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Innovative Research on Transportation using Trucks and Drones

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Abstract: *This paper investigates the development and implementation of a hybrid transportation system that integrates the advantages of trucks and drones to optimise delivery processes. Considering the continuous growth in demand for rapid and efficient delivery services, our approach presents an innovative model that combines the reliability of road transport with the agility and speed of aerial delivery. Starting from a detailed analysis of logistics networks in Bacău County, Romania, our study develops and applies a routing algorithm using Google's OR-Tools. For truck transportation, real distances between towns were utilised, allowing the calculation of routes for both transportation modes, taking into account their specific characteristics. Computational experiments demonstrate that the proposed method is both fast and reliable.*

Keywords: *last mile delivery; truckdrone delivery system; OR-Tools.*

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1. Introduction

Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, have rapidly evolved from niche research tools into versatile assets across both civilian and military domains (Islam, 2023). Their relatively low operational cost, coupled with advances in navigation and sensing technologies, has enabled widespread adoption in tasks, such as precision agriculture, where drones perform crop health assessments, variable-rate spraying, and high-resolution mapping (Ghazali, Azmin, & Rahiman, 2022). Drones can be also used for environmental monitoring, including infrastructure inspection, wildlife tracking, and disaster response missions (Gryech et al., 2024). In logistics and last-mile delivery, the agility of UAVs offers the promise of faster, more flexible parcel transport, reducing reliance on traditional ground fleets and addressing growing consumer demand for expedition services (Li et al., 2024; Shuaibu, Mahmoud, & Sheltami, 2025). Despite these attractive benefits, standalone drone networks face constraints in payload capacity, flight endurance, and regulatory compliance. A compelling solution is the integration of drones with conventional delivery vehicles, commonly named as hybrid "truck-and-drone" systems. In this paradigm, a ground vehicle carries one or more drones, which are sequentially deployed to service nearby customers before rejoining the primary route. By carefully coordinating truck movements and drone sorties, such systems can shorten delivery times, lower fuel consumption, and improve coverage in areas with challenging terrain or limited road infrastructure (Carlsson & Song, 2018). Mathematically, orchestrating a truck-and-drone delivery network can be viewed as an extension of classical combinatorial optimisation models. Researchers have adapted the Vehicle Routing Problem (VRP) and the Traveling Salesman Problem (TSP) to accommodate simultaneous ground and aerial operations, introducing new decision variables to represent drone launch and rendezvous points (Murray & Chu, 2015). While exact methods deliver optimal routes for small instances, their computational burden grows rapidly with problem size. Heuristic and metaheuristic strategies such as greedy constructions, local search, and evolutionary algorithms, have therefore become essential for obtaining high-quality solutions within reasonable time frames, but does not guarantee the optimum solution (Greco, 2008).

In this paper, we employ a two-phase approach for the truck-and-drone delivery problem. In the first phase, we solve an exact TSP for the truck, finding the optimal tour that visits all delivery points and returns to the depot. In the second phase, we scan the consecutive segments of that tour and, for each one or two-segment window, pick the unserved customer, whose drone delivery yields the greatest cost saving versus the truck. We then "reserve" that window, remove the assigned customer from the pool, and repeat until no further savings can be found.

To validate our approach, we conducted a computational experiment based on real cities and geographical coordinates. We developed a custom web scraper using Python to collect the coordinates of every town and commune within Bacău County, Romania, and employed the Google Maps API to generate a rounded-integer distance matrix reflecting ground travel times. These distances serve as input to our hybrid routing algorithm, enabling a realistic assessment of the potential efficiency gains.

The structure of this work is the following: section 2 describes the drones usage and implementations; section 3 represents a short state of the art of truck and drones delivery systems; section 4 describes the TSP and FSTSP problem; section 5 presents the strategical level of implementation; section 6 presents the mathematical model and its constraints; section 7 introduces our data analysis and computational experiment. The paper ends with conclusions and future works.

2. Drone Uses and Applications

Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, represent a class of aerial technologies—autonomous or semi-autonomous capable of carrying out a wide range of tasks without the physical presence of a pilot on board. Initially developed for military purposes, these aircraft were designed to reduce human risk during dangerous missions, being extensively used in reconnaissance, surveillance, and targeted strikes, particularly in active conflict zones (Parrott, 2021; Fish, 2020). Controlled remotely or via onboard autonomous systems, drones are capable of operating in harsh weather conditions and transmitting real-time data essential for tactical decision-making.

