Demand Thresholds, Cost Boundaries, and Sustainable Operating Mechanisms for Scalable Low-Altitude Logistics: A Scenario-Based Analysis of County-Level Urban-Rural Delivery

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Abstract

Whether low-altitude delivery can move from pilot operation to routine service depends less on flight capability itself than on the volume and spatial pattern of demand that must support it. This paper examines that issue through a simple cost-boundary model for county-level urban-rural delivery. The model compares road-only service with an air-ground hybrid and derives two break-even quantities: the daily demand required at a given service radius, $q^*(d)$, and the minimum service radius required at a given demand level, $d^*(q)$. Three operating configurations are considered to show how fixed-cost sharing, utilization, and operating availability move the boundary. A 50,000-draw uncertainty experiment is then used to test whether the main conclusions survive plausible variation in the input assumptions. Under the baseline setting, the break-even radius falls from 29.0 km at 30 parcels/day to 12.5 km at 100 parcels/day and 8.9 km at 200 parcels/day. At a radius of 20 km, the demand threshold is 152.2 parcels/day in the conservative case, 48.5 in the baseline case, and 24.5 in the collaborative case. Across the stipulated uncertainty draws, the hybrid is less costly in 80.5% of cases. Service distance and aggregated demand show the strongest rank associations with the cost difference. The results suggest that low-altitude logistics should be screened by corridor and demand cluster rather than by administrative area alone. They also indicate that demand pooling and shared infrastructure may matter as much as aircraft performance in determining whether a service can be sustained. All numerical inputs are scenario assumptions informed by published studies rather than proprietary operating records.

Keywords

Low-altitude logistics, UAV delivery, demand threshold, cost boundary, air-ground collaboration, county logistics.

1. Introduction

Commercial enthusiasm for drone delivery has moved faster than the evidence available for routine operating decisions. Much of the existing work starts with a routing problem: given a truck, a drone, or a depot, how should deliveries be coordinated? A county-level operator faces an earlier and more basic question. Before routes are optimized, there must be enough demand, at sufficient distance, to justify the additional costs of aircraft, charging equipment, dispatch support, flight coordination, and backup capacity. This issue is particularly important in urban-rural logistics, where parcel flows are often scattered across villages, agricultural production points, medical shipments, and public-service demand rather than concentrated in a dense urban network.

Previous studies identify several factors that determine whether aerial delivery is economical.Truck-drone coordination can shorten completion time and extend effective service reach [1–3], but payload limits, battery use, charging requirements, and range

constraints can offset these gains [4–6]. Work on network design and dynamic dispatch reaches a similar conclusion: the value of unmanned delivery depends on market size, service configuration, and the pattern of incoming demand[7–9]. Environmental assessments are also conditional rather than uniformly favorable. Aircraft size, electricity source, supporting infrastructure, and the characteristics of the ground alternative all influence the result [10–12].

The analysis here therefore starts from a break-even question rather than from an assumption that drones should be deployed. Demand scale and service distance are treated jointly, because neither variable is informative on its own. The model also separates fixed-cost sharing from operating utilization. That distinction matters in settings where several firms can use the same take-off facilities, where public platforms provide flight-service support, or where rural orders can be pooled across shippers. The aim is not to identify a globally optimal vehicle or route. It is to identify the combinations of demand and distance for which a hybrid service is worth examining in greater engineering detail.

2. Related Literature and Analytical Positioning

One part of the literature treats drones primarily as routing assets. Murray and Chu [3] provided an early formulation of the truck-drone delivery problem, and later studies extended the setting to synchronization, energy use, pickup-and-delivery operations, and heterogeneous dispatch [1,4,9]. Reviews by Macrina et al. [13] and Garg et al. [14] show how far this work has developed technically. Even so, most routing models begin after the more strategic adoption decision has already been made. They explain how to operate a drone-enabled system, but not necessarily when such a system has enough economic basis to be introduced.

A second body of work addresses network design and economic viability. Baloch and Gzara[7] show that regulation, customer choice, and network configuration can materially change the attractiveness of drone service. Paul et al.[8] demonstrate that planning decisions also depend on how online demand is learned and incorporated into service design. More recent welfare analysis identifies delivery distance, labor cost, and battery cost as major economic drivers [15]. Strategic adoption studies likewise warn against assuming that an expanded unmanned-delivery option will automatically improve either firm performance or social welfare [16].

Sustainability research adds another qualification. Energy use and life-cycle performance are not properties of the aircraft alone; they depend on the complete delivery system and on the alternative against which the drone is compared [10-12]. The present model does not attempt a life-cycle assessment. Carbon emissions, noise, safety, and wider social externalities are deliberately kept outside the break-even equations. The narrower objective is to determine whether the service is operationally and economically plausible before those additional criteria are introduced.

