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Environmental and economic impacts of drone-assisted truck delivery under the carbon market price

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A R T I C L E I N F O

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A B S T R A C T

Logistics delivery companies today are under high pressure from the carbon market. As an emerging commercial delivery tool, the drone has the advantages of low carbon emissions and cost. This study proposes an innovative dual-objective mixed-integer linear programming model to explore the environmental and economic impacts of drone-assisted truck delivery under the carbon market price. It uses JD.com in China as a case study to explore the company's benefits of adopting drone-assisted delivery. The results show that compared to traditional truck delivery, drone-assisted delivery reduced carbon emissions by 24.90%, reduced total cost by 22.13%, and shortened delivery time by 20.65%. In addition, the effects of some key elements on the total cost and carbon emissions are compared. The analysis shows that drone battery cycle life, fuel price, driver's wage, truck speed, and drone speed are vital for drone-assisted truck delivery.

1. Introduction

With e-commerce and economic globalization rapidly developing, the frequency of commercial delivery has increased dramatically, resulting in a sharp increase in carbon emissions (Neves-Moreira et al., 2019; Figliozzi, 2020; Zhang et al., 2021). These emissions are caused mainly by the unabated fossil fuel combustion from trucks that require hundreds of years to offset the environmental impact (Shindell and Smith, 2019). Furthermore, as environmental awareness and sustainable development goals become prevalent today (Rustam et al., 2020; Calculli et al., 2021; Zhang and Kong, 2022), companies must address sustainability-related problems (Linton et al., 2007; Liu et al., 2021). In addition, most governments have mandated companies to practice environmental protection measures for their supply chains (Dooley et al., 2019), which commonly use trucks for their last-mile deliveries, producing carbon dioxide and toxic pollutants (Shindell and Smith, 2019). Therefore, delivery vehicle innovation that mitigates carbon emissions is necessary for companies to implement environmental protection practices.

An important measure to mitigate carbon emissions is carbon pricing. Carbon pricing has been regarded as an essential component of any sensible climate policy and an effective, flexible, and low-cost method of reducing carbon emissions (Green, 2021). It encourages polluters to reduce the use of coal, oil and natural gas, and other major sources of global warming by increasing the carbon emission cost, which is widely recognized and considered effective (Hagmann et al., 2019). Carbon pricing usually takes the form of carbon emission trading or carbon tax (Gugler et al., 2021). Carbon pricing is the core of carbon market operation and plays an important role in global mitigation of carbon emissions (Feng, 2015).

Following the European Union emission trading system, companies worldwide must explore low-carbon commercial delivery. During the past decade, drones originating from military research have entered the environmentally-sustainable commercial delivery arena (Stolaroff et al., 2018; Pei et al., 2021) as they are cost-effective and significantly reduce energy consumption and carbon emissions (Dell'Amico et al., 2021). Several logistics companies have deployed drones for commercial deliveries. For example, Amazon took the lead in 2013 to introduce the Prime Air plan that uses drones to deliver goods to customers' doors in 30 min or less. As one of the four major international logistics giants, DHL is also at the forefront of drone logistics research. With the help of the local government, DHL used unmanned aerial vehicles (UAVs) to deliver cargo on Yuster Island in the North Sea in Germany in 2014 (Bryan, 2014). In China, Taobao.com, a subsidiary of Alibaba Group,

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used drone delivery for the first time in early 2015. JD.com, another Chinese e-commerce giant, tried drone-based delivery to customers' offices in the same year. Despite the outbreak of COVID-19 in 2020 severely disrupting the supply chains of almost all industries in the world, JD used drones to achieve better results in its last-mile delivery (Shen and Sun, 2021).

Driven by the carbon trading market, many e-commerce companies in China strive to use drones to optimize low-carbon commercial delivery. However, due to the light load capacity, drones can only serve customers with small demands, and the rest of the customers still need to be served by traditional vehicles. In addition, the lithium batteries used by drones limit flight time. To overcome these shortcomings, this study applies drone-assisted truck delivery to optimize environmental and economic impacts. The drone-assisted truck delivery enables the truck to deliver various goods and simultaneously charge the drone's batteries on the road. In addition, truck delivery on tortuous routes or traffic jams exacerbates delivery time, fuel consumption, and carbon emissions. The drone's straight-line distance flights could significantly reduce these costs. This study aims to optimize drone-assisted low-carbon commercial delivery at a JD's operational location where truck deliveries have a high environmental impact. The selected location is Guang'an, Sichuan, China.

The contributions to the literature of our research can be summarized as follows. First, prior research has focused on the environmental and economic impacts of drone-assisted truck delivery. As more and more countries have developed carbon pricing initiatives to tackle climate change, we further consider such impacts from the carbon-emission price under the carbon market and develop an optimal model to make such a joint delivery sustainable. Specifically, this study proposes an innovative dual-objective mixed-integer linear programming model to make a trade-off between carbon emissions and the total cost of drone-assisted truck delivery. Previous studies have not considered the trade-off between these two objectives regarding the joint delivery of drones and trucks.

Additionally, we compare the differences in carbon emissions, total cost, and delivery time between drone-assisted and truck-only deliveries, showing that drone-assisted delivery is effective for environmental and economic costs under the carbon market price. Finally, we present a sensitivity analysis by changing six parameters (viz., carbon price, truck fuel price, drone battery cycle life, truck driver hourly wage, truck speed, and drone speed) to analyze their impacts on drone-assisted truck delivery.

