

Research Article

Comparative Analysis of Drones and Riders in On-Demand Meal Delivery Based on Prospect Theory

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At present, the demand for on-demand meal delivery is increasing, and the main delivery pattern is rider delivery. However, rider delivery has certain problems in terms of timeliness and security. Due to its advantages of being fast, convenient, and safe, drone delivery can, to a certain extent, solve the problems of rider delivery. However, can drone delivery completely replace rider delivery? The paper mainly uses the prospect theory to discuss the conditions under which drone delivery is superior to rider delivery based on four factors: delivery distance, degree of rider delay, pickup time, and consumer attitudes towards drone delivery. Based on the research, it was found that when the delivery distance is more than 7 kilometres, the pickup time is within 2 minutes, or when consumers accept drone delivery, drone delivery is better than rider delivery. When the rider's delay caused the delivery time to increase by more than 20%, the advantages of drone delivery began to stand out. Moreover, research has proven that drone delivery will help expand the scope of instant delivery, and the rational layout of drone airports and strengthening of consumer awareness and friendliness towards drone delivery will also help promote the development of drone delivery.

1. Introduction

With the acceleration of the pace of life, consumers have an increasing demand with regard to the timeliness of delivery, and the dynamic characteristics of demand have become more and more obvious. On-demand delivery has emerged. Currently, food accounts for the largest proportion of all on-demand goods in China [1]. According to Trustdata mobile data, the value of China's takeaway industry transactions was 134.8 billion yuan in 2015, 461.3 billion yuan in 2018, and 603.5 billion yuan in 2019. This shows that on-demand meal delivery is a very large market with unlimited development potential. Similarly, the development of Uber Eats in the United States has also verified this idea [2]. To realize high-quality delivery, an effective delivery pattern is very important.

At present, considering the special needs for timeliness, on-demand meal delivery is mainly performed by door-to-door delivery by riders. To reduce delivery costs and improve delivery efficiency, crowdsourced delivery is the common

practice [3, 4]. Crowdsourced delivery refers to a new delivery pattern that introduces the concept of crowdsourcing into the field of logistics. It uses social labour instead of company employees for delivery [5]. In crowdsourced delivery, the social labour may be nonprofessional drivers, travelers, or commuters [4]. They can act as a free courier, obtain task information through the crowdsourced delivery platform, choose the appropriate task according to their own time and schedule, and complete the delivery [4, 5]. In China, crowdsourced delivery staff is called rider. The advantages of crowdsourced delivery are flexibility, convenience, and cost reduction [6]. However, there are still some problems for on-demand meal delivery. First, in the delivery process, there will be problems such as low delivery efficiency and delays due to uncertain factors such as unreasonable dispatch and route optimization, traffic jams, and inconsistent connections between rider and consumers [7, 8]. Second, due to the excessive pursuit of delivery speed, the riders frequently cause traffic accidents during the delivery process, which put some pressure not only on the

riders themselves but also on society. Riders have suffered traffic fatalities in many countries, including China, the United States, Mexico, and Argentina [9]. Finally, because the crowdsourced delivery staff is mainly based on social labour, that is to say, the delivery is completed by non-company employees, and the management of crowdsourced delivery riders is not perfect, there are uncertainties surrounding crowdsourced delivery riders' ability and quality [10, 11]. In addition to the problem of delayed delivery, there may be hidden dangers to consumer safety [12] and privacy.

Because of the above problems, on-demand meal delivery has attracted more and more attention from consumers and scholars. In terms of how to improve the efficiency of delivery, scholars mainly focus on the delivery path [8, 13], capacity scheduling [14], order management [15, 16], and other perspectives to find a way to solve the problem. Moreover, with the emergence and popularization of drones and considering the advantages of drones, drones have also become one of the ways to improve the efficiency of delivery [2, 17, 18]. Drones are unmanned aerial vehicles that have the advantages of fast speed, environmental protection, and so forth [17, 18]. To meet the on-demand delivery needs, scholars are exploring better mathematical models, algorithms, and technical means to solve the problem of delivery efficiency. In particular, emerging technology such as drone delivery can not only improve the efficiency of delivery and avoid the impact of traffic congestion but also make the delivery pattern more and more diversified, and consumers will face more choices of delivery patterns. Therefore, how should consumers choose the on-demand delivery pattern? Under what delivery scenarios can the delivery pattern maximize its advantages? How do different delivery patterns coexist in the delivery system [19]? In particular, how can development of drone delivery, which is more environment-friendly and efficient, be promoted? These are issues worthy of further research.

The paper proposes a drone + self-collection delivery pattern mainly considering the advantages of fast speed and the environmental protection effects of drones and the consumers' trust in self-collection [18]. Based on prospect theory, from the perspective of delivery distance, degree of rider delay, degree of consumer acceptance of drone delivery, and convenience of drone delivery, the paper takes the consumer's expected delivery time as a reference point to measure whether the consumer's choice of a certain delivery pattern will result in a loss or profit and calculates the prospect value of two delivery patterns of rider and drone. According to the size of the prospect value, the paper compares and analyses the two delivery patterns and then clarifies the scenarios under which the delivery pattern of drone or rider can maximize their advantages. The final purpose of the paper is to find applicable scenarios for drone delivery, to provide some reference for the development of drone delivery, last-mile delivery, and on-demand delivery of meals, and to promote drones as a green and environment-friendly delivery pattern to play a more important role in the future of on-demand delivery.

The structure of the paper is as follows: the second part mainly presents relevant literature; the third part describes

the methodology used in this study; the fourth part describes the model of drone delivery and rider delivery; the fifth part conducts data survey; the sixth part discusses the scenarios under which the delivery pattern of drone or rider can maximize their advantages from the delivery distance, degree of rider delay, degree of consumer acceptance to drone delivery, and the convenience of drone delivery; and the seventh part is the conclusion of this paper and discusses the next steps in this research.

2. Literature Review

In this section, we review the literature in the related areas of drone delivery and choice of delivery pattern.

2.1. Drone Delivery. In response to social issues such as environmental protection and traffic safety caused by on-demand delivery, some scholars have begun to consider the use of subways, electric vehicles, and so forth for urban delivery. Zhou et al. [20, 21] proposed that the subway was involved in the urban logistics delivery network, and the path optimization problem was solved by improving the recursive granularity algorithm and the iterative search algorithm of random variable neighbourhood. Ge and Li [22] mainly studied the vehicle scheduling problem of electric vehicle delivery, the intelligent algorithm of electric vehicle logistics delivery, the location of electric vehicle service facilities, and the intelligent charging schedule of electric vehicles. With the advent of drones, people have begun to practice and discuss drone delivery.

Amazon tested its delivery drones in USA [23], and Alibaba's online instant delivery giant attempted to operate drone delivery and takeaway in Shanghai in 2015 [24]. At present, JD and other logistics providers have started to operate the drone urban logistics delivery. Fast Ant has also launched drone meal delivery services in Hangzhou. In October 2019, Uber Eats announced the design of drones for takeaway delivery. Although many logistics providers are trying drone delivery, the drone delivery in the city is still in the trial stage and has not yet officially operated.