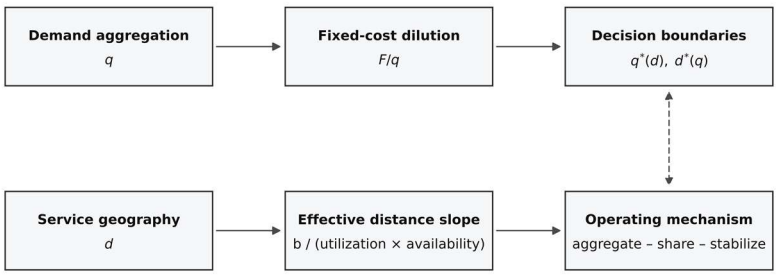


Figure 1. Boundary-based logic for scale-up decisions.

3. Boundary Model and Experimental Design

3.1. Cost Formulation

Let $q>0$ represent the number of parcels consolidated into the service each day and let $d\geq 0$ denote the representative one-way service radius. Two operating forms are compared: ground-only delivery, denoted by G, and an air-ground hybrid, denoted by H. AC_G and AC_H are average parcel costs. The daily fixed-cost terms are F_G and F_H, while a_G and a_H capture base variable cost. Distance-related unit costs are represented by b_G and b_H. For the aerial component, u describes payload utilization and η operating availability. Both lie in (0, 1]. The term $b_H/(u\eta)$ is therefore an effective distance coefficient rather than a nominal flight-cost coefficient: poor loading or unreliable availability raises the cost attributed to each parcel-kilometre.

$$AC_G(q, d) = F_G/q + a_G + b_G\, d \tag{1}$$

$$AC_H(q, d) = F_H/q + a_H + b_H\, d/(u\eta) \tag{2}$$

The cost difference is written as $\Delta(q, d) = AC_G(q, d) - AC_H(q, d)$. A positive value of Δ means that the hybrid has the lower average parcel cost. Expanding the two cost expressions gives $\Delta = (F_G - F_H)/q + (a_G - a_H) + [b_G - b_H/(u\eta)]d$. The break-even boundary is obtained by setting Δ=0. Solving that condition once for q and once for d yields the demand and distance thresholds in (3) and (4).

$$q^*(d) = (F_H - F_G) \,/\, [(a_G - a_H) + (b_G - b_H/(u\eta))d] \tag{3}$$

$$d^*(q) = [(F_H - F_G)/q + (a_H - a_G)] \,/\, [b_G - b_H/(u\eta)] \tag{4}$$

Table 1. Baseline values and uncertainty envelope (triangular entries: [minimum, mode, maximum]).

Parameter	Baseline	Uncertainty / distribution
F_G	160 CNY/day	Uniform [144, 176]
F_H	370 CNY/day	Triangular [300, 370, 440]
a_G	4.20 CNY/parcel	Uniform [3.78, 4.62]
b_G	0.45 CNY/(parcel·km)	Uniform [0.405, 0.495]
a_H	5.80 CNY/parcel	Triangular [5.0, 5.8, 6.5]
b_H	0.12 CNY/(parcel·km)	Triangular [0.09, 0.12, 0.16]
u	0.85	Triangular [0.70, 0.85, 0.95]
η	0.92	Triangular [0.80, 0.92, 0.98]

The interpretation of the two thresholds depends on the sign of the denominator. The parameterization used here assumes $F_H > F_G$, so the hybrid begins with a fixed-cost disadvantage. Define $S = b_G - b_H/(u\eta)$. When $S > 0$, longer distances improve the hybrid's relative cost position. At a fixed d, a finite positive $q^*(d)$ exists only if $[(a_G - a_H) + Sd] > 0$; in that case the hybrid is less costly for $q > q^*(d)$. At a fixed q and $S > 0$, a positive $d^*(q)$ exists when the numerator of (4) is positive, and the hybrid is less costly for $d > d^*(q)$. If that numerator is zero, break-even occurs at $d = 0$; if it is negative, the hybrid is already less costly at $d = 0$ and no

positive lower distance threshold is required. If $S \leq 0$, increasing distance does not create the lower-threshold interpretation used in Figure 2.

3.2. Scenario Calibration and Uncertainty

The parameter values are intended to create plausible operating scenarios rather than reproduce the accounts of a specific logistics company. Their relative ordering follows the literature: hybrid systems generally carry additional equipment and coordination cost; their variable cost is sensitive to loading, weather, automation, and charging; and aerial delivery becomes more attractive when road distance or road friction increases [6,10,14]. Three configurations are used. The conservative setting combines relatively high hybrid fixed cost with low utilization and availability. The baseline represents a more mature but still imperfect operation. The collaborative setting assumes pooled demand and shared take-off or support facilities, which reduces the effective fixed-cost burden and improves the aerial distance term.