The remainder of this paper is constructed as follows. Section 2 reviews the relevant literature on companies' environmentally sustainable supply chain logistics. Section 3 defines the drone-assisted delivery problem. Section 4 proposes a bi-objective programming model to minimize carbon emissions and the total cost. Section 5 conducts a performance analysis to explore the company's benefits of adopting drone-assisted delivery. Section 6 provides conclusions and policy implications. Finally, Section 7 presents the limitations of this study and future research.

2. Literature review

With the development of the carbon market, the impact of using drones to assist trucks in delivery has attracted increasing attention. Many excellent works focus on delivery. For example, Guo et al. (2019) proposed a crowdsourcing delivery model to study its role in last-mile logistics, believing that it could reduce the cost of logistics companies and be conducive to sustainable development. Jamali and Rasti-Barzoki (2019) studied the impact of third-party logistics companies on sustainable supply chains and concluded that they could reduce delivery time and carbon emissions. Abdi et al. (2020) improved the efficiency of the supply chain by considering simultaneous delivery and separate pick-up, which they believed would lead to the minimization of total costs and the maximization of customer service. Recently, Xue (2022) constructed a multi-warehouse cooperative logistics network with transfer points, which was considered superior to the traditional non-transfer scheme, and its effectiveness in reducing transportation costs and carbon emissions was verified. Furthermore, the role of the drone-assisted truck model in commercial delivery was receiving more and more attention.

The first study on drone-assisted delivery defined a flying sidekick traveling salesman problem (FSTSP) to minimize the delivery time of a truck with a drone (Murray and Chu, 2015). By modeling as a mixed-integer linear programming (MILP), it describes a scenario in which the first is truck routing, and the second is the subroute of the drone, which serves the customers who meet the drone delivery conditions and then returns to where the truck of another customer is located. This study adopts the joint delivery mode of FSTSP to optimize environmental and economic effects in commercial delivery. Agatz et al. (2015) studied the travel salesman problem with a drone (TSP-D), allowing the UAV back to the demand node relaunch node. Mathew et al. (2015) studied the heterogeneous delivery problem in which a drone can take off from a truck, aiming to find the shortest path to complete all required delivery tasks when multiple warehouses are available. Marinelli et al. (2018) demonstrated a different heuristic to solve TSP-D, minimizing waiting times and battery consumption. In particular, they consider the possibility of launching and retrieving the drone at the depot or the demand node and along the routing arc. Ha et al. (2018) proposed a novel type of TSP-D, namely min-cost TSP-D, aiming to minimize the total operational cost, including the transportation cost and the waiting time between the truck and its drone. Bouman et al. (2018) presented dynamic programming to solve more extensive situations in TSP-D, which is more suitable for actual application scenarios.

In addition to a single drone that assists in truck delivery, Poikonen et al. (2017) studied a fleet of m homogeneous trucks, each carrying k drones, to find the minimum completion time of the delivery. Wang et al. (2017) analyzed the problem of drone-assisted vehicle routing from worst-case scenarios and found significant savings in the joint delivery of trucks and drones. Chang and Lee (2018) studied a delivery route based on a truck and drones, demonstrating the cost and speed advantages of drones by maximizing the drone route and minimizing the truck route. Ham (2018) proposed a new application of constraint programming to solve the multi-truck, multi-drone, and multi-depot scheduling problem, considering drones' pick-up, time window, and multi-visit simultaneously. Finally, Murray and Raj (2020) proposed the multiple flying sidekicks traveling salesman problem (mFSTSP) about a single truck and a heterogeneous fleet of drones having different speeds, capacities, and flight endurance. They scheduled the drone's launches and inbound flights to meet reality. They considered fuel consumption and driver as the cost of the joint delivery in the FSTSP and its variants. Moreover, since there are carbon pricing initiatives in many countries, the cost of joint delivery should also include the cost of carbon emissions, similar to the cost components in the pollution routing problem (PRP) and its variants (Ham, 2018; Qiu et al., 2020; Aldieri et al., 2022; Wen et al., 2022). However, these cost components focus only on the truck delivery, not the drone's carbon emissions.

Some excellent work focuses on the carbon emissions from drones. Figliozzi (2017) analyzed the energy consumption and carbon emissions of drones and different ground commercial vehicles. Goodchild and Toy (2018) compared carbon emissions and vehicle miles traveled between truck and drone delivery models. Figliozzi (2020) evaluated the potential of drones and ground autonomous delivery robots to reduce CO_2 emissions in the delivery industry and showed that these new vehicles could reduce energy consumption. Finally, Baldisseri et al. (2022) evaluated the environmental and economic sustainability of a last-mile delivery solution involving electric trucks equipped with drones and indicated that drone-assisted truck delivery led to significant reductions in emissions.

Inspired by the above works, this study follows the systematic approach of Figliozzi (2017) to calculate a drone's energy consumption and carbon emissions from a lifecycle perspective. Moreover, we combine the joint delivery model of FSTSP, the cost components in the PRP and drone energy consumption model, consider the environmental and economic costs simultaneously during the delivery process, and minimize carbon emissions and the total cost through a dual-objective mixed-integer linear programming.

