

Cost Game Analysis of the Hybrid Delivery Model Combining Drones and Riders: A Study on the Collaborative Mechanism Based on the Stackelberg Competition Model

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Abstract. As the demand for instant delivery surges and labor costs rise, collaborative delivery between drones and traditional couriers has become the key to breaking the deadlock in the industry. This study constructs a two-stage Stackelberg leader-follower game model, with the Unmanned Aerial Vehicle (UAV) as the leader (decision service density and pricing Pd), delivery rider for followers (dynamically adjust order volume qr), model incorporates specific parameters for the low-altitude economy (airspace congestion cost β , density utility coefficient θ), using backward induction to solve for the optimal strategy, revealing the equilibrium mechanism of the dynamic game of resources under a hybrid delivery model, provide decision-making support for the government in (ting low-altitude economy policy platforms and optimizing resource allocation. Results show that when the airspace congestion cost increases, an increase in drone density is required to reduce marginal congestion loss. The government can optimize resource allocation through the "Dynamic Airspace Access Threshold" and "Density-Subsidy Linkage" policies, thereby reducing the total system cost. This study provides quantitative tools for the (tion of low-altitude economy policies and promotes the transition of collaborative delivery between drones and couriers from theoretical concepts to large-scale practical implementation.

Keywords: Low-altitude economy, Stackelberg game model, hybrid delivery model, congestion cost.

1. Introduction

With the gradual and orderly opening of low-altitude airspace, "low-altitude economy" has become a new driving force for the economic development of various countries, representing a typical example of new productive forces [1]. Many countries and regions are standardizing airspace management and developing a low-altitude economy. For example, China has approved the operation of 20 civil unmanned aerial logistics system test bases (13 in the first batch and 7 in the second batch, with Henan, Zhejiang, and Shenzhen targeting urban-scenario unmanned trials), including two unmanned logistics test zones and three unmanned delivery city test zones [2]. Compared to the traditional rider delivery model, the drone-assisted rider delivery model can effectively reduce the number of technologies used and lower delivery costs [3]. Studies have shown that drones have delivery costs that are only half of what a rider would cost [4]. This advantage is further validated in a cost-benefit analysis of Amazon Prime Air, determining whether drone delivery is more cost-effective than land transport [5]. The use of drones not only improves the speed and efficiency of goods delivery but also enables navigation in complex urban environments and remote areas [6-8]. Existing studies are advancing along three directions. First is techno-economic analysis. Fu et al. have investigated the path optimization problem of drone and vehicle collaborative delivery [9]. The second is interaction research on models. Zhaoju et al. quantified the complex interactions of logistics sharing in a hybrid e-commerce model through the Stackelberg game model, clarifying the optimal strategy combinations for platforms and sellers under different market conditions [10]. Third is game mechanism design. Yutao, based on game theory, explores the power coordination and interest allocation among different interest stakeholders [11]. In summary, while there are some studies on drone rider joint delivery, existing results lack embedded analysis of low-altitude economy-specific parameters, such as aerial congestion cost β and density utility θ . This study establishes a Stackelberg game model to analyze the cost game relationship between drones and couriers,

constructs an optimal resource allocation strategy for a hybrid delivery system, and provides theoretical support for enterprises to optimize their capacity structure. This study constructs a two-stage leader-follower game model, where drones are designated as leaders responsible for determining delivery density and pricing strategies, while riders act as followers, dynamically adjusting their order volume. The research employs backward induction to solve the response function. Research objective: Based on Stackelberg game theory, investigate the collaborative mechanism between drones and couriers, and reveal the equilibrium state and optimal strategies of the hybrid delivery system.

2. Problem Description

In the current food delivery industry, the hybrid delivery model combining drones and couriers is gradually becoming a key solution to enhance efficiency and reduce costs. However, the collaboration between the two entities involves complex strategic interactions. Drones have the characteristics of high fixed costs and low marginal costs, requiring massive deployment to reduce unit costs. However, over-deployment may lead to airspace congestion. By comparison, delivery riders are part of the flexible workforce, with their order volume constrained by fatigue levels and their pricing needing to respond to drone competition.