The research on drone delivery is currently focused on the following aspects. First, some scholars have predicted and analysed the application prospects of drones. Narkus-Kramer [25] predicted that the number of drones used in urban delivery in Washington would reach 1 million by 2050. Second, considering that drones are an emerging technology and there are some unknowns and concerns among the public, some scholars have studied the public's attitudes towards drone delivery [26] and the factors impacting consumers' acceptance of drones. Yoo et al. [17] surveyed 296 American consumers regarding their attitudes towards drone delivery online, including drone speed, environmental comparative advantages, complexity, performance and privacy risks, personal innovation, and other factors, and the factors influencing consumers' acceptance of drone delivery were analysed. Some scholars have pointed out that consumers are still trying to accept the service of drones [18]. Third, more scholars focus on the issue of drone

delivery being more cost-effective and environment-friendly. Mario et al. [27] proposed a drone-truck non-fixed-point connection model to be used in delivery and proved by example verification that this method could reduce costs. Goodchild and Toy [28] proposed that, in some scenarios, with regard to carbon dioxide emissions, drone delivery has advantages over truck delivery and is more environment-friendly. Chianga et al. [29] also used the mixed-integer model and genetic algorithm to verify that the use of drones for last-mile delivery could save costs and protect the environment. In addition, there are some scholars who focus on the path optimization of drones [2] and the optimal location of drone-beehives and service range [30]. Finally, some scholars also discuss issues about potential limitations of the use of drones, including local legislation, the safety of autonomous systems, and level of maturity of the technology. Zheng pointed out that ICAO had begun to develop standards and recommended measures for drones and related systems, air navigation service procedures, and instructional materials. There are some legal obstacles to using drones in China, including the lack of a clear regulatory body and unclear rules for sharing responsibilities in the event of a drone accident [31]. Lidynia et al. pointed out people's concerns about the malfunction of drones and invasion of privacy [32]. Koh et al. used simulation methods to simulate the direct damage caused by falling drones hitting the human head and conducted a comprehensive analysis about it [33].

2.2. Choice and Comparison of Delivery Pattern. For last-mile delivery and on-demand delivery, there are two main types of delivery pattern: home delivery and self-collection delivery. Because the delivery staff delivers the goods directly to the customer's home in the home delivery, this pattern is more convenient for customers, but customers must wait for the delivery staff at home. Moreover, due to the problem of delivery efficiency, the delivery staff may not deliver the goods to the customer's home within the promised time and the customer will wait longer than expected at home. For the self-collection method, the delivery staff deliver the goods to the nearest delivery box, for example, the delivery box in the community where the customer lives. The customer picks up the goods from the delivery box at the appropriate time. This pattern solves the shortcomings of home delivery, such as the need to wait at home [34, 35], but it requires some time for customers to leave their homes to go to the delivery box.

Each delivery pattern has its own characteristics, advantages, and disadvantages. Additionally, different consumers have different attitudes towards different delivery pattern. Yuen et al. [36] studied the factors that influenced consumers' choice of delivery pattern. There are also some scholars who compare and analyse different delivery patterns. Zhu et al. [18] discussed the joint selection behaviour of delivery pattern, service type, and delivery time slot based on the cross-nested logit model. Chen et al. [37, 38], based on the nested logit model, constructed a delivery service selection model under bounded rationality and discussed the balance of customer and enterprise selection of the last-mile

delivery service from the perspectives of freight and customer limited rationality.

There is less related literature on meal delivery. Bräysy et al. [13] first applied the salesman problem with a time window to discuss the problem of communal home meal delivery service in 2009. Liu [2] mainly proposed effective algorithms for how to more effectively conduct fleet operations and path planning for the drones being applied to meal delivery. There is very little existing literature comparing and analysing drone delivery and rider delivery. Moreover, there is no literature to discuss the respective advantages of different delivery patterns in the delivery system. Especially for drone delivery, it is important to explore under what circumstances drone delivery is better than rider delivery and under what conditions drone delivery is more applicable. The paper will take the on-demand delivery of meals as the research object and use prospect theory to calculate the prospect value of the two delivery patterns in different scenarios. It will then use this as a basis to compare the two delivery patterns and determine the applicable conditions of the two delivery patterns, especially drone delivery.

3. Prospect Theory

3.1. Introduction to Prospect Theory. For the comparison and choice of delivery patterns, the entire process is in an uncertain environment due to the influence of factors such as road conditions, order allocation, route planning, selection of delivery rider, and the time of receipt. In other words, consumers conduct a comparative analysis of patterns in an uncertain environment and ultimately make behavioural choices. Therefore, this paper will choose a theory of behaviour choice under an uncertain environment to study the problem of delivery service pattern choice and comparison.

In the study of individuals making behavioural choices under uncertain circumstances, the prospect theory proposed by Kahneman and Tversky in 1979 is considered to make up for the shortcomings of traditional economic theory based solely on individual rational factors [39, 40] because it fully considers the characteristics of individuals' incomplete rationality in actual decision-making and integrates personal value perception factors into decision-making behaviour [41]. Additionally, the prospect theory points out that people will avoid risks when facing gains, and people will pursue risks when facing damages. Decision-makers present different choice attitudes in different scenarios. In the actual decision-making process, the individual's concern is not the maximum value of the utility but rather the change in the utility, that is, the change relative to a reference point. Compared with other theories, the prospect theory is more practical and has been widely used in many fields for related research [42–44].

Prospect theory uses two steps to evaluate alternative decision options. First, the reference point for behavioural decision-making and the profit or loss according to the relationship between the alternatives and the reference point will be determined. Then, the prospect value of each scheme will be calculated through the value function and the weight

function. The scheme with the greatest prospect value is the optimal scheme [39, 40]. The calculation method of the prospect value is shown in the following formula:

$$EV_i = \sum_{i=1}^n v(x_i)w_p, \quad (1)$$

EV_i represents the prospect value of the scheme i , $v(x_i)$ represents the value function of the scheme i , and w_p represents the weight function.

The calculation formula of the value function is as shown in formula (2). x_i represents the profit and loss value of the decision-maker's choice of scheme i . $x_i \geq 0$ means profit; $x_i < 0$ means loss. ∂ and β are the decision-makers' sensitivity to risk. The larger the value of ∂ and β is, the more sensitive the individual is to risk. λ is the individual's sensitivity to loss, and $\lambda > 1$ always holds, indicating that decision-makers are more sensitive to loss. A large number of experimental results show that $\partial = \beta = 0.88$ and $\lambda = 2.25$ are more suitable.

$$v(x_i) = \begin{cases} x_i^\partial, & x_i \geq 0, \\ -\lambda x_i^\beta, & x_i < 0. \end{cases} \quad (2)$$

When a decision-maker faces profit, the behaviour's probability weight function is shown in formula (3), and when a decision-maker faces loss, the behaviour's probability weight function is shown in formula (4):

$$w_p^+ = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{(1/\gamma)}}, \quad (3)$$

$$w_p^- = \frac{p^\delta}{(p^\delta + (1-p)^\delta)^{(1/\delta)}}. \quad (4)$$

Among parameters, p is the actual probability of occurrence of the behaviour, and the parameters γ and δ determine the curvature of the weight function. The smaller the corresponding values of γ and δ , the greater the degree of bending of the weight function. According to Kahneman's calibration, $\gamma = 0.61$, $\delta = 0.69$ are generally used.

3.2. Reference Points. In determining the value function, whether a choice is a gain or a loss for the decision-maker depends mainly on the relative relationship between the decision scheme and the reference point. The reference point is the cut-off point for measuring the gain or loss of a decision plan. Considering that the pricing method of drone delivery is still in the exploratory stage and, more importantly, considering that the on-demand delivery service emphasizes timeliness, the paper chooses the individual expected delivery time (T_{expect}) as the reference point. In comparing the relationship between the actual delivery time (T_{actual}) produced by each delivery pattern and the expected delivery time, when the actual delivery time is shorter than the expected delivery time, the individual will profit; when the actual delivery time is longer than the expected delivery time, there will be a loss.

