62,64,65], which highlights the environmental benefits of using electric trucks and integrating drones into delivery systems. The GHG emissions of electric vehicles and drones in delivery models are heavily influenced by the emissions intensity of the regional electricity grid, with greater environmental benefits realized when renewable energy sources dominate the grid mix. The calculations in this study assume an equal grid mix, further underscoring the potential for emissions reductions when the share of renewable energy increases.

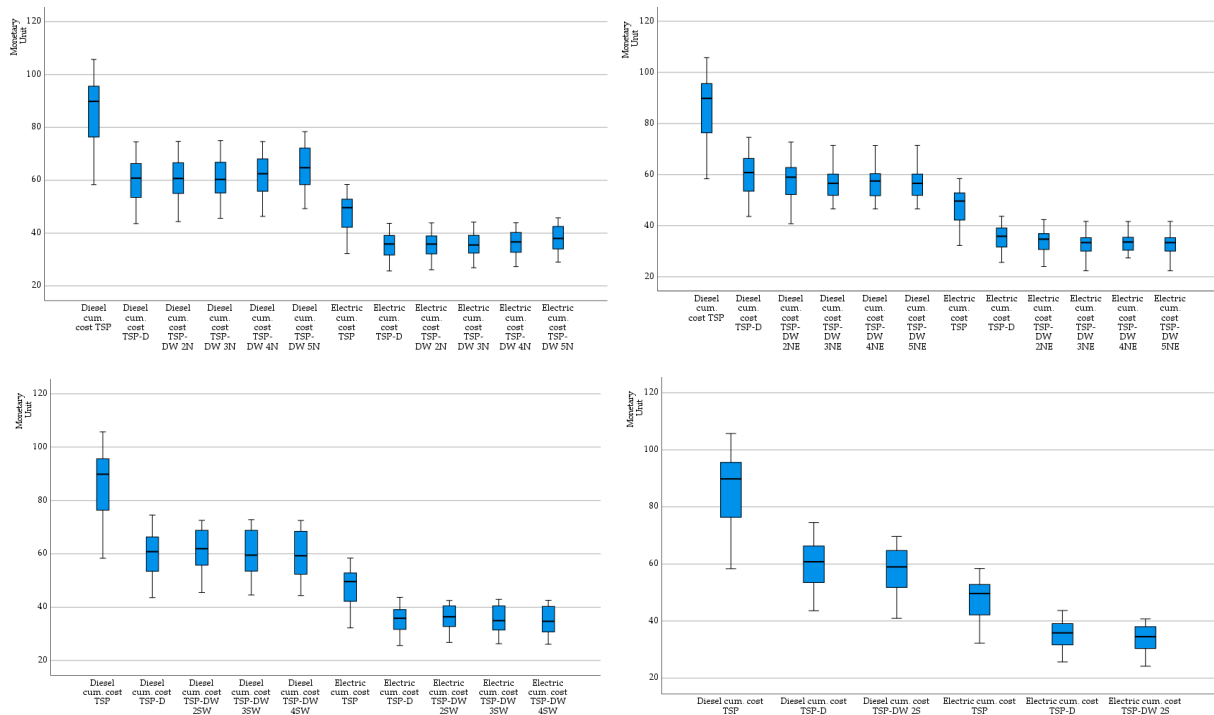


Figure 5. Comparison of route cost for diesel and electric vehicles across delivery scenarios.