3. Problem statement

The drone-assisted delivery problem is briefly defined based on JD's logistics maps with six demand nodes, as shown in Fig. 1.

(1) The truck and drone can leave or return to the depot simultaneously or separately. The total delivery time is defined as the time between the two vehicles departing the depot and the last vehicle arriving at the depot.
(2) All the demand nodes must be served. Each can be served only once by the truck or drone.
(3) When the drone is launched to serve one demand node, the truck can serve multiple other demand nodes.
(4) The truck should depart from a demand node where the drone launches and arrive at another demand node where the drone is retrieved. However, the drone cannot return to the demand node where it was launched.

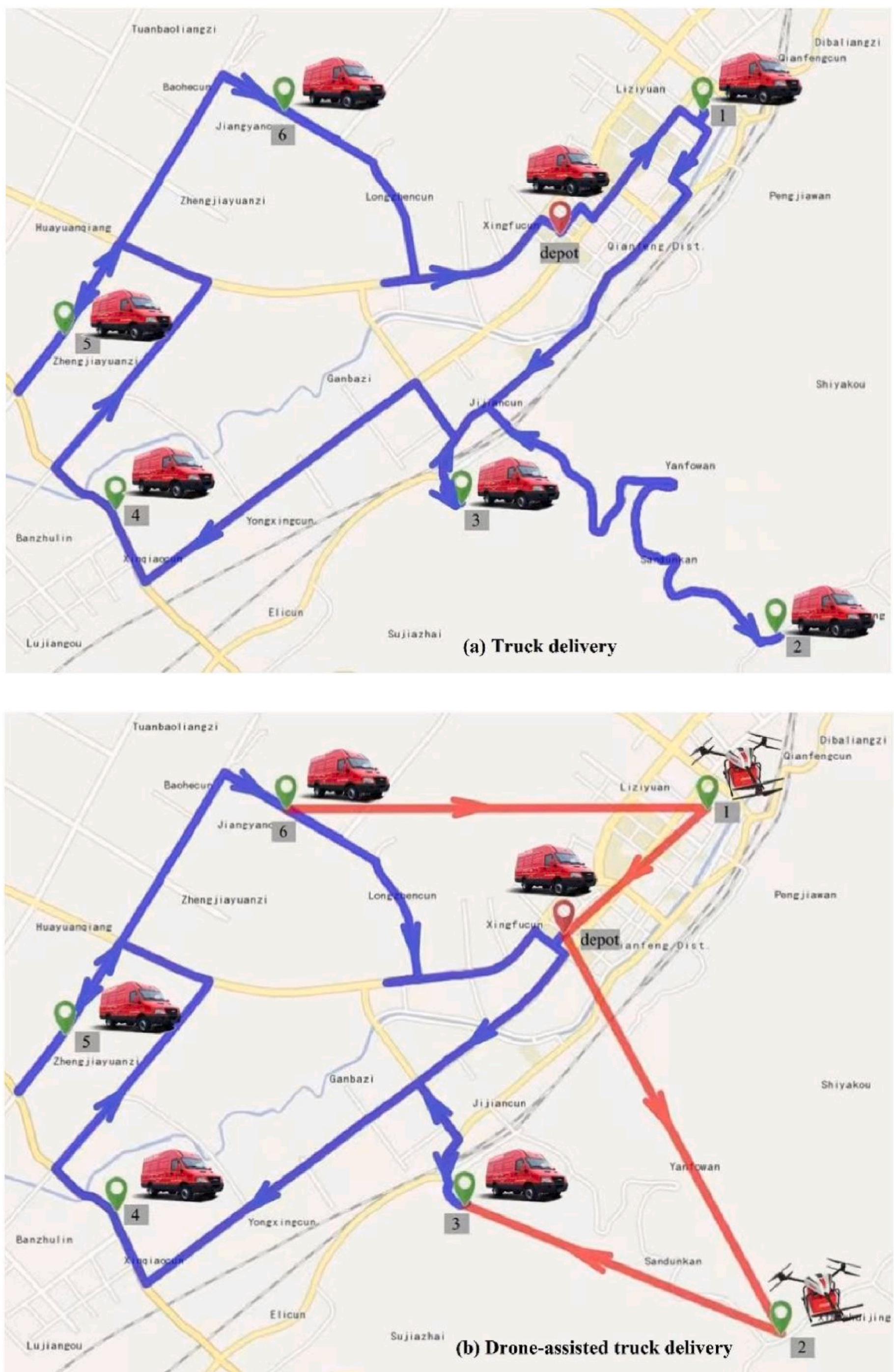

Fig. 1. JD Logistics Maps for (a) truck delivery and (b) drone-assisted truck delivery.

(5) JD's Y-3 drone models and mini-box trucks are the delivery tools in this case.
(6) The objective is to minimize carbon emissions and total cost, including energy consumption, carbon emissions, and driver's wage. The parameters are carbon price, truck fuel price, drone battery cycle life, driver's wage, truck speed, and drone speed.

4. Model description

This section introduces the calculation functions for the energy consumption and carbon emission of trucks and drones. Next, the FSTSP (Murray and Chu, 2015) is adapted to introduce the dual-objective mixed-integer linear programming model with a drone and a truck. One objective is to minimize the weight of carbon emissions, and another is to minimize the total cost (i.e., the sum of carbon emission, energy, and labor costs).