Researchers have found that when different decision-makers face different scenarios, their reference points for making decisions are often different [45]. Therefore, reference points are heterogeneous for different decision-makers and in different decision scenarios. In this study, considering that individuals will have different expected delivery times for different delivery distances, different reference points are set according to delivery distances in the paper.

3.3. Prospect Value of Drone Delivery and Rider Delivery. According to the reference point stated above, the value function of the delivery pattern is shown as

$$v(x_i) = \begin{cases} (T_{\text{expect}} - T_{\text{actual}})^\partial, & T_{\text{expect}} - T_{\text{actual}} \geq 0, \\ -\lambda(T_{\text{expect}} - T_{\text{actual}})^\beta, & T_{\text{expect}} - T_{\text{actual}} < 0. \end{cases} \quad (5)$$

According to the definition of the prospect theory, the calculation method of the prospect value EV_1 of rider delivery and the prospect value EV_2 of drone delivery is

$$EV_1 = [T_{\text{expect}} - T_{\text{actual}1}]^\alpha \times W_p^+ + [-\lambda(T_{\text{actual}1} - T_{\text{expect}})^\beta] \times W_p^-, \quad (6)$$

$$EV_2 = [T_{\text{expect}} - T_{\text{actual}2}]^\alpha \times W_p^+ + [-\lambda(T_{\text{actual}2} - T_{\text{expect}})^\beta] \times W_p^-, \quad (7)$$

where $T_{\text{actual}1}$ represents the actual delivery time of the rider and $T_{\text{actual}2}$ represents the actual delivery time of the drone.

In the same delivery scenario, if $EV_1 > EV_2$, then rider delivery is better than drone delivery; if this equation is reversed, then drone delivery is better than rider delivery.

4. Operation Model of Delivery Service

At present, the main service pattern of on-demand delivery is rider delivery. Its operation model is the following: the consumer places an order on the platform, the restaurant prepares the food after receiving the order, and the rider receives the order, rushes to the restaurant to get the food, and then delivers it to the consumer. The specific situation is shown in Figure 1.

The actual delivery time is the time from the consumer placing order to the time of receiving the food.

This paper defines the drone delivery model as follows: the consumer places an order, the restaurant and drone operator receive the order at the same time, the restaurant prepares the food, and then the food is delivered to the nearest drone at airport 1. The drone fetches the food, and then it delivers the food to drone at airport 2, which is near the consumer, and the consumer picks up the food from the drone at airport 2. The specific situation is shown in Figure 2.

Take the drone airport of Fast Ant as an example: the drone airport is shown in Figure 3. The article assumes that the drone airport is distributed with sufficient density around the restaurant, the workplace, and residential areas of customers to facilitate placing and picking up food for the

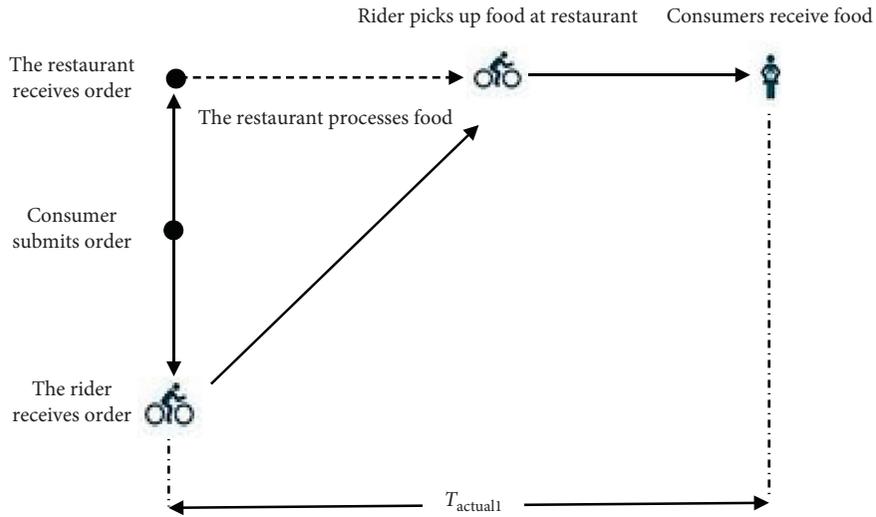


FIGURE 1: Schematic diagram of rider delivery model.

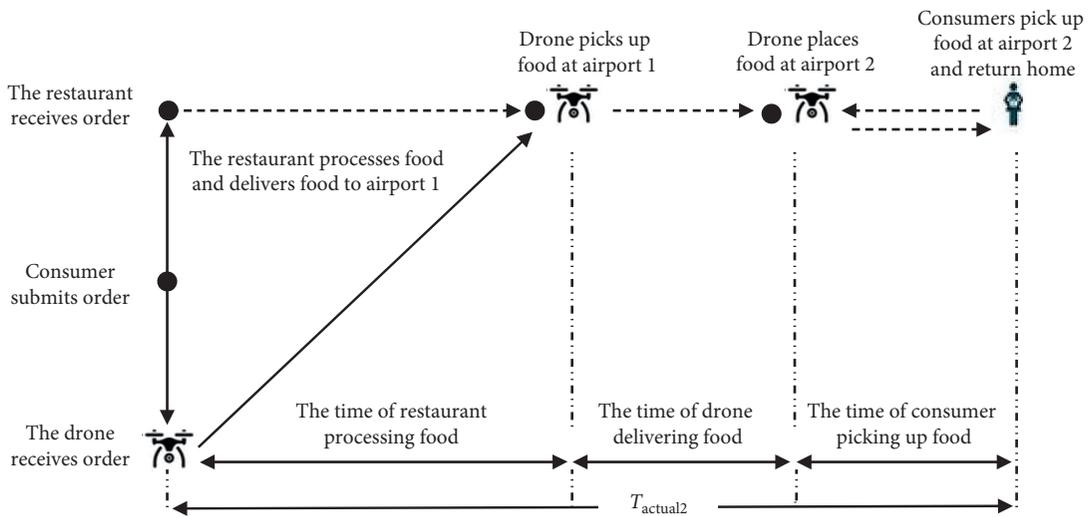


FIGURE 2: Schematic diagram of drone delivery model.



FIGURE 3: Schematic diagram of drone airport.

restaurant and consumers. When the restaurant places the food at the drone airport, the drone will automatically take the food and fly to the destination airport. After the drone arrives at the destination airport, the food is automatically put into the drone airport to wait for consumers to pick it up.

According to the definition of the drone delivery model, the drone delivery time is mainly composed of the time of restaurant preparing food and delivering the food from the restaurant to airport 1, the drone’s flight time from airport 1 to airport 2, and the time of customer pickup to the airport. Additionally, considering that drone cannot be delivered to the door, consumers may have some resistance to it. To reflect the consumer’s rejection of the drone delivery, the paper uses a penalty coefficient (δ) to adjust the actual delivery time of the drone. A larger coefficient indicates that the individual is less able to accept the fact that drones cannot deliver to the door and then considers that the delivery time is longer. In addition, since drones cannot

deliver to the door, consumers need to pick up the food by themselves from the drone airport. Considering that the pickup distance is an important factor affecting the efficiency of the delivery pattern [46], the time it takes the customer to travel to the drone airport is considered in the actual time of drone delivery. This time is used to measure the convenience of drone delivery. The shorter the pickup time is, that is, the shorter the pickup distance, the more convenient the drone delivery is. The actual delivery time for the drone is

$$T_{\text{actual}2} = \left(\frac{L}{V} \times 60 + t_b + 2 \times t \right) \times \delta. \quad (8)$$

In the previous formula, L represents the delivery distance, V represents the flying speed of the drone, t_b represents the sum of the time to prepare food and the time to deliver the food from the restaurant to the airport 1, t represents the individual's one-way pickup time from home to the drone airport, and δ represents the penalty coefficient because the drone cannot deliver to the door. In addition, the paper assumes that the drone operation is relatively stable, and no accidents such as power outages and falls will occur during the delivery process. According to the actual operation of drone delivery, the paper sets the drone's flight speed to 30 km/h [47] and sets the sum of the time to prepare food and the time to deliver the food from the restaurant to airport 1 to 15 minutes.