Beyond military applications, UAVs have significantly broadened their range of uses in the past two decades. In the medical field, for instance, drones are now employed to deliver medications, equipment, or biological samples, particularly in remote or hard-to-reach areas. Trials conducted in Indian hospitals have demonstrated that drones can be efficiently integrated into emergency protocols, enabling rapid transport of essential supplies and real-time surveillance of disaster zones or mass casualty incidents (Subhan, Ghazi, & Nabi, 2019; Khandagale et al., 2021). In agriculture, the use of drones has revolutionised monitoring and intervention practices. Through multispectral sensors and data analysis algorithms, farmers can assess crop health in real time, detect early signs of disease, and apply localised treatments thus reducing pesticide and fertiliser use. Case studies in India have shown that drones help improve operational efficiency, reduce labor dependence, and promote a more sustainable model of farming (Dhivya et al., 2024; Ram & Arunachalam, 2024).

Drone applications have also expanded into civil engineering, where they are used for mapping, site monitoring, topographic surveying, and infrastructure inspections. Due to their high precision and ability to deliver detailed aerial images, UAVs have become standard tools in construction projects, significantly cutting time and costs compared to traditional monitoring methods (Tkác & Mésároš, 2019; Adepoju, 2021).

Another emerging domain is logistics and rapid delivery. Companies such as Amazon have expressed strong interest in developing aerial delivery networks for small packages using autonomous drones. Recent studies have successfully tested automatic deliveries in dense urban environments, with drones capable of avoiding obstacles and landing accurately at predefined locations (Wisudawan, Nugraha, & Akmal, 2024; Campos & Andrés, 2015).

In environmental protection efforts, UAVs are used to monitor forests, track wildlife, and map ecosystems affected by climate change. These so-called "eco-drones" can collect crucial data to support better-informed environmental policies and rapid response in cases of pollution or illegal deforestation (Commons, 2013).

3. Literature Overview on Truck-and-Drone Delivery Models

Hybrid truck-and-drone delivery models have emerged as a prominent topic in logistics research, driven by the increasing demand for faster last-mile delivery solutions in the context of urbanisation and e-commerce growth. These systems leverage the complementary strengths of trucks for bulk transport and drones for rapid, localised delivery, offering substantial potential for cost and time reductions.

The foundational contribution in this field was made by Murray & Chu (2015), who proposed a cooperative model where a truck and a drone operate in parallel. The drone is dispatched to serve a customer while the truck continues along its route, with the two vehicles reuniting at a previously unvisited location. The primary objective of their model, known as the Flying Sidekick Traveling Salesman Problem, was to minimise total delivery time (Murray & Chu, 2015). Shortly after, Agatz, Bouman, & Schmidt (2018) extended this framework with the Traveling Salesman Problem with Drone (TSP-D), allowing drone launch and retrieval at already visited nodes and enabling the truck to move during the drone's flight. This enhanced model broadened the feasible solution space and improved operational flexibility (Agatz, Bouman, & Schmidt, 2019). Subsequent studies explored more complex configurations. Tu (2020) introduced a multi-drone model in which several drones could be launched and retrieved asynchronously, subject to synchronisation constraints and maximum waiting times. Their results demonstrated the efficiency gains of such systems in high-density demand areas (Tu, 2020). In parallel, Kitjacharoenchai & Lee (2019) proposed a multi-truck, multi-drone model, formulated as a min-max multiple traveling salesman problem. The framework allows flexible drone routing, including depot-to-truck and inter-truck operations.

On the methodological side, Freitas, Penna, & Toffolo (2023) developed a novel mixed-integer programming formulation for truck-drone delivery, combined with a hybrid metaheuristic that integrates the Variable Neighborhood Search and Tabu Search. Their approach significantly outperformed prior methods on benchmark instances and proved scalable to larger problem sizes (Freitas, Penna, & Toffolo, 2023). From a strategic planning perspective, Zhang, Campbell, & Sweeney II (2024) introduced a continuous approximation model comparing the truck-only, drone-only, and hybrid operations. Their findings highlight the dominance of hybrid systems in scenarios with moderate to high customer density, particularly when drones exhibit favorable speed and cost parameters.