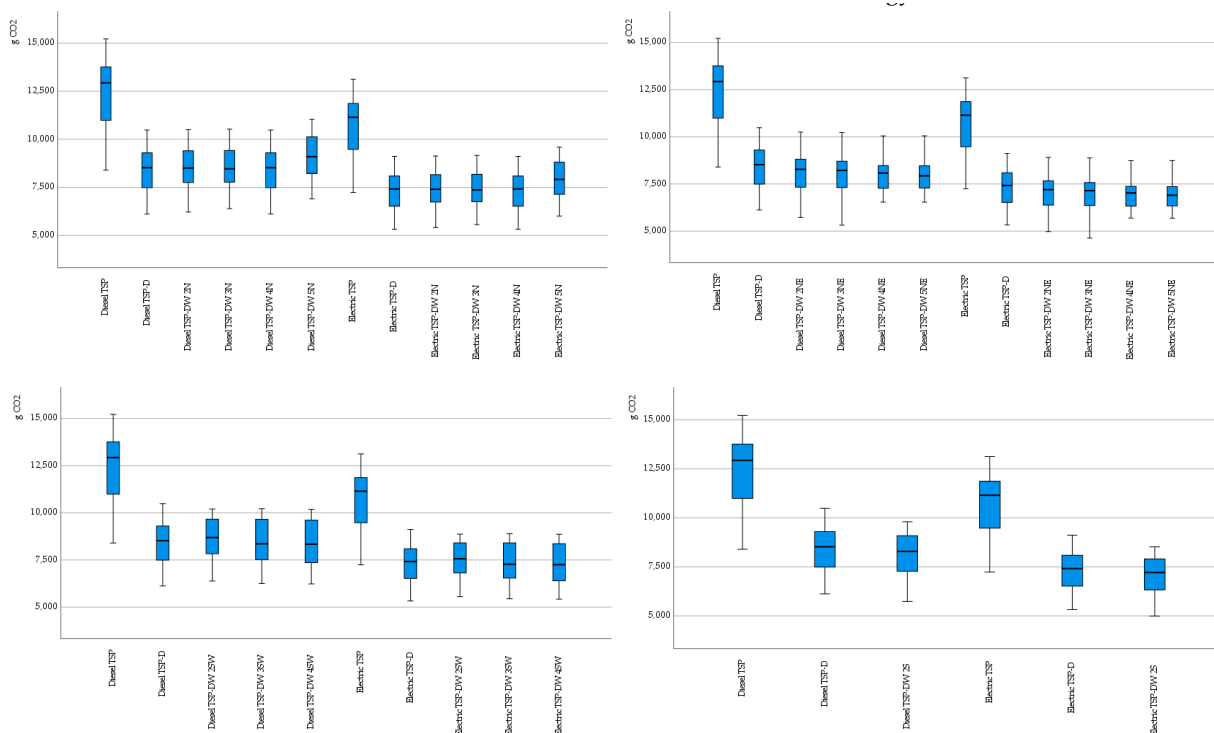


Figure 6. Comparison of CO₂ emissions for diesel and electric vehicles across delivery scenarios.

In this study, the noise levels of delivery vehicles are based on a source-centric model, meaning that the noise level (L_{Aeq}) remains constant for each vehicle type regardless of the distance traveled or time spent on the road. As seen in Figure 7, the noise emission comparison shows minimal differences across the methods and vehicle types, with all scenarios presenting similar values around 92 dB and 98 dB. Since noise levels are calculated using energetic sum, the drone's noise has a minimal effect on the overall noise impact

when combined with the louder source of the van. This suggests that the integration of drones into delivery systems does not significantly impact noise levels, which may be beneficial for maintaining urban noise pollution standards.

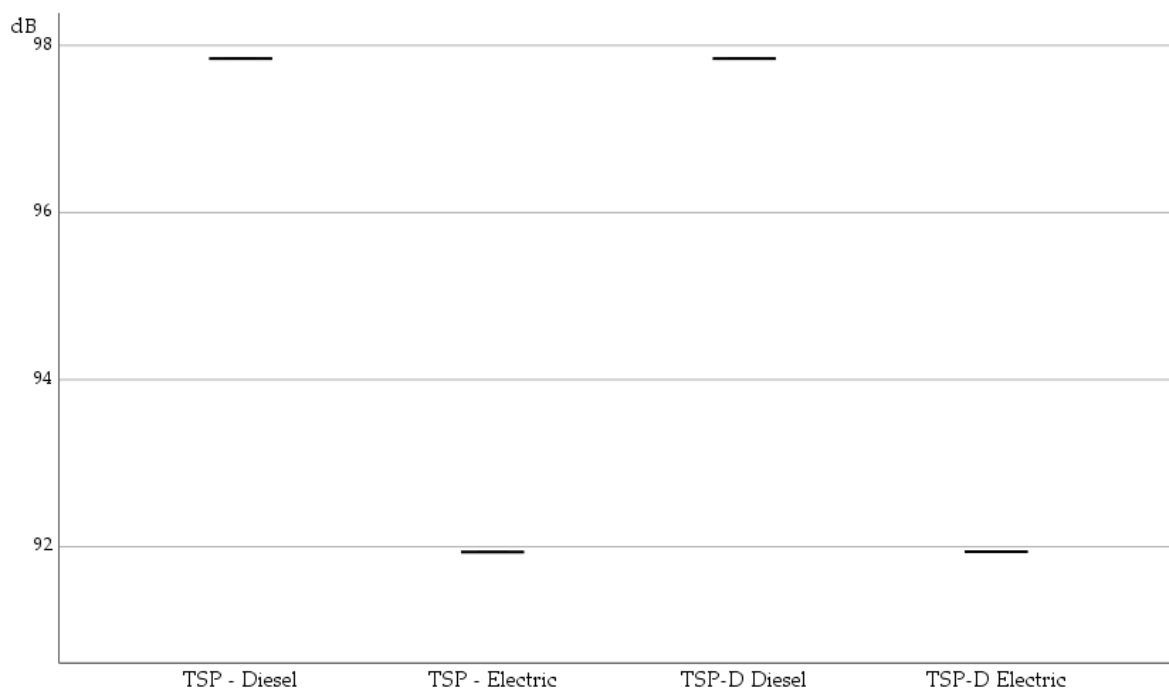


Figure 7. Comparison of noise levels (dBs) across delivery scenarios.

However, although factors like building façades, population density, route path, and meteorological conditions could further affect noise impact in urban areas, these were not incorporated in the current analysis. Additionally, while our model includes wind effects in route planning, we did not account for wind's influence in the noise calculations. Complex interactions of wind speed and air temperature gradients with sound propagation, such as refraction and barrier attenuation, require detailed meteorological classifications and adjustments, as described in CNOSSOS-EU [53], which were beyond the scope of this study.