5. Survey

5.1. Survey Results of Expected Delivery Time. To determine the reference point, the paper investigates consumers' expected delivery times at different delivery distances through a questionnaire. The survey was done in September 2019, and the survey subjects were recruited from the urban public population. A total of 232 valid questionnaires were obtained. The sample of the questionnaire is shown in Table 1. The expected delivery time of consumers is shown in Table 2. Questionnaire about expected delivery time is shown in Table 3.

5.2. Rider's Actual Delivery Time. To determine the delivery time of rider delivery, data were collected, and the average value of promised delivery times at different delivery distances on a takeaway platform in China was calculated. Considering that there may be some uncertain factors during the rider delivery process that may cause delays in delivery, the delivery time should consider two scenarios of on-time delivery and delayed delivery. The paper assumes that the rider's delivery will be delivered at the promised delivery time (t_1) with a probability of 60%, and the delivery will be delayed at a 40% probability. Delayed delivery time is calculated as $t_2 = \gamma \times t_1$, where γ is the delay coefficient. The actual delivery time and probability are shown in Table 4.

6. Results

The paper will discuss the comparative advantage of the drone delivery and the rider delivery based on the different values of four parameters: the delay coefficient (γ) of rider delivery, the individual's pickup time to the drone airport (t),

TABLE 1: Sample basic situation.

Factor	Description	Number	Proportion (%)
Gender	Male	139	59.9
	Female	93	40.1
Age	<26	104	44.8
	26–30	82	35.3
	31–40	32	13.8
	>40	14	6.1

TABLE 2: Consumers' expected delivery time at different delivery distances.

Delivery distance (L)	Expected delivery time (minutes)
$L \leq 3$ km	22.1
$4 \text{ km} \leq L \leq 6$ km	28.5
$7 \text{ km} \leq L \leq 10$ km	33.1

the individual's rejection of the drone delivery (penalty coefficient: δ), and the delivery distance (L). The assignment of the four parameters is listed in Table 5. Among them, considering the maximum flight distance of the drone, the paper only considers the interval of a delivery distance below 10 kilometres [48].

6.1. Comparative Analysis of Two Delivery Patterns Based on Delay Coefficient of Rider Delivery. Taking the scenario where the delivery distance is equal to 5 kilometres, the penalty coefficient is 1.5, and the one-way pickup time is equal to 5 minutes (see Table 6). As the rider's delay coefficient increases from 1 to 1.5, the prospect value of the rider delivery decreases. That is, when the three parameters of delivery distance, penalty coefficient, and one-way pickup time are unchanged, as the delay coefficient increases, the prospect value of the rider delivery gradually decreases. Additionally, the difference between the prospect value of drone delivery and rider delivery is also decreasing. In this scenario, consumers are very resistant to drone delivery and drone delivery is the least convenient, but as the delay coefficient increases, the gap between drone delivery and rider delivery gradually decreases. When the parameter values are different, the same characteristics are displayed.

The paper analyses the relative relationship between the two delivery patterns under different parameter values based on Figure 4. Figure 4 shows that when the one-way pickup time is 5 minutes ($t = 5$), under different delay coefficients ($\gamma = 1, 1.1, 1.2, 1.3, 1.4, 1.5$), with the change in the delivery distance and the penalty coefficient, the difference between the prospect value of drone delivery and rider delivery changes. The 0 interface indicates that the prospect value of the two patterns is the same. Above the 0 interface, it is indicated that drone delivery is superior to rider delivery; below the 0 interface, it is indicated that rider delivery is superior to drone delivery. Still taking the scenario where the one-way pickup time $t = 5$ minutes is taken as an example, it can be found that when the delay coefficients are 1 and 1.1, the surface areas of the upper and lower parts of the 0

TABLE 3: Questionnaire about expected delivery time.

Factor	Description
Gender	1 male, 2 females
Age	1 < 26 2.26–30 3.31–40 4 > 40
Expected delivery time	Delivery distance (L) \leq 3 km
	4 km \leq delivery distance (L) \leq 6 km
	7 km \leq delivery distance (L) \leq 10 km

TABLE 4: Actual delivery time and probability of the rider.

Delivery distance (km)	Delivery time (minutes) and probability
0-1	30, 60%; 30 γ , 40%
1-2	34, 60%; 34 γ , 40%
2-3	36, 60%; 36 γ , 40%
3-4	40, 60%; 40 γ , 40%
4-5	45, 60%; 45 γ , 40%
5-6	47, 60%; 44 γ , 40%
6-7	50, 60%; 50 γ , 40%
7-8	59, 60%; 59 γ , 40%
8-9	63, 60%; 53 γ , 40%
9-10	73, 60%; 73 γ , 40%

TABLE 5: Related parameter assignment.

Parameter	Assignment
Γ	1–1.5
t	1 m–5 m
δ	1–1.5
L	0–10 km

interface are the same (see Figures 4(a) and 4(b) below). That is, the scenario where drone delivery is better than rider delivery is the same. When the delay coefficient increases to 1.2 or above, as the delay coefficient becomes larger, the surface area of the surface above the 0 interface gradually increases (see the following Figures 4(c)–4(f)); that is, in more and more conditions, drone delivery is better than rider delivery. After the delay coefficient reaches 1.2, the comparative advantage relationship between the two delivery patterns will change abruptly. Taking the delivery distance as an example, the delivery distance range of drones being better than that of riders will show a significant expansion trend. For details, see Table 7. Additionally, it can also be found from Figures 4(a) to 4(f) that, under different delay coefficients, the inflection points of drone delivery being superior to rider delivery are also different. When the one-way pickup time takes other values, the same characteristics are also presented.

From the above analysis, it can be seen that when rider delivery is delayed because of road congestion, dispatch delay, the last consumer receiving food later than scheduled, the last customer being not at home, and so forth, the prospect value of the rider delivery will continue to decline as the delay of the rider increases, and the advantages of drone delivery will gradually become prominent and its superiority will continue to expand as the delay coefficient increases. When the delay coefficients of rider delivery increase to 1.2 and above, the superiority of drone delivery to rider delivery will be more obvious.

6.2. *Comparative Analysis of Two Delivery Patterns Based on the One-Way Pickup Time.* Taking the scenario with a delay coefficient of 1.3, a penalty coefficient of 1, and a delivery distance of 5 kilometres as an example (see Table 8), it can be found that, for the drone delivery, when the individual one-way pickup time is gradually reduced from 5 minutes to 1 minute, under the same delay coefficient, penalty coefficient, and delivery distance, the prospect value of the drone delivery gradually increases. Additionally, the difference between the prospect values of drone delivery and rider delivery also increases. That is, the advantage of drone delivery over rider delivery is gradually increasing. In this scenario, as the one-way pickup time is shortened compared to the rider delivery, drone delivery is not only always superior to the rider delivery, but its comparative advantage has been continuously enhanced.

