Stochastic Pickup and Delivery Problem with Drone Stations

ITB Research Program 2026 – Research Capacity Building Scheme

Muchammad Arya Zamal[1,*], Suprayogi[1], Setyo Tri Windras Mara[2]

[1] Fakultas Teknologi Industri, Institut Teknologi Bandung

[2] School of Systems and Computing, University of New South Wales, Canberra | *m.zamal@itb.ac.id

Abstract

On-demand food pickup and delivery runs on tight time windows, yet riders' travel times are uncertain because of congestion and miscoordination, so a slight delay can cause costly lateness. We propose **drone stations as an operational back-up**. The **Pickup and Delivery Problem with Time Windows and Stochastic Travel Times (PDPTW-STT)** is formulated as a two-stage stochastic program with a **drone station-based recourse**: when a rider would reach a pickup after its closing time, the request is either served late or reallocated to a rented drone. It is solved by an **adaptive large neighborhood search (ALNS) embedded in sample average approximation (SAA)** and tested on the Li & Lim benchmark and derived instances.

Keywords: urban logistics, pickup-and-delivery problem, drone stations, dronesharing, time windows, uncertainty.

Introduction

Global e-commerce sales are estimated to rise from **US$ 5.13 trillion (2022) to US$ 7.06 trillion (2026)**. Same-day and time-specific delivery make last-mile logistics fragmented and time-critical, while urban congestion makes travel times hard to predict.

Drones bypass traffic, but limited payload and range rule out "pure-play" drone delivery, and owning drones is capital-intensive. **Drone stations** let a firm rent third-party drones only when they are needed.

Research gap. Few PDP studies consider uncertainty, and none uses drone stations to recover route failures caused by stochastic travel times.

Contribution. A novel drone station-based recourse action, using drones as an operational back-up plan rather than as truck–drone tandems.

Objectives

- Formulate a two-stage PDPTW model of food pickup and delivery.
- Design a drone station-based recourse action.
- Develop an ALNS + SAA solver for realistic instance sizes.
- Evaluate the model and method on benchmark instances.

Positioning against related studies

Study	Drone	Drone station	Uncertainty	Recourse
Ghilas et al. (2016)	–	–	Demand	Reallocate
Kim & Moon (2019)	✓	✓	–	–
Xue et al. (2025)	–	–	Customer	Skip
Rios & Xavier (2025)	–	–	Customer	Skip, reallocate
Huang et al. (2026)	✓	–	Travel time	–
Mara et al. (2026)	✓	✓	–	–
This study	**✓**	**✓**	**Travel time**	**Reallocate to drone**

Table 1. Excerpt of the comparison with 28 related studies.

Selected references

- Birge, J. R. (1982). The value of the stochastic solution in stochastic linear programs with fixed recourse. *Math. Program.*, 24(1), 314–325.
- Ghilas, V., Demir, E., & Van Woensel, T. (2016). A scenario-based planning for the PDPTW, scheduled lines and stochastic demands. *Transp. Res. B*, 91, 34–51.
- Kim, S., & Moon, I. (2019). Traveling salesman problem with a drone station. *IEEE Trans. SMC: Systems*, 49(1), 42–52.
- Li, H., & Lim, A. (2001). A metaheuristic for the pickup and delivery problem with time windows. *Proc. ICTAI 2001*, 160–167.
- Ropke, S., & Pisinger, D. (2006). An adaptive large neighborhood search heuristic for the PDPTW. *Transp. Sci.*, 40(4), 455–472.

Research Method

Two-stage stochastic program. *Stage 1* plans motorbike routes (pairing, precedence, payload, time windows) with nominal travel times, minimizing travel cost. *Stage 2* executes them under realized times $t_{ij}(\omega) = t_{ij} \cdot \exp(\sigma Z), Z \sim N(0,1)$.

A **route failure** occurs when a rider would reach the next pickup α after its closing time. The recourse compares two options, re-optimizes the rest of the tour in both, and implements the cheaper one:

Option A: Keep
Rider serves α late and pays the lateness penalty $\beta \cdot f(L)$.

Option B : Drone
Drone flies $s \to \alpha \to \alpha + n \to s$ at cost $\rho \times$ distance (payload, endurance).

Objective: min F(x) = (1/|Ω|) Σω Q(x,ω), the expected distance + drone cost + lateness penalty over sampled scenarios.