Furthermore, it is increasingly acknowledged that noise pollution encompasses more than sound levels alone; the concept of noise annoyance is critical in understanding the broader impacts on affected communities. While traditional metrics such as L_{Aeq} provide a standardized quantitative assessment of noise levels and are used as a predictor of noise annoyance [66], they may fail to account for non-acoustic factors that contribute significantly to perceived annoyance [67,68]. Recent studies on drone noise suggest that the high-frequency tonality and rapid amplitude modulation of drones significantly contribute to higher perceived annoyance, even if the overall sound level remains the same [19,54]. Thus, while the noise levels we calculated remain constant across different routes and vehicle combinations, factors such as the duration of exposure (e.g., 37 vs. 67 min) and acoustics characteristics such as tonality and modulation may influence the overall noise impact on individuals.

Future work could adopt a spatiotemporal approach to better capture dynamic noise influences, including the effects of meteorological conditions. Utilizing noise-exposure sensitivity maps, as suggested by [58], would enable a more accurate estimation of noise impacts and help optimize traffic routing and scheduling to minimize noise. This would enhance the effectiveness of drone-assisted delivery systems in reducing noise pollution in urban environments.

In this study, we employed an exact approach using the CPLEX solver to solve the TSP-DW. The average computation time over all computations for TSP-DW was 888 s. While our approach guarantees optimal solutions, it becomes computationally expensive for larger

problem instances due to the complexity of combinatorial problems like TSP. To address this, researchers have utilized decomposition algorithms [69–71] or heuristics [72–74] as a solution approach, which can provide optimal/near-optimal solutions more efficiently. Additionally, machine learning-based methods such as reinforcement learning [75,76], or clustering customers into subregions [72], offer promising alternatives. By utilizing such approaches, we can significantly reduce computational complexity and yield solutions within a reasonable time without sacrificing much on solution quality for larger real-world applications.

The integration of drones into delivery systems significantly enhances efficiency, particularly when combined with electric vehicles. The truck–drone combination (TSP-D) emerges as the most efficient in terms of time, energy consumption, and cost, even with the presence of wind (TSP-DW). These results are supported by existing literature, highlighting the potential of truck–drone combinations to revolutionize the logistics industry by offering a more sustainable and cost-effective solution for last-mile deliveries. Considering the effect of wind makes drone operations more realistic, since wind can either accelerate or decelerate drone movements, impacting their efficiency and energy consumption. Wind conditions, therefore, add an important dimension to the analysis, providing a more comprehensive understanding of drone delivery systems under real-world conditions.

6. Conclusions

In an era where companies are seeking efficient LMD solutions with a focus on speed, cost, and environmental sustainability, the use of drones is gaining attention. This study addresses a critical gap in LMD research by evaluating air and noise pollution, while also integrating wind effects into drone-assisted delivery modeling. By extending the FSTSP to include wind conditions, the paper offers a more realistic and comprehensive assessment of delivery efficiency. The findings indicate that the truck–drone combination (TSP-D) enhances delivery performance even in windy conditions (TSP-DW), outperforming the truck-only method (TSP) in terms of time, cost, and pollution. Although adverse wind increases delivery time and energy consumption slightly, the overall benefits of the truck–drone combination remain evident.

The study explores the environmental and social impacts of drone-assisted deliveries, with a focus on air and noise pollution. Key contributions of this study include insights into the environmental and social effects of drone operations, support for sustainable LMD practices, and identification of research gaps in dynamic noise modeling and the integration of meteorological factors in delivery planning.

Furthermore, the application of urgent pharmacy deliveries demonstrates that integrating drones into delivery systems significantly improves delivery efficiency and energy savings, along with cost and emissions (both air and noise) reductions, especially when paired with electric vehicles even when wind is present. This highlights drone-assisted delivery's potential to advance sustainable logistics practices by reducing environmental impacts more effectively than traditional diesel-powered trucks. Our findings also indicate that, from a source-centric perspective, the noise impact of drones is minimal in terms of overall noise levels.

While drones have the potential to reduce road traffic noise levels, they introduce new noise sources that could impact public perception and well-being, necessitating further research and regulation. As part of broader sustainability efforts, including the Zero Pollution Action Plan, these insights can guide policy and regulatory measures to mitigate environmental impacts and enhance urban livability.

Future research can build upon this study by moving beyond the static, source-centric noise model currently employed. Integrating dynamic, spatiotemporal-oriented tools could capture noise impacts with better accuracy, taking into account factors like wind effects and the complexities of urban environments. This approach would necessitate the use of more detailed data and advanced analytical methods, enhancing the precision of noise impact assessments and aligning them more closely with real-world conditions.

Such advancements would lead to more accurate and efficient routing decisions that fully consider the dynamic nature of environmental noise, ultimately reducing the impact on residents.

Additionally, future studies could explore various delivery scenarios for different items involving larger customer sets with multiple vehicles and drones. To address the computational challenges posed by solving large-scale instances of the TSP-DW, future research should investigate the integration of decomposition techniques, heuristic approaches, as well as machine learning-based methods. Incorporating diverse urban dynamics, such as urban wind fields or exploring different drone technologies would further enrich the analysis and contribute to sustainable LMD solutions.

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