In addition, Figure 5 shows that when the delay coefficient is 1.3 ($\gamma = 1.3$), under different one-way pickup time ($t = 5, 4, 3$, and 2), with the change in the delivery distance and the penalty coefficient, the difference between the prospect values of drone delivery and rider delivery changes. As the one-way pickup time is shortened, drone delivery is better than rider delivery in more conditions. It can be found that as the one-way pickup time is shortened, the area above the 0 interface is getting bigger and bigger (see Figures 5(a)–5(c)), and when the one-way pickup time is shortened to 2 minutes, drone delivery is completely better than rider delivery (see Figure 5(d)). Additionally, it can also be found from the figure below that when the one-way pickup time is different, the distance inflection point at which drone delivery is better than rider delivery is different. Similarly, according to Table 9, it can be found that when the one-way pickup time is shortened to 2 minutes or less, the drone delivery is superior to the rider delivery in any case. It can be seen that reducing the individual’s pickup time to the drone airport, increasing the layout density of the drone airport, and improving the convenience of picking up food in the drone delivery will play a positive role in promoting the deployment of drone delivery.

6.3. *Comparative Analysis of Two Delivery Patterns Based on the Penalty Coefficient.* With the decrease in the penalty coefficient for the inability of the drone to deliver door to the door, indicating that consumers are becoming more accepting of drone delivery, the prospect value of the drone delivery gradually increases. Take the scenario of $\gamma = 1.1$, $t = 3$, and $L = 5$ as an example: drone delivery gradually shows its advantages with the acceptance of drone delivery increasing, and its advantages become more and more obvious as acceptance increases. See Table 10 for details.

TABLE 6: $T=5$, $\delta=1.5$, and $L=5$. The comparison of the prospect value of the two delivery patterns under different delay coefficients.

	$\gamma=1$	$\gamma=1.1$	$\gamma=1.2$	$\gamma=1.3$	$\gamma=1.4$	$\gamma=1.5$
The prospect value of rider delivery	-26.52	-26.58	-28.96	-31.29	-33.58	-35.84
The prospect value of drone delivery	-36.88	-36.88	-36.88	-36.88	-36.88	-36.88
Difference in prospect value between the two patterns	-10.36	-10.30	-7.92	-5.88	-3.29	-1.04

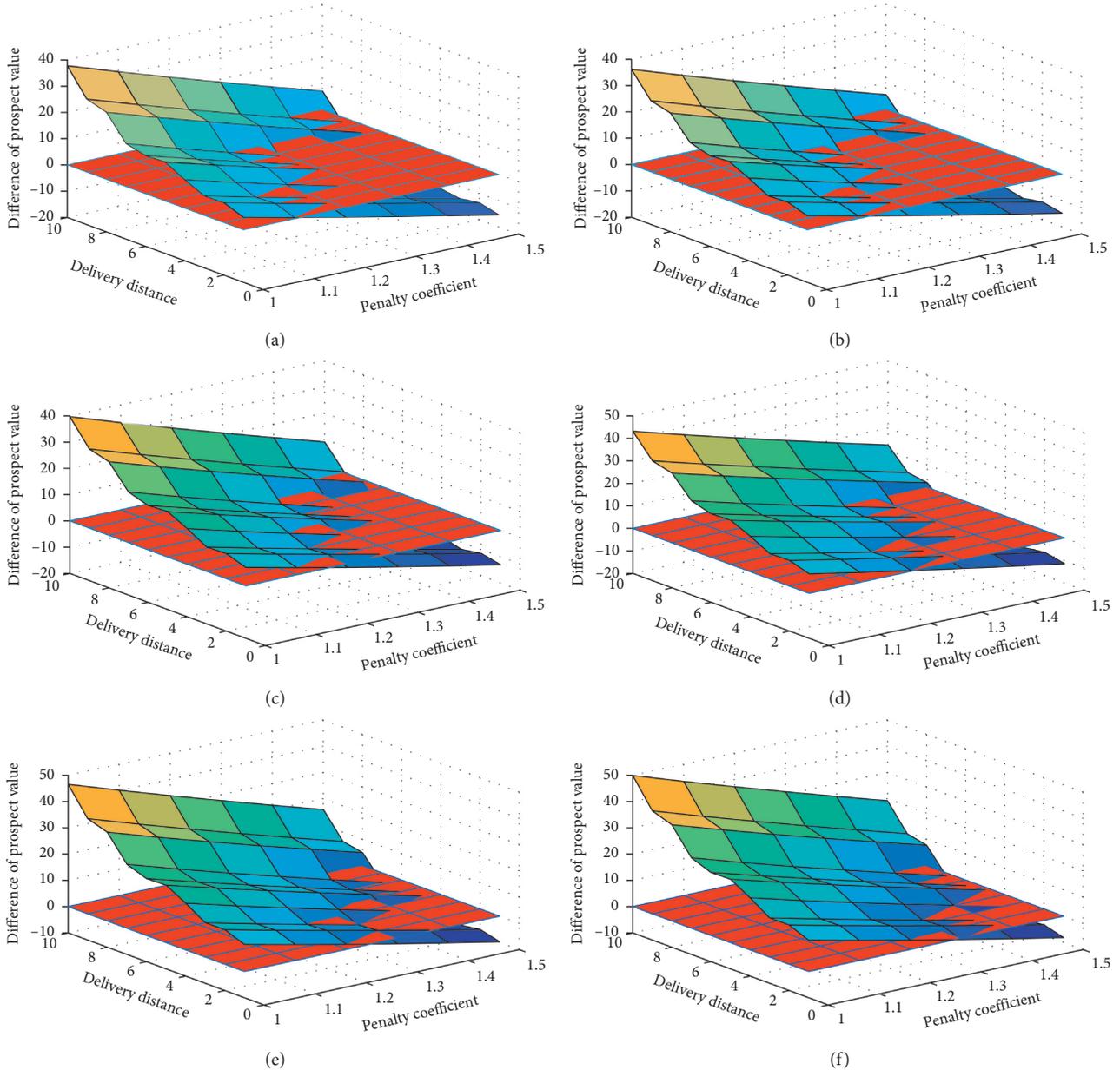


FIGURE 4: Difference of prospect value between drone delivery and rider delivery under different delay coefficients. (a) Difference of prospect value when $t=5$ and $\gamma=1$; (b) difference of prospect value when $t=5$ and $\gamma=1.1$; (c) difference of prospect value when $t=5$ and $\gamma=1.2$; (d) difference of prospect value when $t=5$ and $\gamma=1.3$; (e) difference of prospect value when $t=5$ and $\gamma=1.4$, (f) difference of prospect value when $t=5$ and $\gamma=1.5$.

In addition, according to Table 11, in all scenarios regardless of the values of the parameters γ and t , when the penalty coefficient is reduced to 1.1 and 1, drone delivery is superior to rider delivery at all delivery distances. It can be

seen that the activities of increasing and enhancing the individual's awareness and acceptance of drone delivery will be more conducive to the promotion of drone delivery.

TABLE 7: The delivery distance of drone superior to rider when $t = 5$.