Uncertainty is examined through 50,000 simulation draws. Daily aggregated demand is sampled from a triangular distribution spanning 20-250 parcels/day with a mode of 100. The service radius is sampled over 5-35 km with a mode of 18 km. Ground cost parameters vary within ±10% of their baseline values, whereas the hybrid parameters follow the ranges reported in Table 1. These distributions are design assumptions for stress-testing the boundary. The resulting frequencies should therefore be read as conditional simulation outcomes rather than estimates of the probability that a real market will be profitable.

4. Results

4.1. Threshold Geometry

Figure 2 shows that the baseline boundary is steep at low demand and becomes progressively flatter as volume increases. With only 30 parcels/day, the hybrid requires a service radius of about 29.0 km to reach break-even. At 50 parcels/day the threshold falls to 19.6 km. It falls again to 12.5 km at 100 parcels/day, 10.1 km at 150, and 8.9 km at 200. The reason is straightforward. When demand is small, each additional parcel absorbs a meaningful share of the fixed-cost premium FH-FG. Once the daily volume is already high, another increment of demand has a much smaller effect on average fixed cost.

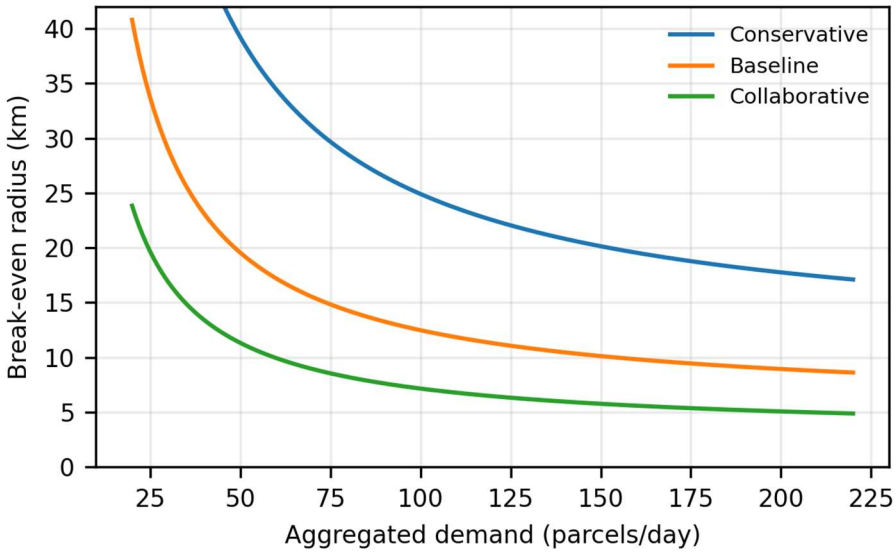


Figure 2. Break-even service radius under three operating configurations.

Table 2. Demand threshold $q^*(d)$, parcels/day (N/A = no positive finite threshold at that distance).

d (km)	Conservative	Baseline	Collaborative
10	N/A	153.8	59.4
15	325.2	73.7	34.7
20	152.2	48.5	24.5
25	99.4	36.1	18.9
30	73.8	28.8	15.4

The difference among the three configurations is substantial. At a 20-km radius, the conservative case does not reach break-even until daily demand reaches 152.2 parcels. The corresponding threshold is 48.5 parcels in the baseline case and 24.5 in the collaborative case. Two mechanisms explain the shift. Shared infrastructure reduces the hybrid fixed-cost premium, while better utilization and availability lower the effective aerial distance cost. This is also why pilot projects that appear technically similar can produce very different economic results.

4.2. Robustness and Sensitivity

The uncertainty experiment does not produce a uniformly favorable result for the hybrid. Δ is positive in 80.5% of the 50,000 draws, but the remaining cases favor ground-only delivery. The median modeled advantage is 1.85 CNY per parcel, and the central 95% simulation interval extends from -2.48 to 6.25 CNY per parcel. The negative portion of that interval matters. It shows that the model does not imply an inherent cost advantage for aerial delivery; the sign of the result still depends on the operating conditions represented by the sampled parameters.