4.1. Energy consumption and carbon emissions from the truck

The truck energy consumption model is adapted from Bektaş and Laporte (2011). W is the fuel consumption of the truck, assuming a minimum truck speed of 40 km/h. The carbon emissions of truck E are evaluated based on fuel consumption, and the carbon emission is measured by weight (Kg-CO_2).

$$W = (w + l)\ (a + g\sin\theta + gC_r\cos\theta)d + 0.5C_d A\rho v^2 d \tag{1}$$

Let $\alpha = a + g\sin\theta + gC_r\cos\theta$ and $\beta = 0.5C_d A\rho$, then

$$W = \alpha(w + l)d + \beta v^2\ d \tag{2}$$

$$E' = \delta\left[\alpha(w + l)d + \beta v^2 d\right] \tag{3}$$

The parameters utilized in Eqs. (1)–(3) are described in Table 1.

4.2. Energy consumption and carbon emissions of a drone

Regarding the energy consumption of the drone, this study adopted the energy consumption model of Figliozzi (2017). The drone carries the cargo for a flight distance d_1 to reach the demand node and then returns to the truck or warehouse in a no-load state for a flight distance d_2. The energy consumption of the drone during this process is represented by W'.

Drone carbon emissions are based on the comprehensive lifecycle assessment (LCA) perspective. Although there are no direct emissions during drone delivery, the emission computation must include indirect carbon emissions in the power generation stage. From Goodchild and Toy (2018), drone carbon emissions in the delivery process are calculated based on the power generation process of power plants. This study calculates the indirect carbon dioxide emitted by the drone during operation, considering the carbon dioxide emitted by electricity production. There are two major costs in the process of electricity use. One is the cost of transporting the electric grid, and the other is the drone's battery charging efficiency. Since charging efficiency has been considered in energy consumption, only the electric grid cost must be considered. e represents the amount of carbon dioxide emitted by the drone's unit of electricity demand. E' is used to represent the carbon emissions of drones. The descriptions of each parameter of Eqs. (4)–(6) are shown in Table 2.

$$W' = (w' + l')\frac{gd_1}{\vartheta_s\eta_p\eta_r} + w'\frac{gd_2}{\vartheta_s\eta_p\eta_r} \tag{4}$$

Let $\gamma = \frac{g}{\vartheta_s\eta_p\eta_r}$, then

$$W' = \gamma[(w' + l')d_1 + w'd_2] \tag{5}$$

$$E' = e\,f_{kwh}\gamma[(w' + l')d_1 + w'd_2] \tag{6}$$

4.3. Drone cost estimates

The cost of the drone in the delivery includes energy consumption and carbon emission costs. The drone energy-consumption cost can be calculated as the drone energy consumption (see Eq. (5)) multiplied by the drone energy-consumption cost coefficient c_2. This cost parameter can be calculated by battery price, battery cycle life, and the drone lithium battery's energy density (capacity) (Dorling et al., 2017; Dukkanci et al., 2021). However, no previous work considers the drone's energy consumption and carbon emission costs in the delivery simultaneously. This paper contributes to the literature by taking both costs into account for the total cost of delivery, which is more in line with reality. In other words, the calculated total delivery cost is more accurate than the previous related papers considering only one cost. The drone energy-consumption cost coefficient can be expressed as $c_2 = \frac{l_p}{l_b s_e}$, where l_p is the battery price, l_b is the battery cycle life, and s_e is the energy density (capacity) of the drone's lithium battery. Therefore, the energy-consumption cost of the drone is $\frac{l_p}{l_b s_e}\gamma\ [(w' + l')\ d_1 + w'd_2]$. For the drone's carbon emission cost, it can be calculated as the carbon emissions of the drone (see Eq. (6)) multiplied by the carbon price c_3. Then the drone carbon emission cost can be expressed as $c_3 e f_{kwh}\gamma[(w' + l')d_1 + w'd_2]$. In general, the drone's delivery cost can be calculated as $\frac{l_p}{l_b s_e}\gamma\ [(w' + l')\ d_1 + w'd_2] + c_3 e f_{kwh}\gamma[(w' + l')d_1 + w'd_2]$..

4.4. Definition of the delivery route model

This study defines a model with a combination of a drone and a truck based on the FSTSP proposed by Murray and Chu (2015). It aims to minimize the total logistics cost of the joint truck and drone delivery under the carbon market price. This objective is similar to the proposed vehicle PRP model (Bektaş and Laporte, 2011), which considers the costs of time, path, fuel consumption, and carbon emissions. In contrast, the vehicle routing problem (VRP) model considers only the time and distance costs (Du et al., 2005). The delivery route model in this study is defined below.

Table 1
The relevant parameters of the truck.

Parameters	Description
w	Truck curb weight (kg)
l	Weight of cargo carried by truck (kg)
v	Truck speed (km/h)
a	Acceleration (m/ s^2)
g	Acceleration of gravity (m/ s^2)
θ	Road angle
C_r	Coefficient of rolling resistance
C_d	Coefficient of aerodynamic drag
A	the frontal surface area of the vehicle (m^2)
ρ	Air density (kg/ m^3)
d	Truck driving distance (km)
δ	Carbon emissions index parameter (kg-CO_2/kJ)

Table 2
The relevant parameters of the drone.