	$\delta = 1.5$	$\delta = 1.4$	$\delta = 1.3$	$\delta = 1.2$	$\delta = 1.1$	$\delta = 1$
$\gamma = 1$	≥ 9 km	≥ 7 km	≥ 7 km	≥ 3 km	All	All
$\gamma = 1.1$	≥ 9 km	≥ 7 km	≥ 7 km	≥ 3 km	All	All
$\gamma = 1.2$	≥ 8 km	≥ 7 km	≥ 4 km	≥ 1 km	All	All
$\gamma = 1.3$	≥ 7 km	≥ 7 km	≥ 3 km	All	All	All
$\gamma = 1.4$	≥ 7 km	≥ 4 km	≥ 3 km	All	All	All
$\gamma = 1.5$	≥ 7 km	≥ 3 km	≥ 1 km	All	All	All

TABLE 8: The comparison of the prospect value of the two delivery patterns under different one-way pickup times when $\gamma = 1.3$, $\delta = 1$, and $L = 5$.

	$t = 5$	$t = 4$	$t = 3$	$t = 2$	$t = 1$
The prospect value of rider delivery	-31.29	-31.29	-31.29	-31.29	-31.29
The prospect value of drone delivery	-11.68	-8.45	-5.04	-1.22	1.43
Difference in prospect value between the two patterns	19.61	22.84	26.25	30.07	32.72

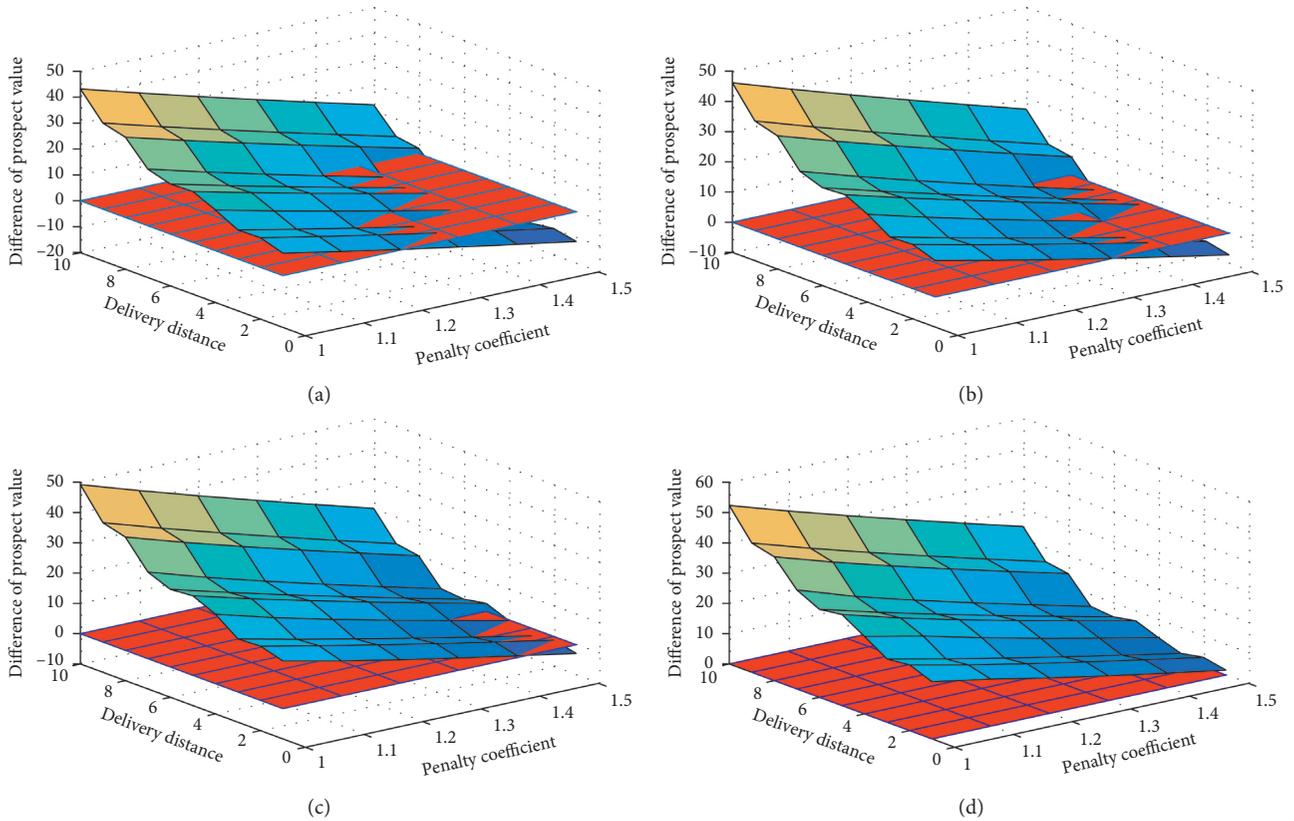


FIGURE 5: Difference in prospect value between drone delivery and rider delivery for different one-way pickup times. (a) Difference of prospect value when $\gamma = 1.3$ and $t = 5$; (b) difference of prospect value when $\gamma = 1.3$ and $t = 4$; (c) difference of prospect value when $\gamma = 1.3$ and $t = 3$; (d) difference of prospect value when $\gamma = 1.3$ and $t = 2$.

TABLE 9: The delivery distance of drone superior to rider when $\gamma = 1.3$.

	$\delta = 1.5$	$\delta = 1.4$	$\delta = 1.3$	$\delta = 1.2$	$\delta = 1.1$	$\delta = 1$
$t = 5$	≥ 7 km	≥ 7 km	≥ 3 km	All	All	All
$t = 4$	≥ 7 km	≥ 4 km	All	All	All	All
$t = 3$	≥ 4 km	All	All	All	All	All
$t = 2$	All	All	All	All	All	All
$t = 1$	All	All	All	All	All	All

TABLE 10: The comparison of the prospect value of the two delivery patterns with different penalty coefficient when $\gamma = 1.1$, $t = 3$, and $L = 5$.

	$\delta = 1$	$\delta = 1.1$	$\delta = 1.2$	$\delta = 1.3$	$\delta = 1.4$	$\delta = 1.5$
The prospect value of rider delivery	-26.58	-26.58	-26.58	-26.58	-26.58	-26.58
The prospect value of drone delivery	-5.04	-10.25	-15.10	-19.74	-24.24	-28.63
Difference in prospect value between the two patterns	21.54	16.33	11.48	6.83	2.34	-2.05

TABLE 11: Scenarios of drone delivery superior to rider delivery.