2.1. Model Assumptions and Parameter Settings

This study sets up a two-stage leader-follower game. In the first stage, the drone is set as the leader (drone delivery system), controlling the service density ρd (number of drones per square kilometer) and pricing strategy Pd (single delivery fee). In the second stage, the rider acts as the follower, adjusting their order volume qr in response to the drone's ρd and Pd .

Assume the drone's cost structure is divided into fixed costs (hardware acquisition, system development, regulatory compliance) Fd , variable costs (energy costs: hourly energy consumption \times electricity price \times average daily flight hours, insurance costs: 1-3% per year \times drone price \times 2% \div 365, maintenance costs: drone purchase price \div design life hours \times average daily flight hours) Cd , and congestion costs ($\beta Q/\rho d$, where β represents the average delay time \times user time value + accident loss rate). Assume the rider's order acceptance cost is Cr , the base wage rate is Wr , the fatigue elasticity coefficient is γ , and the quadratic term represents efficiency losses due to accumulated fatigue.

2.2. Construction of the Stackelberg Game Model

Assume the game between drones and couriers is a Stackelberg game based on a drone delivery system. The profit function of drones is

$$\pi d = Pd \times Qd - Fd - Cd(\rho d) - \frac{\beta Q}{\rho d} \quad (1)$$

The cost for a delivery rider to accept an order is

$$Cr(qr) = Wr \times qr + \gamma(qr^2) \quad (2)$$

Thus, the rider's earnings are

$$\pi r = Pr \times qr - Cr(qr) (Pr \text{ is influenced by } Pd) \quad (3)$$

Building a user choice model based on Hotelling's linear city assumption: When $X = 0$, it represents a pure preference for drones; when $X = 1$, it represents a pure preference for delivery riders, with $X \in [0, 1]$

$$Ud = V - Pd + \theta \rho d - tx \quad (4)$$

$$Ur = V - Pr - t(1 - x) \quad (5)$$

Among these, V represents the basic value of delivery services, reflecting users' overall willingness to pay for delivery services. Pd and denote the delivery prices of drones and couriers, respectively. represents the positive externality of drone density, which can be understood as a network effect, such as dense deployment reducing the average delivery distance and decreasing user waiting time. t represents users' sensitivity to location differences, and x represents the user's position in a linear space (with a value range of $[0, 1]$). It is assumed that users are uniformly distributed in the linear space.

$$Ur = Ud, x = \left(\frac{1}{2} + \frac{Pr - Pd + \theta \rho d}{2t}\right) \tag{6}$$

Where x represents the market share, can derive that

$$Qd = \left(\frac{1}{2} + \frac{Pr - Pd + \theta \rho d}{2t}\right) * Q \text{ (Q is the total order quantity)} \tag{7}$$

2.3. Using Backward Induction to Solve

The optimal response of the rider in the second stage is driven by profit maximization

$$\pi r = Pr \times qr - Cr(qr) \tag{8}$$

Take the derivative of qr , when maximizing profit, which means MR equals MC

$$Pr - Wr - 2qr\gamma = 0 \quad qr * = \frac{Pr - Wr}{2\gamma} = \frac{Pd - \alpha \rho d - Wr}{2\gamma} \tag{9}$$

Among them

$$Pr = Pd - \alpha \rho d \text{ (\alpha is the competitive response coefficient, reflecting the strength of price following)} \tag{10}$$

First phase drone decision-making, because

$$\pi d = Pd \times Qd - Fd - Cd(\rho d) - \frac{\beta Q}{\rho d} \tag{10}$$

Therefore, substitute $qr *$, pr into the profit function, take the partial derivative with respect to ρd to derive the optimal density

$$\rho d * = \sqrt{\frac{\beta Q}{Cd - \frac{(\theta - \alpha) Pd}{2t}}} \tag{11}$$

Then take the partial derivative of Pd to derive the optimal pricing

$$Pd * = Wr + 2\gamma \cdot qr * + \frac{t}{2} * \left(1 - \frac{(\theta - \alpha) \cdot \rho d *}{t}\right) \tag{12}$$

2.4. Model Parameters and Their Mapping to Real-World Problems

2.4.1 Airspace congestion cost β

The physical meaning refers to the losses incurred per order due to airspace congestion, including time delays (such as user complaints caused by delivery delays) and accident risks (such as collision repair costs). Practical issue: In densely populated cities, the β value is relatively high, necessitating an increase in to share the congestion costs. However, this is constrained by the upper limit of airspace density specified by policy regulations.