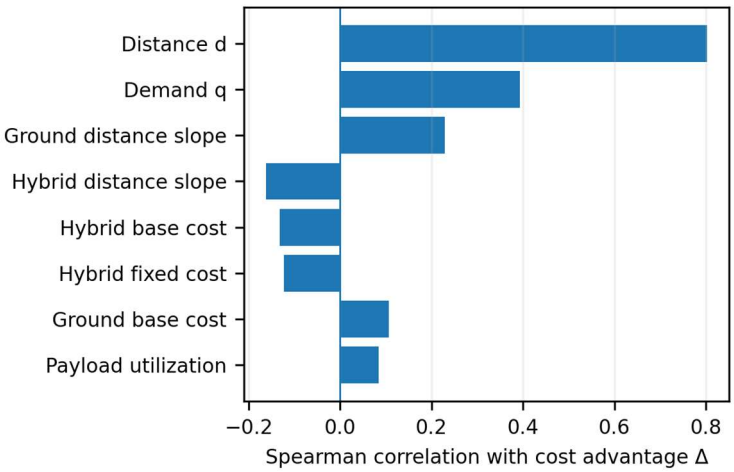


Figure 3. Global sensitivity ranking from the uncertainty experiment.

Service distance has the strongest rank association with the cost difference, with Δ (ρ_s = 0.803). Aggregated demand is next at (ρ_s = 0.394). The coefficients governing ground and aerial distance cost also have relatively strong effects. Fixed and base variable costs matter, although their influence weakens as demand increases because fixed-cost dilution becomes less important. Utilization and operational availability are different from the geographic variables in one important respect: managers can influence them. Parcel screening, departure scheduling, backup capacity, and shared dispatch can all change u or η, whereas service geography is largely given.

4.3. Regime Map and Decision Rules

The separate demand and distance thresholds are useful for calculation, but the joint demand-distance plane is easier to use for screening. Figure 4 plots Δ across the experimental range. The contour where Δ=0 separates the two modeled cost regimes. Low demand and short service radii fall on the ground-favored side because the hybrid fixed-cost premium remains large and the distance saving is too small to offset it. As demand and spatial dispersion increase, the balance moves toward the hybrid. The contour should not be interpreted as an adoption forecast. It is better viewed as a first-stage filter for identifying corridors that warrant more detailed technical and financial analysis.

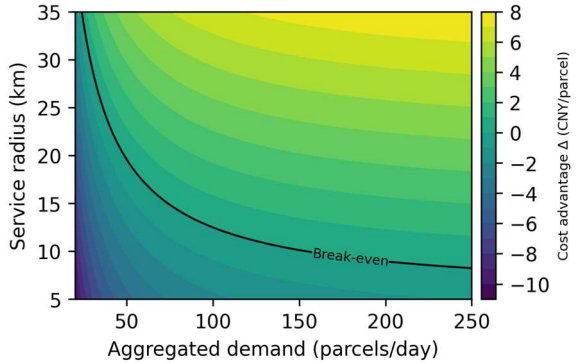


Figure 4. Baseline operating-regime map; the black contour marks $\Delta = 0$.

This map also shows why county-wide averages can hide the relevant economics. Two counties may process the same total number of parcels but have very different service structures. A compact county with short road links can remain ground-dominant, while the same volume spread across distant villages may lie on the other side of the boundary. Different regimes can also coexist inside one county. Dense urban neighborhoods may remain suitable for conventional delivery, whereas township-to-village corridors or emergency medical shipments may justify aerial service. For this reason, the service corridor or demand cluster is a more useful unit of analysis than the administrative area as a whole.

For planning purposes, the boundary can be translated into three practical states. When $q < q^*(d)$, the immediate priority is not aircraft acquisition but demand pooling and ground-route consolidation. Near $q^*(d)$, limited shared flights can be used to measure reliability, demand regularity, and actual cost coefficients. Only when demand remains above the threshold over repeated planning periods-and when u and η remain stable as volume grows-does larger-scale deployment become a credible option. This distinction is important because temporary pilot demand can otherwise be mistaken for a durable commercial market.

Table 3. Boundary-based deployment states.

State	Diagnostic	Recommended action
Ground-first	$q < q^*(d)$	Pool orders; improve ground consolidation
Transition	$q \approx q^*(d)$	Shared pilot; measure utilization and disruptions
Scale candidate	$q > q^*(d)$ persistently	Expand selectively; retain air-ground fallback

5. Sustainable Operating Mechanisms and Implications

The boundary results imply a different order of investment decisions from the one often seen in technology-led pilots. Demand aggregation should come first. County logistics usually

contains several small flows-express parcels, agricultural products, medical items, and public-service shipments-that are too thin individually to support a dedicated aerial service. Combining compatible flows raises q without requiring a new aircraft. If outbound and return cargo can also be matched, utilization improves at the same time. Both changes move the service toward the economically feasible region before additional capital is committed.