	$t = 5$	$t = 4$	$t = 3$	$t = 2$	$t = 1$
$\gamma = 1$	$\delta = 1.5, L \geq 9$ km	$\delta = 1.5, L \geq 7$ km;	$\delta = 1.5, L \geq 7$ km;	$\delta = 1.5, L \geq 4$ km	$\delta = 1.5, L \geq 0$ km
	$\delta = 1.4, L \geq 7$ km	$\delta = 1.4, L \geq 7$ km	$\delta = 1.4, L \geq 4$ km	$\delta = 1.4, L \geq 0$ km	$\delta = 1.4, L \geq 0$ km
	$\delta = 1.3, L \geq 7$ km	$\delta = 1.3, L \geq 3$ km	$\delta = 1.3, L \geq 0$ km	$\delta = 1.3, L \geq 0$ km	$\delta = 1.3, L \geq 0$ km
	$\delta = 1.2, L \geq 3$ km	$\delta = 1.2, L \geq 3$ km	$\delta = 1.2, L \geq 0$ km	$\delta = 1.2, L \geq 0$ km	$\delta = 1.2, L \geq 0$ km
	$\delta = 1.1, L \geq 0$ km	$\delta = 1.1, L \geq 0$ km	$\delta = 1.1, L \geq 0$ km	$\delta = 1.1, L \geq 0$ km	$\delta = 1.1, L \geq 0$ km
	$\delta = 1, L \geq 0$ km	$\delta = 1, L \geq 0$ km	$\delta = 1, L \geq 0$ km	$\delta = 1, L \geq 0$ km	$\delta = 1, L \geq 0$ km
$\gamma = 1.1$	$\delta = 1.5, L \geq 9$ km;	$\delta = 1.5, L \geq 7$ km;	$\delta = 1.5, L \geq 7$ km;	$\delta = 1.5, L \geq 4$ km	$\delta = 1.5, L \geq 0$ km
	$\delta = 1.4, L \geq 7$ km	$\delta = 1.4, L \geq 7$ km	$\delta = 1.4, L \geq 4$ km	$\delta = 1.4, L \geq 0$ km	$\delta = 1.4, L \geq 0$ km
	$\delta = 1.3, L \geq 7$ km	$\delta = 1.3, L \geq 3$ km	$\delta = 1.3, L \geq 0$ km	$\delta = 1.3, L \geq 0$ km	$\delta = 1.3, L \geq 0$ km
	$\delta = 1.2, L \geq 3$ km	$\delta = 1.2, L \geq 0$ km	$\delta = 1.2, L \geq 0$ km	$\delta = 1.2; L \geq 0$ km	$\delta = 1.2, L \geq 0$ km
	$\delta = 1.1, L \geq 0$ km	$\delta = 1.1, L \geq 0$ km	$\delta = 1.1, L \geq 0$ km	$\delta = 1.1, L \geq 0$ km	$\delta = 1.1, L \geq 0$ km
	$\delta = 1, L \geq 0$ km	$\delta = 1, L \geq 0$ km	$\delta = 1, L \geq 0$ km	$\delta = 1; L \geq 0$ km	$\delta = 1, L \geq 0$ km
$\gamma = 1.2$	$\delta = 1.5, L \geq 8$ km;	$\delta = 1.5, L \geq 7$ km;	$\delta = 1.5, L \geq 7$ km;	$\delta = 1.5, L \geq 1$ km	$\delta = 1.5, L \geq 0$ km
	$\delta = 1.4; L \geq 7$ km	$\delta = 1.4, L \geq 4$ km	$\delta = 1.4; L \geq 1$ km	$\delta = 1.4, L \geq 0$ km	$\delta = 1.4, L \geq 0$ km
	$\delta = 1.3; L \geq 4$ km	$\delta = 1.3, L \geq 1$ km	$\delta = 1.3; L \geq 0$ km	$\delta = 1.3, L \geq 0$ km	$\delta = 1.3, L \geq 0$ km
	$\delta = 1.2; L \geq 1$ km	$\delta = 1.2, L \geq 0$ km	$\delta = 1.2; L \geq 0$ km	$\delta = 1.2; L \geq 0$ km	$\delta = 1.2, L \geq 0$ km
	$\delta = 1.1; L \geq 0$ km	$\delta = 1.1, L \geq 0$ km	$\delta = 1.1; L \geq 0$ km	$\delta = 1.1, L \geq 0$ km	$\delta = 1.1, L \geq 0$ km
	$\delta = 1; L \geq 0$ km	$\delta = 1, L \geq 0$ km	$\delta = 1; L \geq 0$ km	$\delta = 1, L \geq 0$ km	$\delta = 1, L \geq 0$ km
$\gamma = 1.3$	$\delta = 1.5, L \geq 7$ km;	$\delta = 1.5, L \geq 7$ km;	$\delta = 1.5, L \geq 4$ km;	$\delta = 1.5, L \geq 0$ km	$\delta = 1.5, L \geq 0$ km
	$\delta = 1.4, L \geq 7$ km	$\delta = 1.4, L \geq 4$ km	$\delta = 1.4; L \geq 0$ km	$\delta = 1.4, L \geq 0$ km	$\delta = 1.4, L \geq 0$ km
	$\delta = 1.3, L \geq 3$ km	$\delta = 1.3, L \geq 0$ km	$\delta = 1.3; L \geq 0$ km	$\delta = 1.3, L \geq 0$ km	$\delta = 1.3, L \geq 0$ km
	$\delta = 1.2, L \geq 1$ km	$\delta = 1.2, L \geq 0$ km	$\delta = 1.2; L \geq 0$ km	$\delta = 1.2, L \geq 0$ km	$\delta = 1.2, L \geq 0$ km
	$\delta = 1.1, L \geq 0$ km	$\delta = 1.1, L \geq 0$ km	$\delta = 1.1, L \geq 0$ km	$\delta = 1.1, L \geq 0$ km	$\delta = 1.1, L \geq 0$ km
	$\delta = 1; L \geq 0$ km	$\delta = 1; L \geq 0$ km	$\delta = 1, L \geq 0$ km	$\delta = 1, L \geq 0$ km	$\delta = 1, L \geq 0$ km
$\gamma = 1.4$	$\delta = 1.5, L \geq 7$ km;	$\delta = 1.5, L \geq 6$ km;	$\delta = 1.5, L \geq 3$ km	$\delta = 1.5, L \geq 0$ km	$\delta = 1.5, L \geq 0$ km
	$\delta = 1.4, L \geq 4$ km	$\delta = 1.4, L \geq 3$ km	$\delta = 1.4, L \geq 0$ km	$\delta = 1.4, L \geq 0$ km	$\delta = 1.4, L \geq 0$ km
	$\delta = 1.3, L \geq 3$ km	$\delta = 1.3, L \geq 0$ km	$\delta = 1.3, L \geq 0$ km	$\delta = 1.3, L \geq 0$ km	$\delta = 1.3, L \geq 0$ km
	$\delta = 1.2, L \geq 0$ km	$\delta = 1.2, L \geq 0$ km	$\delta = 1.2, L \geq 0$ km	$\delta = 1.2, L \geq 0$ km	$\delta = 1.2, L \geq 0$ km
	$\delta = 1.1, L \geq 0$ km	$\delta = 1.1, L \geq 0$ km	$\delta = 1.1, L \geq 0$ km	$\delta = 1.1, L \geq 0$ km	$\delta = 1.1, L \geq 0$ km
	$\delta = 1, L \geq 0$ km	$\delta = 1, L \geq 0$ km	$\delta = 1, L \geq 0$ km	$\delta = 1, L \geq 0$ km	$\delta = 1, L \geq 0$ km
$\gamma = 1.5$	$\delta = 1.5, L \geq 7$ km;	$\delta = 1.5, L \geq 4$ km;	$\delta = 1.5, L \geq 0$ km	$\delta = 1.5, L \geq 0$ km	$\delta = 1.5, L \geq 0$ km
	$\delta = 1.4; L \geq 3$ km	$\delta = 1.4, L \geq 1$ km	$\delta = 1.4, L \geq 0$ km	$\delta = 1.4, L \geq 0$ km	$\delta = 1.4, L \geq 0$ km
	$\delta = 1.3; L \geq 1$ km	$\delta = 1.3, L \geq 0$ km	$\delta = 1.3, L \geq 0$ km	$\delta = 1.3, L \geq 0$ km	$\delta = 1.3, L \geq 0$ km
	$\delta = 1.2; L \geq 0$ km	$\delta = 1.2, L \geq 0$ km	$\delta = 1.2, L \geq 0$ km	$\delta = 1.2, L \geq 0$ km	$\delta = 1.2, L \geq 0$ km
	$\delta = 1.1; L \geq 0$ km	$\delta = 1.1, L \geq 0$ km	$\delta = 1.1, L \geq 0$ km	$\delta = 1.1, L \geq 0$ km	$\delta = 1.1, L \geq 0$ km
	$\delta = 1; L \geq 0$ km	$\delta = 1, L \geq 0$ km	$\delta = 1, L \geq 0$ km	$\delta = 1, L \geq 0$ km	$\delta = 1, L \geq 0$ km