Parameters	Description
w'	Drone curb weight (kg)
l'	Weight of cargo carried by drone (kg)
d_1	Drone delivery distance (km)
d_2	Drone return distance (km)
ϑ_s	Lift-to-drag ratio
η_p	Total power transmission efficiency
η_r	Battery charging efficiency
f_{kwh}	The coefficient from kJ to kW
e	Carbon emissions emitted per unit of electricity (kg-CO_2/kWh)

The complete circuit diagram $G=(N,A)$. $N=\{0,1,2,\ldots,n,n+1\}$, 0 and $n+1$ are the same node, i.e., starting from and returning to the depot. A is the set of arcs defined between each pair of nodes. $N_0=\{0,1,2,\ldots,n\}$ represents the nodes from where the truck and the drone can depart, and $N_+=\{1,2,\ldots,n,n+1\}$ represents the nodes at which they can arrive. $N_c=\{1,2,\ldots,n\}$. $N_c^{'}\subseteq N_c$ means demand nodes that a drone can serve. $x_{ij}=1$ if the truck leaves from node i to node j; if not, it is 0. $y_{ijk}=1$ represents that the drone launches from node i and delivers cargo to node j, and then flies to node k to rendezvous with the truck for landing; otherwise, $y_{ijk}=0$. The distance for the truck from $i\in N_0$ to $j\in N$ is denoted by d_{ij}, the speed is denoted as v_{ij}, and the load weight is l_{ij}. Q is the maximum load weight of the truck, and m_i is the weight of the cargo required by the demand node at $i\in N_c$. The drone launches from $i\in N_0$ to $j\in N_c^{'}$ for delivery, the distance is denoted as $d_{ij}^{'}$, its load weight is $l_{ij}^{'}$, and the maximum load weight is $Q^{'}$; then, it meets the truck at $k\in N_+$, and the distance is denoted as $d_{jk}^{'}$. $0\le u_i\le n+1$ specifies the position of node i on the truck path because the demand node visited by the truck is unknown, and it is set to avoid subtours. $p_{ij}\in\{0,1\}=1$ indicates the truck arriving at node i and then at node j in the truck path. The time when the truck arrives at node $j\in N_+$ is t_j. τ_{ij} represents the time of the truck from node i to node j, and $\tau_{ij}^{'}$ represents the time of the drone from node i to node j. s_i is the time for the driver to provide delivery service at point $i\in N_c$, s_L is the time for the driver to assemble cargo for the drone and launch it, and s_R is the time for the driver to bring back the drone and charge it. F_j is the total working time of driving the truck from the depot and returning after serving all demand nodes.

The set of tuples $\langle i,j,k\rangle : i,j,k\in N,\ i\neq j, j\neq k, k\neq i,\ \tau_{ij}^{'}+\ \tau_{jk}^{'}\le\varepsilon$, in which ε represents the drone's flight endurance. P is the drone delivery that satisfies all possible endurance requirements in the entire route, $P=\{\langle i,j,k\rangle : i,k\in N, j\in N_c^{'}, i\neq j, j\neq k, k\neq i, \tau_{ij}^{'}+\ \tau_{jk}^{'}\le\varepsilon\}$.

v_{ij-} and v_{ij+} represent the minimum and maximum speed limits of the route between i and j, respectively. c_1 is the cost required for the unit energy consumption of truck fuel, and c_2 is the cost required for the unit energy consumption of the drone lithium battery, which can be expressed as $\frac{l_p}{l_b s_e}$. c_3 is the unit carbon-emission cost. p is the driver's wage. M is an infinite number.

Referring to Bektaş and Laporte (2011) in the nonlinear linearization of decision variables, since v_{ij} and x_{ij} are decision variables in calculating energy consumption and carbon emissions, the multiplication of the two leads to nonlinearity, and it is necessary to linearize v_{ij}. Assuming that the speed limit of each arc is the same, in $(i,j)\in A$, let $v_{ij-}=v_-$, $v_{ij+}=v_+$. Define a set of speed levels $R=\{1,2,\ldots,r,\ldots\}$, where each $r\in R$ of a given arc (i,j) corresponds to the speed interval $[v_-^r, v_+^r]$ with $v_-^r\ =\ v_-$, $v_+^r\ =v_+$. Therefore, the average speed for each level $r\in R$ is calculated as $\overline{v}^r=(v_-^r+v_+^r)/2$. Introduce a new 0–1 variable $z_{ij}^r=1$ if the truck is traveling in the arc (i,j) with a speed level $r\in R$; otherwise, it is zero. It is expressed as $\sum_{r\in R} z_{ij}^r=x_{ij}$, where $\forall i\in N_0, j\in\{N_c: j\neq i\}$.