2.4.2 Density utility coefficient θ

Physical meaning: The positive externalities brought by increased drone density, such as expanded coverage and reduced response time. Practical issues: In suburban areas (higher θ), increasing ρd can significantly enhance user experience; however, in central urban areas (lower θ), over-deployment may lead to resource wastage.

2.4.3 Competitive response coefficient α

The physical meaning: The sensitivity of rider pricing (Pr) to drone density (ρd) reflects the intensity of competition between them. Practical issue: If it is too high (e.g., riders aggressively lowering prices), it may lead to profit compression for drones, forcing the government to intervene and set minimum pricing or density.

3. Research Limitations and Future Prospects

This study highlights several limitations of the current models. First, the assumption of a linear uniform distribution of user preferences does not align with the spatial heterogeneity and clustering characteristics observed in reality, potentially leading to biased market share predictions. Additionally, the quantification of parameters such as the airspace congestion cost and density utility coefficient primarily relies on theoretical settings, making accurate calibration challenging in practical applications due to dynamic environments and regional disparities. Second, the model does not adequately account for external factors such as weather changes and policy implementation barriers, for example, the disruptive impact of extreme weather on drone delivery and the technical and regulatory coordination required for airspace access policies. Furthermore, the modeling of courier behavior considers only the fatigue elasticity coefficient γ , overlooking the influence of social factors such as platform incentive mechanisms and job satisfaction.

Future research can be further explored in two directions. On one hand, it is necessary to establish a multi-agent game framework to analyze the competitive and cooperative relationships among drone operators, as well as the collaborative mechanisms between drones and other transportation modes such as couriers and autonomous vehicles. Additionally, artificial intelligence technologies like reinforcement learning can be introduced to optimize dynamic decision-making processes. On the other hand, efforts should be made to promote the integration of technological innovations, utilizing IoT technology to build a low-altitude economy simulation platform for complex scenario modeling. Combining big data analysis, this approach can further optimize dynamic pricing and order volume matching mechanisms. This study provides a theoretical foundation for the development of low-altitude economy, and future work can leverage interdisciplinary collaboration to advance theoretical findings into intelligent and scalable practical applications.

4. Conclusion

According to the optimal density formula, dynamically adjust the deployment density of drones. When the airspace cost increases, the corresponding proportion to increase the optimal is needed in order to reduce the marginal congestion loss. Deploy IoT sensors and a big data platform for real-time monitoring of airspace traffic, accident rates, and order volume Q . Automatically trigger elastic deployment strategies during peak periods or extreme weather conditions to temporarily allocate additional drone resources. 3. Set density deployment lower limits and safety thresholds: Enforce the minimum feasible density to prevent congestion costs from running out of control due to insufficient density. For example, during the rainy season or promotional periods (when Q surges), require businesses to maintain ρd above ρd^{min} . Based on regional demand differences, set dynamic density upper limits, and impose congestion taxes on excess amounts to balance efficiency and safety.

Adjust the pricing of drones dynamically based on the optimal pricing formula: - In highly price-sensitive areas (where t increases): Reduce through time-based discounts or coupons to maintain market share, keeping Q stable at $Q = \left(\frac{1}{2} + \frac{Pr - Pd + \theta \rho d}{2t}\right) * Q$. - In highly competitive areas (where t increases): Increase the drone density to enhance the positive externality, while moderately raising to cover costs and offset the pricing advantage of riders (Pr). 2. Optimize the cost and incentive mechanisms for riders' order volume: - Based on the optimal order volume $qr *$ for riders, design flexible employment policies. - Fatigue coefficient adjustment (where γ increases): During peak

hours, increase riders' wages (Wr) or shorten the duration of single-order assignments to ensure remains stable. - Dynamic pricing feedback: Adjust riders' pricing (Pr) in real-time through a bidding system to ensure $Pr = Pd - \alpha pd$.

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