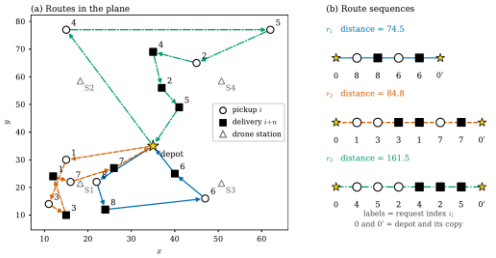
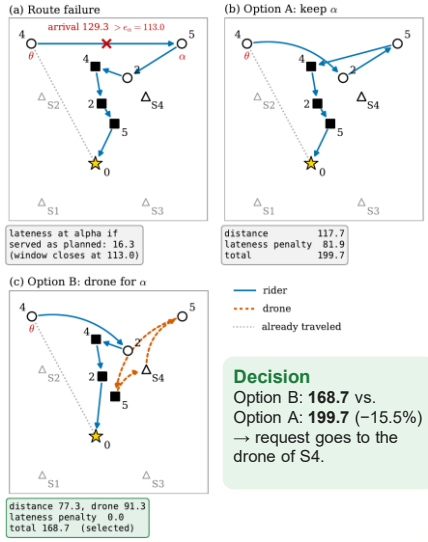


Figure 1. Example first-stage solution (n = 8); drone stations are used only in the recourse.



Decision
Option B: **168.7** vs.
Option A: **199.7** (−15.5%)
→ request goes to the drone of S4.

Figure 2. Recourse on route r_3 (instance lr109-r8) under one travel-time scenario.

Solution method: ALNS embedded in SAA

Initial solution: greedy insertion

Destroy: random, Shaw, worst, route, **failure removal**

Repair: greedy, regret-2, regret-3, with noise

Evaluate F(x′): 51 search scenarios, local-search recourse

Accept & adapt: simulated annealing, adaptive weights

Loop: 5,000 iterations or 60 s

Failure removal (new) targets requests most likely to fail across scenarios.

Final evaluation: x* re-evaluated on 100 out-of-sample scenarios with an exact dynamic program; parameters tuned with Optuna (TPE).

Discussion & Result

Setup. 56 Li & Lim PDPTW instances; 39 lr/lrc instances with 4 drone stations, drone capacity 28, endurance 120 min, $\rho = 1.3, \sigma = 0.35$; 5 seeds; costs on 100 out-of-sample scenarios.

49 / 53
instances reach the best-known distance (mean gap 0.052%)

46×
faster than the exact MIP (0.60 s vs 27.7 s)

−31%
lateness cost vs. plans for nominal travel times

−8.2%
expected lateness with drone stations (ρ = 1.3)

- **Competitive solver:** best-known fleet on 53 of 56 Li & Lim instances.
- **Value of the stochastic solution:** on 142 derived instances with a proven MIP optimum, ALNS plans cost **0.56% less** (p < 0.001); +0.64% planned distance buys −31% lateness and −14% route failures.
- **Scalability:** the MIP proves optimality on all 5- and 8-request instances but on only 11 of 39 with 15 requests; the ALNS needs 0.60 s on average.
- **Value of drone stations:** expected cost −0.22% (p = 0.002), mainly in short-horizon classes (lr1 −0.66%, lrc1 −0.45%).

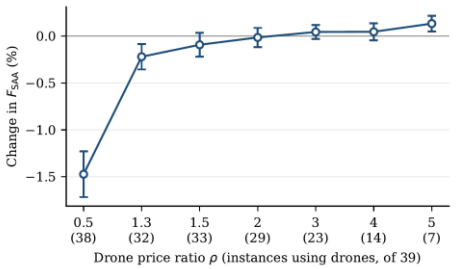


Figure 3. Change in expected cost vs. drone price ratio ρ (95% CI; brackets: instances using drones). Significant up to ρ = 1.3, vanishes at ρ ≈ 2.

Metric	Linear β = 1	Weight β = 2	Grace τ = 5
Lateness (min)	70.67	50.67 (−28%)	75.65 (+7.0%)
Route failures	2.49	1.94 (−22%)	2.70 (+8.6%)
Distance	1188.7	1210.9 (+1.9%)	1190.7 (+0.2%)
Vehicles	8.10	8.53 (+5.3%)	8.08 (−0.3%)
Max lateness	55.9	53.2 (−4.8%)	50.9 (−9.0%)

Table 2. Sensitivity to the lateness penalty (ρ = 1.3, 195 runs per case).

Conclusion

- Drone stations are a **safety buffer**: small cost saving, 8.2% less lateness; value them by service level, not cost alone.
- **Drone price is decisive:** at ρ = 0.5 cost falls 1.47% and the fleet by 0.17 vehicles; break-even at ρ ≈ 2.
- **Cheap drones can replace part of the fleet**; allocate drone capacity first to tight-window settings (dense areas, peak hours).
- Planning under uncertainty yields **more reliable plans in < 1 s**; β sets the lateness level, the penalty shape its distribution.

Future work: real data with correlated travel times, station location, threshold-based drone pricing.

Funded by the ITB Research Program 2026, Research Capacity Building Scheme, Directorate of Research and Innovation (DRI.PN-6-95-2026).