Infrastructure design considerations have also received increasing attention. Dukkanci, Campbell, & Kara (2024) conducted a structured review on facility location decisions for drone-based delivery systems, covering fixed drone bases, mobile platforms, and refueling stations. Their work underscored the lack of integration between facility planning and dynamic routing in the current model (Dukkanci, Campbell, & Kara, 2024). Operational innovations include the work of Liu, Liu, & Qi (2024), who examined the drone resupply systems, where drones deliver the packages to the moving trucks on route. Their scheduling model addresses the timely delivery of late-available packages and demonstrates significant gains in urban delivery responsiveness.

In terms of real-world feasibility, Thasnim et al. (2024) reviewed practical challenges in integrating drones with ground transport. Their study covered battery charging logistics, UAV compatibility with public infrastructure, and the lack of standardised fleet coordination protocols (Thasnim et al., 2024).

4. The FSTSP (Flying Sidekick Traveling Salesman Problem)

In this section, we begin by providing a brief overview of the classical Traveling Salesman Problem (TSP), which serves as the foundational framework for introducing and formulating the Flying Sidekick Traveling Salesman Problem (FSTSP).

4.1. The Traveling Salesman Problem (TSP)

The Traveling Salesman Problem (TSP) is a classical benchmark in theoretical computer science and combinatorial optimisation. Its basic formulation involves identifying the shortest route that visits a given set of cities (or nodes) exactly once and returns to the starting point. The name of the problem stems from a hypothetical scenario, in which a commercial agent must visit multiple locations to perform their duties while minimising the total travel distance. A comprehensive overview of TSP variants and solution methods can be found in Kimbrough & Lau (2016).

Definition. Consider a complete graph $G=(V,E)$, where V={1,2,...,n} represents the set of nodes, and $C=(c_{ij})_{1\leq j,j\leq n}$ is the cost matrix associated with the edges E. The goal is to find a minimum-cost cycle that visits each node exactly once (Gass, 2006). TSP is well known for its computational complexity; it is classified as NP-hard, which implies that no efficient algorithm currently exists that guarantees the optimal solution for all possible instances (Korte & Vygen, 2012). For symmetric cases (where matrix C is symmetric), Concorde is recognised as the most effective exact solver available (Cook et al., 2011). In addition, numerous heuristic and approximation algorithms have been developed, capable of delivering near-optimal solutions for large-scale instances (Punnen, 2007).

Due to its versatility, TSP has direct applications in several domains, including transportation planning, logistics, and network design (Bergel, 2020). Over time, it has served as a foundation for several important generalisations and extensions, by adding new constraints or altering the base structure. Notable examples include the Vehicle Routing Problem (VRP), the Multiple Traveling Salesman Problem (mTSP) (Casquilho, 2012) and the Flying Sidekick Traveling Salesman Problem (FSTSP), which will be detailed in the following section—all developed in response to real-world operational needs.

4.2. The Flying Sidekick Traveling Salesman Problem (FSTSP)

The Flying Sidekick Traveling Salesman Problem (FSTSP) is a variant of the classical TSP, in which a hybrid delivery system consisting of a truck and a drone is deployed from a common depot. The fundamental constraint requires that each customer is visited exactly once by either the truck or the drone (Agatz, Bouman, & Schmidt, 2018). Depending on the geographic distribution of customers and operational requirements, the two vehicles may execute their routes either simultaneously or in coordination. The drone is typically assigned to clients located in areas that are more efficiently accessed via aerial travel, whereas the truck services the remainder. When traveling together, the drone is carried by the truck, conserving energy and extending its limited range.

The primary objective in FSTSP is to improve the temporal efficiency of the integrated system, ensuring that all customers are served and that both vehicles return to the depot. The problem formulation accounts for several critical variables, including drone endurance, travel time for the truck, and synchronisation between vehicle operations. Minimising the overall route duration contributes to higher efficiency and improved delivery system performance, supporting the development of modern and sustainable logistics solutions across various sectors.