Fixed assets are the next issue. Take-off points, charging equipment, digital dispatch, flight-service interfaces, maintenance capacity, and reserve aircraft are expensive when they are dedicated to one small operator. A shared service platform can spread some of those costs across several users. This interpretation is consistent with work showing that network structure and institutional design can affect UAV viability as strongly as route length [7,15,16]. In the model, that effect appears mainly through a lower FH and, indirectly, through more stable utilization and availability.

Air-ground specialization should also remain selective. Dense neighborhoods with short road links and many closely spaced stops are natural candidates for ground service. Aerial legs are more defensible where villages are dispersed, road detours are long, cargo is time-sensitive, or access is constrained. The model therefore points to a staged operating rule rather than blanket substitution: remain ground-first below the boundary, test shared hybrid operations near the frontier, and expand only after demand, utilization, and availability remain stable. This may appear less ambitious than full replacement of ground delivery, but it is easier to justify operationally.

Cost break-even is only one part of the deployment decision. A route can satisfy $\Delta > 0$ and still be unattractive once noise, safety, airspace capacity, carbon intensity, or community acceptance are considered. Those factors should be assessed explicitly after the economic screening stage. Folding all of them into one unexplained cost coefficient would make the model less transparent rather than more complete.

5.1. From Pilot Flights to Recurring Service

A demonstration flight and a recurring logistics service operate under very different conditions. Demonstrations are usually planned around suitable weather, high-priority cargo, prepared routes, and close operational supervision. Routine service must cope with cancellations, maintenance, partially loaded departures, irregular daily demand, and the cost of coordinating several organizations. In the present model, many of these frictions are reflected through η, u, and F_H. A corridor that appears economical only when every flight is full and almost every day is flyable should not yet be treated as a stable commercial route. For scale-up decisions, consolidated daily demand, load factor, successful-flight ratio, backup-ground mileage, and fixed cost per active corridor are therefore more useful than flight time alone.

Infrastructure should be evaluated in the same way. A county does not necessarily need separate take-off sites, charging facilities, maintenance assets, and dispatch systems for every operator. Shared facilities can reduce the fixed-cost burden even when aircraft performance is unchanged. This distinction matters because a reduction in F_H moves the break-even boundary immediately, whereas a modest increase in cruising speed may have little economic effect if demand remains sparse. Public or multi-user infrastructure should therefore be assessed by how much fixed cost it removes from individual corridors and whether it improves operational availability across several users.

5.2. Evidence Requirements for Empirical Deployment

Before the boundary model is used for an actual investment decision, its parameters should be estimated from operating data. A useful calibration dataset would include parcel weight and dimensions, origin-destination coordinates, ground travel distance and time, drone flight distance, battery cycles, labor input, maintenance events, weather-related cancellations, and

the share of demand that can be consolidated into common departure windows. With such records, a_G, b_G, a_H, b_H, u, and η could be estimated separately by corridor and season. The resulting thresholds would then be traceable to observed operations rather than to illustrative scenario values.

Selection bias is another concern. Early drone routes are rarely chosen at random. Operators often select visible, difficult-to-access, or time-sensitive corridors precisely because those routes make the technology look useful. Evaluating only successful pilots can therefore exaggerate the likely performance of a wider rollout. A stronger empirical design would retain failed and cancelled missions, compare similar corridors with and without aerial service, and test alternative assumptions for depreciation, battery replacement, and ground-vehicle utilization. This would help distinguish a genuine technology effect from a result produced by unusually favorable pilot conditions.

6. Conclusion

The results suggest that scalable low-altitude logistics is better understood as a boundary problem than as a simple technology-choice problem. Demand, service distance, fixed-cost sharing, utilization, and operating availability jointly determine whether the modeled hybrid can compete with road-only delivery. Under the baseline assumptions, the required service radius decreases sharply as demand rises. The collaborative configuration shifts the boundary further by reducing both the fixed-cost burden and the effective aerial distance cost. The uncertainty analysis leads to the same broad interpretation: geography and demand provide the strongest structural influence, while utilization, availability, and cost sharing determine how far the feasible region can be moved through management.

The model is deliberately simple, which makes the break-even logic visible but limits what can be inferred from the numerical results. The next step should be calibration with order records, flight logs, maintenance histories, weather disruptions, and observed ground-delivery costs. A later extension should also add carbon, noise, safety, and service-quality effects so that private operating break-even can be distinguished from wider social desirability. Until those data are available, the thresholds reported here are best treated as scenario-based decision aids rather than estimates of the profitability of any specific operator.

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