4.5. Carbon-emission objective function

The first objective function is to minimize the weight of carbon emissions (kg-CO_2), including those produced by the truck and the drone. According to Section 4.1, the carbon emissions of the truck (see Eq. (3)) are evaluated based on fuel consumption, and the carbon emissions of the drone (see Eq. (6)) are measured by indirect carbon emissions from the electricity production process. Therefore, the carbon-emission objective minimization is expressed as follows:

$$\begin{aligned} Min E^{'}+E^{''} &= Min\delta\left[\alpha(w+l)d+\beta v^2 d\right]+ef_{kwh}\gamma\left[(w^{'}+l^{'})d_1+w^{'}d_2\right] \\ &= Min\delta\left\{\alpha\sum_{i\in N_0}\sum_{\substack{j\epsilon N_+\\ i\neq j}} d_{ij}wx_{ij}+\alpha\sum_{i\in N_0}\sum_{\substack{j\epsilon N_+\\ i\neq j}} d_{ij}l_{ij}+\beta\sum_{i\in N_0}\sum_{\substack{j\epsilon N_+\\ i\neq j}} d_{ij}\left[\sum_{r\in R}(\overline{v}^r)^2 z_{ij}^r\right]\right\} \\ &\quad +ef_{kwh}\gamma\sum_{\substack{i\in N_0\\ i\neq j}}\ \sum_{\substack{k\epsilon N_+\\ \langle i,j,k\rangle\in P}}\left[w^{'}\left(d_{ij}^{'}+d_{jk}^{'}\right)y_{ijk}+l_{ij}^{'}d_{ij}^{'}\right] \end{aligned} \tag{7}$$

4.6. Total cost objective function

The second objective function is to minimize the total cost in Yuan, consisting of three individual costs: 1) the energy-consumption cost of the truck and the drone, 2) the carbon-emission cost of the truck and the drone, and 3) the driver's wage. For the energy-consumption cost, the truck energy-consumption cost is calculated by Eq. (2) and then multiplied by the truck's energy-consumption cost coefficient c_1. Similarly, the drone energy-consumption cost calculates the drone energy consumption by Eq. (5) and then multiplies it by the UAV energy-consumption cost coefficient $\frac{l_p}{l_b s_e}$. The total energy-consumption cost is expressed as:

$$c_1\left\{\alpha\sum_{i\in N_0}\sum_{\substack{j\epsilon N_+\\ i\neq j}} d_{ij}wx_{ij}+\ \alpha\sum_{i\in N_0}\sum_{\substack{j\epsilon N_+\\ i\neq j}} d_{ij}l_{ij}+\ \beta\sum_{i\in N_0}\sum_{\substack{j\epsilon N_+\\ i\neq j}} d_{ij}\left[\sum_{r\in\mathscr{R}}(\overline{v}^r)^2 z_{ij}^r\right]\right\}+$$

$$\frac{l_p}{l_b s_e}\gamma\sum_{\substack{i\in N_0\\ i\neq j}}\ \sum k\epsilon N_+ < i,j,k >\in P[w^{'}(d_{ij}^{'}+d_{jk}^{'})\,y_{ijk}+l_{ij}^{'}d_{ij}^{'}].$$

For the cost of carbon emissions, we calculate the carbon emissions of the truck and drone based on Eq. (3) and Eq. (6), and then multiply it by the carbon price c_3 to obtain the total carbon-emission cost, i.e.,

$$c_3\delta\left\{\alpha\sum_{i\in N_0}\sum_{\substack{j\epsilon N_+\\ i\neq j}} d_{ij}wx_{ij}+\ \ \alpha\sum_{i\in N_0}\sum_{\substack{j\epsilon N_+\\ i\neq j}} d_{ij}l_{ij}+\ \ \beta\sum_{i\in N_0}\sum_{\substack{j\epsilon N_+\\ i\neq j}} d_{ij}\left[\sum_{r\in\mathscr{R}}(\overline{v}^r)^2 z_{ij}^r\right]\right\}+$$

$$c_3 ef_{kwh}\gamma\sum_{\substack{i\in N_0\\ i\neq j}}\ \sum k\epsilon N_+ < i,j,k >\in P[w^{'}(d_{ij}^{'}+d_{jk}^{'})\,y_{ijk}+l_{ij}^{'}d_{ij}^{'}].$$

The cost of the driver expressed as pF_j is the driver's wage p multiplied by the total working hours of the driver leaving from and returning to the depot , F_j. Based on the above definitions, the total cost objective can be expressed as follows:

$$Min\ \boldsymbol{c_1}\left\{\alpha\sum_{i\in N_0}\sum_{\substack{j\epsilon N_+\\ i\neq j}}d_{ij}wx_{ij}+\alpha\sum_{i\in N_0}\sum_{\substack{j\epsilon N_+\\ i\neq j}}d_{ij}l_{ij}+\beta\sum_{i\in N_0}\sum_{\substack{j\epsilon N_+\\ i\neq j}}d_{ij}\left[\sum_{r\in R}(\overline{v}^r)^2 z_{ij}^r\right]\right\}$$
$$+\frac{l_p}{l_b s_e}\gamma\sum_{\substack{i\in N_0\\ i\neq j}}\sum k\epsilon N_+ < i,j,k > \in P\left[w'\left(d'_{ij}+d'_{jk}\right)y_{ijk}+l'_{ij}d'_{ij}\right]$$
$$+\boldsymbol{c_3}\delta\left\{\alpha\sum_{i\in N_0}\sum_{\substack{j\epsilon N_+\\ i\neq j}}d_{ij}wx_{ij}+\alpha\sum_{i\in N_0}\sum_{\substack{j\epsilon N_+\\ i\neq j}}d_{ij}l_{ij}+\beta\sum_{i\in N_0}\sum_{\substack{j\epsilon N_+\\ i\neq j}}d_{ij}\left[\sum_{r\in R}(\overline{v}^r)^2 z_{ij}^r\right]\right\}$$
$$+\boldsymbol{c_3}ef_{kwh}\gamma\sum_{\substack{i\in N_0\\ i\neq j}}\sum k\epsilon N_+ < i,j,k > \in P\left[w'\left(d'_{ij}+d'_{jk}\right)y_{ijk}+l'_{ij}d'_{ij}\right]+\sum_{j\epsilon N_+}pF_j. \tag{8}$$