Let $C=\{1,2,...,c\}$ denote the set of customers and $C'\subseteq C$ represent those customers eligible to be served by the drone. The depot is denoted as node 0 at the start and node $c+1$ at the end, indicating that both the truck and the drone depart from and return to the same location. Timekeeping starts at zero when both vehicles leave the depot and ends when they return.

Let π_{ij} be the time it takes the truck to move from node i to node j, and π'_{ij} be the drone's flight time between the same nodes, where $0\leq i\leq c$, $1\leq j\leq c+1$, and $\tau_{0,c+1}=0$. Note that $\tau_{i,j}$ and $\tau'_{i,j}$ are undefined. Additional parameters include:

- SL : time required to prepare the drone for launch,
- SR : time needed to recover the drone upon rendezvous,
- ϵ : maximum flight time available to the drone (endurance),
- α : ratio of drone speed to truck speed.

Both vehicles are assumed to move at constant speeds. For a sortie (a drone flight from launch to recovery), the drone must be launched at a point i, serve a customer j, and return to the truck at a later node, such that the total drone flight time does not exceed the endurance limit ϵ.

5. Strategic Level of Implementation

The paper innovates by employing a calculation system adapted to each mode of transport, as well as by including specific parameters such as S_L and S_R. These parameters are expressed as a cost per kilometer for the drone and represent the launch and recovery costs.

To calculate the distances travelled by the truck, a matrix of real distances was used, assuming the existence of at least one ground route between each pair of points. Data inconsistency was addressed through a compromise: since a round-trip route may have different distances (due to one-way streets), the minimum distances were rounded down to the nearest integer number.

The program begins with a data-preparation stage: a Python scraper mines the geographic coordinates of 93 delivery nodes and saves them to one file, while a second file holds the road distances between every pair of nodes for the truck. From these two inputs it internally builds two cost matrices one reflecting the truck's road network and another representing the drone's direct flight distances (adjusted by the launch overhead S_L, recovery overhead S_R, and efficiency factor α).

Next, it runs a two-phase heuristic:

1. **Truck Route Planning** – OR-Tools uses a "cheapest arc" first-solution strategy paired with guided local search to generate a high-quality (though not guaranteed optimal) tour that visits all nodes and returns to the depot. The routing tool incorporates a variety of search strategies, including Greedy Descent, Guided Local Search, Simulated Annealing, Tabu Search, Generic Tabu Search, and an automatic strategy that selects the most suitable

method based on the problem instance. Additionally, it offers fourteen distinct methods for generating the initial solution (Google OR-Tools). Based on our experience, this tool represents a robust and versatile solver for addressing complex routing problems.

2. **Drone Allocation** – the algorithm slides a window of one or two consecutive truck segments along that tour; for each window and each unserved customer, it estimates the cost saving of serving them by drone instead of by truck. It then greedily picks the window–customer pair with the highest saving, reserves those segments for the drone, removes the customer from the pool, and repeats until no further savings remain.

Finally, the program outputs the list of drone sorties alongside the combined truck-plus-drone cost, yielding a practical, efficient delivery plan.

6. Mathematical Model of Truck-and-Drone Delivery System

Below is a statement of the two-phase mathematical model implemented.

Phase 1: Truck TSP

Sets and Indices

- $N=\{0,1,2,...,n\}$**:** nodes (0 = depot, $1 \ldots n$ = customers).

Parameters

- $c_{ij} \geq 0$ road-distance cost (km) for the truck from node i to node j.

Decision Variables

$$x_{ij} = \begin{cases} 1, & \text{if the truck travels directly from } i \text{ to } j \\ 0, & \text{otherwise.} \end{cases}$$

Objective

Minimise total truck distance:

$$\min \sum_{i \in N} \sum_{j \in N} c_{ij} \; x_{ij}.$$

Constraints

1. *Leaving each node exactly once*
$$\sum_{j \in N} x_{ij} = 1 \forall \, i \in N$$
2. *Visiting each node only once*
$$\sum_{i \in N} x_{ij} = 1 \forall \, j \in N$$
3. *Subtour elimination*
Introduce ordering variables u_i with
$u_0=0, 1 \leq u_i \leq n$, ($\forall i \neq 0$),
and for all $i \neq j$
$u_i - u_j + 1 \leq n(1 - x_{ij})$

Phase 2: Drone-Delivery Assignment

After solving Phase 1 we obtain a sequence (tour)
$r_0=0, r_1, r_2, \ldots, r_m=0$
and define the set of truck-segments $S=\{(r_{k-1}, r_k), k=1,...m\}$.