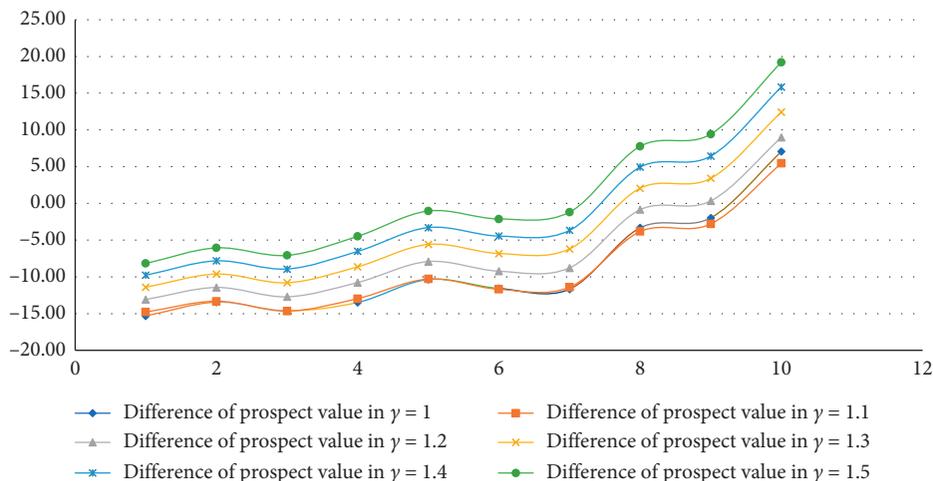


FIGURE 6: $t = 5$ and $\delta = 1.5$. The difference of prospect value between the drone and the rider.

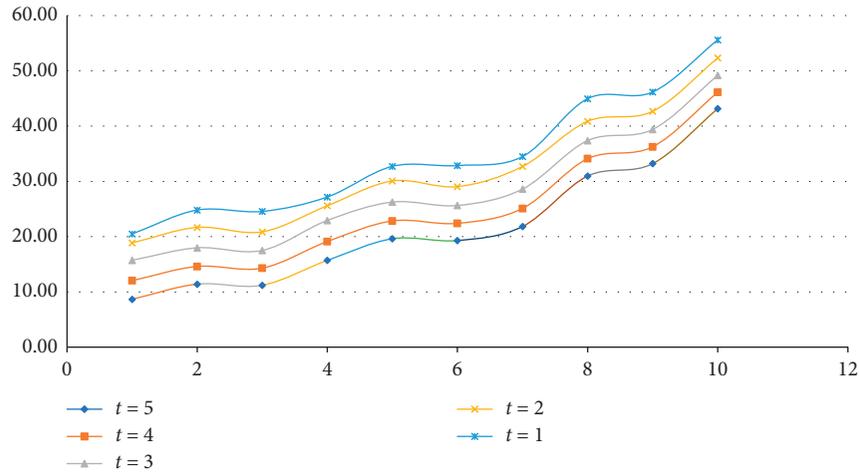


FIGURE 7: $\gamma = 1.3$ and $\delta = 1$. The difference of prospect value between the drone and the rider.

6.4. Comparative Analysis of Two Delivery Patterns Based on the Distribution Distance. It can also be found from Figures 6 and 7 that as the delivery distance increases, the advantages of drone delivery over rider delivery generally increase gradually; that is, for longer delivery distance, the drone’s superiority to the rider will be more obvious.

It can be seen from Table 11 that when $\gamma = 1$ and 1.1, $t = 5$ and 4, and $\delta = 1.5$ and 1.4, these are the worst for drone delivery. The drone delivery still shows an advantage in the delivery distance of 7 kilometres and above, which shows that, for longer delivery distances, the advantages of the drone delivery are more prominent.

7. Conclusions and Future Research

7.1. Conclusions. Through the above analysis, it was found that, under different conditions, rider delivery and drone delivery have their own respective advantages. The scenarios of $t \leq 2$, $\delta \leq 1.1$, and $L \geq 7$ are the absolute advantage range for drone delivery. Under these conditions, the advantages of the drone delivery are extremely prominent.

As the delivery distance increases, the advantages of drone delivery over rider delivery become more obvious. Especially when the delivery distance is longer than 7 kilometres, the curve of the difference between the prospect value of drone delivery and rider delivery becomes steeper, which indicates that drone delivery is more suitable for longer delivery distances. When the delivery distance is longer than 7 kilometres, no matter what the value of other parameters is, drone delivery is better than rider delivery. In the short-distance delivery scenario, whether the drone is superior to the rider depends on the values of other parameters. The advantage of drone delivery in the long-distance delivery scenario provides a favourable explanation for expanding the scope of service of instant delivery through drone delivery.

Because drone delivery cannot achieve door-to-door delivery, consumers need to pick up the goods by

themselves. When the one-way time to reach the drone airport is controlled within 2 minutes, the advantages of drone delivery are still obvious. Therefore, increasing the number of drone airports to shorten the time for consumers to pick up goods should be one of the ways to promote consumers to accept drone delivery.

Congestion of ground traffic will increase the risk of delayed delivery by riders, which will lengthen the delivery time, reducing the advantage of rider delivery. In contrast, because drone delivery is not affected by ground traffic conditions, in increasingly congested cities, drone delivery will have more and more applicable space. When the delay coefficient is continuously increased due to ground congestion and other reasons, the advantages of drones will become more and more obvious. Studies have shown that when the delay coefficient reaches 1.2 and above, that is, if the delivery time exceeds 20% of the original scheduled time, the rider delivery will increase consumer losses. In contrast, the drone delivery will be relatively more likely to benefit consumers.

Consumers may have some resistance to emerging technologies such as drones, which will affect the implementation of drone delivery. As consumers increase their recognition of drone delivery, the advantages of drone delivery will become more obvious. When the penalty coefficient is reduced to 1.1 and 1, that is to say, when consumers fully accept drone delivery or mostly accept drone delivery, drone delivery will be superior to rider delivery in any case.

7.2. Future Research. In the choice of delivery pattern, in addition to time, cost is also a very important factor, so the prospect value of the drone delivery and rider delivery should also consider the delivery cost, which will be studied later. In addition, in the urban delivery system, different delivery patterns have their own advantages, which has been reflected in the research of the paper. The paper mainly adopts the perspective of consumers and discusses each of the two patterns’ advantages. If the perspective of the main

body is that of merchants, logistics companies, and so forth, the results may be different, so it is necessary to further explore the advantages and disadvantages of the two delivery patterns based on the different main bodies in the delivery system. In the setting of the reference points, only the expected delivery time of different delivery distances is considered, and the difference in the expected delivery time of consumers with different attributes is not considered. The next step is to further improve the reference point of heterogeneity. Furthermore, in the setting of the delivery time, the characteristics of the delay probability dynamically changing as the delivery distance increases should be considered, so that the delivery time is closer to reality. Finally, the paper assumes that the delivery of drones is in an ideal state; that is, it does not take into account special circumstances such as lack of power, flight interruption, and the probability of these scenarios. The future space crowding and delays due to the increase in the number of drones, weather, and the urban environment leading to delays in delivery, drone airport layout, and the number of available drones may also lead to increased delivery time and other problems. These are also issues that should be considered in the future.

Data Availability

The data used and analysed during the study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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