4.7. Total dual objective function

For the dual-objective solution with two different units of measure, this study follows Xu et al. (2015) and refers to the carbon emissions of the first objective measured by kg-CO_2 as E and the total cost of the second objective measured by Yuan (¥) as C. Furthermore, the minimum value of E is E^{min} while the maximum value is E^{max}. Likewise, the minimum value of C is C^{min} while the maximum value is C^{max}. The minimum and maximum values of each objective can be obtained by MATLAB's CPLEX when only one objective is considered at a time. The weight coefficients of the two objectives are w_1 and w_2, and $w_1+w_2=1$. In this vein, the dual objectives can be transformed into a single objective, and the objective function becomes

$$Min\ w_1\left(E-E^{min}\right)/\left(E^{max}-E^{min}\right)+w_2\left(C-C^{min}\right)/\left(C^{max}-C^{min}\right) \tag{9}$$

4.8. Constraints

The dual-objective mixed-integer linear programming constraints are expressed below and explained in Table 3.

$$\sum_{\substack{i\in N_0\\ i\neq j}}x_{ij}+\sum_{\substack{i\in N_0\\ i\neq j}}\sum_{\substack{k\in N_+\\ \langle i,j,k\rangle\in P}}y_{ijk}=1,\forall j\in N_c, \tag{10}$$

$$\sum_{j\in N_+}x_{0j}=1, \tag{11}$$

$$\sum_{i\in N_0}x_{i,n+1}=1, \tag{12}$$

$$u_i-u_j+1\leq(n+2)\left(1-x_{ij}\right),\forall i\in N_c,\forall j\in\{N_+:j\neq i\}, \tag{13}$$

$$\sum_{\substack{i\in N_0\\ i\neq j}}x_{ij}=\sum_{\substack{k\in N_+\\ j\neq k}}x_{jk},\forall j\in N_c, \tag{14}$$

$$\sum_{\substack{j\in N_c\\ j\neq i}}\sum_{\substack{k\in N_+\\ \langle i,j,k\rangle\in P}}y_{ijk}\leq 1,\forall i\in N_0, \tag{15}$$

$$\sum_{\substack{i\in N_0\\ i\neq k}}\sum_{\substack{j\in N_c\\ \langle i,j,k\rangle\in P}}y_{ijk}\leq 1,\forall k\in N_+ \tag{16}$$

$$2y_{ijk}\leq\sum_{\substack{h\in N_0\\ h\neq i}}x_{hi}+\sum_{\substack{f\in N_c\\ f\neq k}}x_{fk},\forall i\in N_c,j\in\{N_c:j\neq i\},k\in\{N_+:\langle i,j,k\rangle\in P\}, \tag{17}$$

$$y_{0jk}\leq\sum_{\substack{h\in N_0\\ h\neq k\\ h\neq j}}x_{hk},j\in N_c,k\in\{N_+:\langle 0,j,k\rangle\in P\} \tag{18}$$

$$u_k-u_i\geq 1-(\mathrm{n}+2)\left(1-\sum_{\substack{j\in N_c\\ \langle i,j,k\rangle\in P}}y_{ijk}\right),\forall i\in N_c,k\in\{N_+:k\neq i\}, \tag{19}$$

$$t'_i\geq t_i-M\left(1-\sum_{\substack{i\in N_c\\ j\neq i}}\sum_{\substack{k\in N_+\\ \langle i,j,k\rangle\in P}}y_{ijk}\right),\forall i\in N_c, \tag{20}$$

$$t'_i\leq t_i+M\left(1-\sum_{\substack{i\in N_c\\ j\neq i}}\sum_{\substack{k\in N_+\\ \langle i,j,k\rangle\in P}}y_{ijk}\right),\forall i\in N_c, \tag{21}$$

$$t'_k\geq t_k-M\left(1-\sum_{\substack{i\in N_0\\ i\neq k}}\sum_{\substack{j\in N_c\\ \langle i,j,k\rangle\in P}}y_{ijk}\right),\forall k\in N_+, \tag{22}$$

$$t'_k\leq t_k+M\left(1-\sum_{\substack{i\in N_0\\ i\neq k}}\sum_{\substack{j\in N_c\\ \langle i,j,k\rangle\in P}}y_{ijk}\right),\forall k\in N_+, \tag{23}$$

Table 3
Constraints of the objective function.