Additional Sets

- $K=\{1,...,n\}$ customers to serve by drone.

W: windows of consecutive segments of length 1 or 2, i.e.
$W=\{w=(i,j) \mid j=i+L, \in \{1,2\}\} \subseteq \{0,...,m-2\} \times \{1,...,m\}$

Additional Parameters

- h_{uv}: Haversine (air-distance) cost (km) for the drone between nodes u, v.
- SL, SR: fixed launch and recovery overheads (km).
- $\alpha>0$: drone-efficiency factor (scales flight distance).

For each window $w=(i,j) \in W$ and each customer $k \in K \setminus \{r_i, r_j\}$ define:

- *Truck-cost on window*

$$C_W^{truck} = \sum_{\ell=i}^{j-1} c_{r_\ell, r_{\ell+1}}$$

- *Drone-cost to serve* k

$$C_{w,k}^{drone} = SL + \frac{h_{r_i,k} + h_{k,r_j}}{\alpha} + SR$$

- *Saving*

$$s_{w,k} = C_W^{truck} - C_{w,k}^{drone}$$

Decision Variables

$$y_{w,k} = \begin{cases} 1, & \text{if window } w \text{ is used by the drone to serve customer } k, \\ 0, & \text{otherwise.} \end{cases}$$

Objective

Maximise total saving:

$$\max \sum_{w \in W} \sum_{k \in K} s_{w,k}\, y_{w,k}$$

Constraints

4. *Each customer at most once*

$$\sum_{w \in W} y_{w,k} \leq 1 \forall k \in K$$

5. *Each truck-segment used at most once*

For every segment $\ell = 1, \dots, m$

$$\sum_{\substack{w=(i,j) \in W \\ i \leq \ell < j}} \sum_{k \in K} y_{w,k} \leq 1$$

6. *Binary*

$$y_{w,k} \in \{0,1\}$$

Combined Cost Interpretation

Equivalently, one can view a single MILP that *minimises*

$$\sum_{i,j} c_{ij}\, x_{ij} + \sum_{w,k} \left[SL + \frac{h_{r_i,k} + h_{k,r_j}}{\alpha} + SR \right] y_{w,k}$$

subject to the above constraints. In implementation, we solve the TSP for x first, then apply the greedy assignment for the y variables.

7. Computational Experiment

The computational experiments were conducted using two platforms: a MacBook Pro (2021) equipped with 32 GB RAM, running macOS Ventura 13.2, and a Dell PowerEdge R620 server featuring dual Intel Xeon E5 processors and 384 GB RAM, operating under Windows Server 2025. The implementation was developed in Python. The extraction of geographic coordinates and the construction of the distance matrix used as input data were automated using a web scraper. The data collection process takes approximately 10 minutes. These datasets are available upon request from the corresponding author for future research purposes.

The mathematical model was tested using ten different parameter settings, combining various values for launch/recovery times and speed ratios. The configurations were as follows:

1. $SL = SR = 0, \propto = 2$
2. $SL = SR = 0, \propto = 3$
3. $SL = SR = 0.25, \propto = 2$
4. $SL = SR = 0.25, \propto = 3$
5. $SL = SR = 5, \propto = 2$
6. $SL = SR = 0.5, \propto = 3$
7. $SL = SR = 0.75, \propto = 2$
8. $SL = SR = 0.75, \propto = 3$
9. $SL = SR = 1, \propto = 2$
10. $SL = SR = 2, \propto = 3$

All our experimental runs yielded an identical truck-only distance of 1037 km, underscoring the robustness of the routing phase against variations in drone parameters. This invariance demonstrates that the “cheapest-arc” first-solution strategy combined with guided local search consistently converges to the same high-quality tour for the truck, irrespective of SL, SR or α. In practical terms, it means that once the ground path is fixed, decision-makers can tweak drone launch, recovery or efficiency settings without ever compromising the coherence or predictability of the truck’s route. By cleanly decoupling the road-network optimisation from the aerial-allocation heuristic, our two-phase framework both simplifies operational planning and enhances the resilience of the combined delivery system.

The analysis reveals that the truck-and-drone system’s effectiveness hinges critically on the balance between the drone’s flight efficiency and its fixed launch/recovery overhead. When the drone operates more efficiently, cumulative savings grow substantially, and the hybrid route remains resilient even under slight variations in overhead parameters. Conversely, as launch or recovery costs rise, the advantage of aerial delivery gradually diminishes, prompting the algorithm to schedule fewer flights. The two-phase framework adds robustness: the truck’s baseline tour stays stable, while the drone assignment dynamically adapts to new conditions, capturing available savings without disrupting route coherence. In practice, achieving optimal performance requires precise calibration of the drone’s technical parameters alongside a flexible allocation strategy that maximizes potential gains without overtaxing resources.

Table 1 presents the detailed results for each configuration, including the drone-only cost, the combined delivery cost, total savings, and the number of drone sorties. Standard deviation and standard error are also provided to assess the variability and precision of the results. Across our ten parameter configurations, the *mean* values give us a sense of the “typical” system performance: the drone flies about 333 km per run, the combined truck + drone route totals roughly 1 370 km, the overall savings average 655 km, and about 46 drone sorties are flown. The *standard deviation* then tells us how much each of those metrics bounces around: roughly ±49 km for both drone and combined distances, ±70 km for the savings, and ±3.4 sorties. Finally, the *standard error* (the standard deviation divided by $\sqrt{n}$) quantifies how precisely we’ve estimated those means from just ten trials: about ±15 km on the drone cost mean, ±49 km on the combined cost, ±70 km on the savings mean, and ±3.4 sorties. In practice, this means our average estimates are fairly stable (small standard error relative to the means), even though individual runs can vary by a few dozen kilometers or a handful of sorties.

Table 1. Results of computational experiments
SL= launch overhead, SR= recovery overhead, α= efficiency factor

SL	*SR*	*α*	DRONE COST (KM)	COMBINED COST (KM)	SAVINGS	SORTIES
0	0	2	346,0	1383,0	640,0	46,00
0	0	3	255,4	1292,4	762,8	50,00
0,25	0,25	2	353,1	1390,1	618,3	43,00
0,25	0,25	3	280,4	1317,4	737,8	50,00
0,5	0,5	3	305,4	1342,4	712,8	50,00
0,5	0,5	2	374,6	1411,6	596,8	43,00
0,75	0,75	2	387,7	1425,0	575,5	42,00
0,75	0,75	3	308,0	1345,0	688,1	47,00
1	1	2	408,7	1445,7	554,5	42,00
1	1	3	315,9	1352,8	665,6	44,00
STANDARD DEVIATION			48,87632636	48,9	70,2	3,37
MEAN			333,525	1370,6	655,2	45,70
STANDARD ERROR			15,4560515	48,91252358	70,2474554 8	3,368151488

This paper distinguishes itself from the study conducted by Conea & Crișan (2023) through the complexity and flexibility of its proposed model, as well as its emphasis on scalability and rigorous statistical analysis. While their paper introduces a greedy heuristic focused on minimising total delivery time in a truck-and-drone system, without detailing launch and recovery costs, or the influence of operational parameters on the system's performance, this work presents a two-phase model that clearly separates the truck route optimisation from drone flight allocation. By incorporating the SL and SR parameters and evaluating ten distinct experimental configurations, it provides a comprehensive view of how these factors affect achieved savings and the number of aerial sorties. Furthermore, the proposed solution demonstrated high scalability, completing computations for 93 nodes in under two seconds, an aspect not addressed in the previous study. Therefore, the present contribution advances the existing literature both through methodological refinement and its practical potential for application in complex operational scenarios.

8. Conclusions and Future Work

In this study, we introduce a unified framework for optimising truck–drone delivery operations by automatically harvesting data from online sources and constructing two complementary cost matrices. Road distances for the truck are obtained via a web scraper and assembled into a dedicated distance matrix, thereby capturing the true topology and constraints of the highway network. Simultaneously, drone routes are modelled using straight-line (Haversine) distances, which are further adjusted by the operational parameters of launch overhead (SL), recovery overhead (SR), and efficiency factor (α). By combining these two distinct distance metrics ground versus aerial, we accurately represent the unique movement characteristics of each vehicle. To our knowledge, no prior truck–drone routing model has jointly employed real-world road metrics alongside parameterised aerial distances in this manner.

In terms of performance, the program was also tested in a parallelised environment, running on 93 computing nodes and completing execution in under 2 seconds. This result highlights not only the efficiency of the proposed algorithm but also its scalability, demonstrating its suitability for distributed computing environments and large-scale problem instances.

In the future work, we plan to extend our evaluation by running experiments on multiple node sets, as detailed as in Conea & Crişan (2023), in order to assess the scalability and robustness of our approach across varied scenarios. We also intend to enrich the model with additional operational constraints such as vehicle capacity, delivery time windows, and drone battery endurance and to incorporate electric charging stations for both trucks and drones, thereby advancing the framework toward a fully realistic, real-world delivery system.

References

Adepoju, O. (2021). Drone/Unmanned aerial vehicles (UAVs) technology. Re-skilling Human Resources for Construction 4.0. *Springer Tracts in Civil Engineering,* 65-89. https://doi.org/10.1007/978-3-030-85973-2_4 .

Agatz, N., Bouman, P., & Schmidt, M. (2018). Optimization approaches for the traveling salesman problem with drone. *Transportation Science, 52*(4), 965–981. https://doi.org/10.1287/trsc.2017.0791.

Bergel, A. (2020). The traveling salesman problem. *Agile Artificial Intelligence in Pharo*, 209-224. https://doi.org/10.1007/978-1-4842-5384-7_10.

Campos, R., & Andrés, J. (2015). Uso de drones en logística para entrega de mercancías. *Universitat Militar Nueva Granada.*

Carlsson, J., & Song, S. (2018). Coordinated logistics with a truck and a drone. *Management Science, 64*, 4052–4069. https://doi.org/10.1287/mnsc.2017.2824.

Casquilho, M. (2012). Travelling salesman problem. *Instituto Sauperior Techinco.*

Commons, W. (2013). A new eye in the sky: Eco-drones. *Environmental Development, 7,* 155-164. https://doi.org/10.1016/j.envdev.2013.05.011.

Conea, S., & Crişan, C. (2023). Hybrid transportation system using trucks and drones. *Procedia Computer Science, 225*, 3153-3162. http://dx.doi.org/10.1016/j.procs.2023.10.309.

Cook, W., Cunningham, W., Pulleyblank, W., & Schrijver, A. (2011). The traveling salesman problem. *Combinatorial Optimization*, 241-271. https://doi.org/10.1002/9781118033142.CH7.

Dhivya, C., Arunkumar, R., Murugan, P. P., & Senthilkumar, M. (2024). Drone technology in agricultural practices: A SWOC analysis. *Journal of Scientific Research and Reports*, *30*(11), 626-635. https://doi.org/10.9734/jsrr/2024/v30i112590.

Dukkanci, O., Campbell, J., & Kara, B. (2024). Facility location decisions for drone delivery: A literature review. *European Journal of Operational Research, 316*(2), 397–418. https://doi.org/10.1016/j.ejor.2023.10.036.

Fish, A. (2020). Drones. *The Routledge International Handbook of Ethnographic Film and Video.* https://doi.org/10.4324/9780429196997-28.

Freitas, J., Penna, P., & Toffolo, T. (2023). Exact and heuristic approaches to truck-drone delivery problems. *EURO Journal on Transportation and Logistics, 12*, 100094. https://doi.org/10.1016/j.ejtl.2022.100094.

Gass, S. (2006). Traveling salesman problem. *Encyclopedia of Statistical Sciences*. https://doi.org/10.1002/0471667196.ESS2753.PUB2.

Ghazali, M., Azmin, A., & Rahiman, W. (2022). Drone implementation in precision agriculture – A survey. *International Journal of Emerging Technology and Advanced Engineering*. https://doi.org/10.46338/ijetae0422_10.

Google OR-Tools [Online], Available: https://developers.google.com/optimization/.

Greco, F. (2008). Traveling salesman Problem. *IntechOpen*.

Gryech, I., Vinogradov, E., Saboor, A., Bithas, P., Mathiopoulos, P., & Pollin, S. (2024). A systematic literature review on the role of UAV-enabled communications in advancing the UN's sustainable development goals. *Frontiers in Communications and Networks.* https://doi.org/10.3389/frcmn.2024.1286073.

Islam, S. M. R. (2023). Drones on the rise: Exploring the current and future potential of UAVs. *arXiv*. https://doi.org/10.48550/arXiv.2304.13702.

Khandagale, P., Eranjikal, D., Parab, S., & Garg, B. (2021). Design and implementation of drone in healthcare applications. *ITM Web of Conferences*. https://doi.org/10.1051/itmconf/20214002004.

Kimbrough, S., & Lau, H. (2016). The traveling salesman problem. *Business Analytics for Decision Making.* https://doi.org/10.1201/9781315372426-6.

Kitjacharoenchai, P., & Lee, S. (2019). Vehicle routing problem with drones for last mile delivery. *Procedia Manufacturing, 39*, 314–324. https://doi.org/10.1016/j.promfg.2020.01.338.

Korte, B., & Vygen, J. (2012). The traveling salesman problem. Combinatorial optimization. Algorithms and combinatorics. *Springer, 21.* https://doi.org/10.1007/978-3-642-24488-9_21.

Li, X., Yan, P., Yu, K., Li, P., & Liu, Y. (2024). Parcel consolidation approach and routing algorithm for last-mile delivery by unmanned aerial vehicles. *Expert Systems with Applications, 238*, 122149. https://doi.org/10.1016/j.eswa.2023.122149.

Liu, W., Liu, L., & Qi, X. (2024). Drone resupply with multiple trucks and drones for on-time delivery along given truck routes. *European Journal of Operational Research, 318*, 457–468. https://doi.org/10.1016/j.ejor.2024.05.025.

Murray, C., & Chu, A. (2015). The flying sidekick traveling salesman problem: Optimization of drone-assisted parcel delivery. *Transportation Research Part C, 54*, 86–109. https://doi.org/10.1016/j.trc.2015.03.005.

Parrott, E. (2021). Drones. Encyclopedia of Security and Emergency Management. *Springer*, 235-242. http://dx.doi.org/10.1007/978-3-319-70488-3_286.

Punnen, A. P. (2007). The traveling salesman problem: Applications, formulations and variations. The traveling salesman problem and its variations. *Springer, 12.* https://doi.org/10.1007/0-306-48213-4_1

Ram, A., & Arunachalam, A. (2025). Drone application in agriculture and agroforestry. *International Journal on Agricultural Sciences*. https://doi.org/10.53390/ijas.2024.15103.

Shuaibu, A. S., Mahmoud, A. S., & Sheltami, T.R. (2025). A review of last-mile delivery optimization: Strategies, technologies, drone integration, and future trends. *Drones, 9*(3), 158. https://doi.org/10.3390/drones9030158.

Subhan, I., Ghazi, S. S., & Nabi, S. (2019). Use of drones (unmanned aerial vehicles) for supporting emergency medical services in India. *Apollo Medicine, 16(1)*, 61-65.

Thasnim, J., ElGhanam, E., Hassan, M. S., & Osman, A. (2024). Towards efficient collaborative delivery solutions using drones and ground transportation: A review. *2024 International Telecommunications Conference (ITC-Egypt),* 727-732. https://doi.org/10.1109/ITC-Egypt61547.2024.10620589.

Tu, W. (2020). An efficient transition algorithm for seamless drone multicasting. *arXiv*. https://doi.org/10.48550/arXiv.2008.07105.

Tkác, M., & Mésároš, P. (2019). Utilizing drone technology in the civil engineering. *Selected Scientific Papers-Journal of Civil Engineering, 14*(1), 27-37. https://doi.org/10.1515/sspjce-2019-0003.

Zhang, J., Campbell, J. F., & Sweeney II, D. C. (2024). A continuous approximation approach to integrated truck and drone delivery systems. *Omega, 126*, 103067. https://doi.org/10.1016/j.omega.2024.103067.

Wisudawan, H. N. P., Nugraha, A., & Akmal, A. M. (2024). An efficient automatic packet delivery using quadcopter drone. *2024 4th International Conference on Electronic and Electrical Engineering and Intelligent System (ICE3IS)*, 170-174. https://doi.org/10.1109/ICE3IS62977.2024.10775718.