Constraints	Explanation
(10)	Each demand node must be served once and only by the drone or the truck.
(11)–(12)	The truck should leave the depot and return to the same depot.
(13)	The elimination of the sub-route of the truck.
(14)	The truck should leave after visiting the demand node.
(15)–(16)	The drone launches or lands at a specific demand node; the flight path is not closed.
(17)	If the drone launches from *i* to *j* to *k*, the truck should leave from *i* to *k*.
(18)	When the drone departs from the depot to deliver cargo at node *j* and then lands at node *k*, the truck should meet the drone at point *k*.
(19)	If the drone travels from *i* to *j* to *k*, the truck must first go to *i* and then to *k*.
(20)–(23)	The effective time for the drone and the truck to reach a certain point is consistent.
(24)	The time from the truck to *k* includes the time to reach the last point *h*, the travel period from *h* to *k*, and the service time for launching and retrieving the drone, and delivering at point *k*.
(25)	If the drone launches from *i* to *j*, its time to reach delivery node *j* includes the time to reach *i* plus the flight time from *i* to *j*.
(26)	If the drone launches from point *j* to landing node *k*, then the time to reach *k* includes the time the drone arrives at *j* plus the flight time from *j* to *k* plus the time the driver receives the drone.
(27)	The drone's flight time from *i* to *k* via *j* must not exceed flight endurance.
(28)	If the drone travels from *i* to *k, from l* to *n*, and *l* is after *i*; then the drone must arrive at *k* before *l*.
(29)	Calculate the total driving time.
(30)–(32)	Guarantee the regular order in which the truck visits the node.
(33)–(34)	The drone must not overload for delivery.
(35)	The load limit of the truck.
(36)	The change in the quantity of trucks on the delivery route.
(37)	Only a speed level is selected for each arc.
(38)–(45)	The range of value of the decision variables.

$$t_k \geq t_h + \sum_{r\in R}\left(d_{h,k} / \overline{v}^r\right) z^r_{hk} + s_L\left(\sum_{\substack{l\in N_c\\ l\neq k}}\sum_{\substack{m\in N_+\\ \langle k,l,m\rangle\in P}} y_{klm}\right) + s_k + s_R\left(\sum_{\substack{i\in N_0\\ i\neq k}}\sum_{\substack{j\in N_c\\ \langle I,j,k\rangle\in P}} y_{ijk}\right) - M(1-x_{ik}), \forall h\in N_o, k\in\{N_+ : k\neq h\}, \quad (24)$$

$$t'_j \geq t'_i + \tau'_{ij} - M\left(1 - \sum_{\substack{k\in N_+\\ \langle i,j,k\rangle\in P}} y_{ijk}\right), \forall j\in N'_c, i\in\{N_0 : i\neq j\}, \quad (25)$$

$$t'_k \geq t'_j + \tau'_{jk} + s_R - M\left(1 - \sum_{\substack{i\in N_0\\ \langle i,j,k\rangle\in P}} y_{ijk}\right), \forall j\in N'_c, k\in\{N_+ : k\neq j\}, \quad (26)$$

$$t'_k - \left(t'_j - \tau'_{ij}\right) \leq \varepsilon + M\left(1-y_{ijk}\right), \forall k\in N_+, j\in\left\{N_c : j\neq k\right\}, i\in\left\{N_0 : \langle i,j,k\rangle\in P\right\} \quad (27)$$

$$t'_l \geq t'_k - M\left(3 - \sum_{\substack{j\in N_c\\ \langle i,j,k\rangle\in P\\ j\neq l}} y_{ijk} - \sum_{\substack{m\in N_c\\ m\neq i\\ m\neq k\\ m\neq l}}\sum_{\substack{n\in N_+\\ \langle l,m,n\rangle\in P\\ n\neq i\\ n\neq k}} y_{lmn} - p_{il}\right), \forall i\in N_0, k\in\{N_+ : k\neq i\}, l \in\{N_c : l\neq i, l\neq k\}, \quad (28)$$

$$t_j - F_j + \sum_{r\in\mathscr{R}}\left(d_{j,n+1} / \overline{v}^r\right) z^r_{j,n+1} \leq M\left(1-x_{j,n+1}\right), \forall j\in N_c \quad (29)$$

$$u_i - u_j \geq 1 - (n+2)p_{ij}, \forall i\in N_0, j\in\{N_+ : j\neq i\}, \quad (30)$$

$$u_i - u_j \leq -1 + (n+2)\left(1-p_{ij}\right), \forall i\in N_0, j\in\{N_+ : j\neq i\}, \quad (31)$$

$$p_{ij} + p_{ji} = 1, \forall i\in N_c, j\in\{N_c : j\neq i\}, \quad (32)$$

$$0 \leq m_j y_{ijk} \leq Q', \forall i\in N_0, j\in\left\{N'_c : j\neq i\right\}, k\in\{N_+ : \langle i,j,k\rangle\in P\}, \quad (33)$$

$$l'_{ij} = m_j y_{ijk}, \forall i\in N_0, j\in\left\{N'_c : j\neq i\right\}, k\in\{N_+ : \langle i,j,k\rangle\in P\}, \quad (34)$$

$$0 \leq l_{ij} \leq Q x_{ij}, \forall i\in N_c, j\in\{N_c : j\neq i\}, \quad (35)$$

$$\sum_{j\in N} l_{ij} - \sum_{j\in N} l_{ji} = \sum_{j\in N} x_{ij} m_j + \sum_{j\in N} l'_{ji}, \forall i\in N, \quad (36)$$

$$\sum_{r\in\mathscr{R}} z^r_{ij} = x_{ij}, \forall i\in N_0, j\in\{N_c : j\neq i\}, \quad (37)$$

$$x_{ij}\in\{0,1\}, \forall i\in N_0, j\,\varepsilon\{N_+ : i\neq j\}, \quad (38)$$

$$y_{ijk}\in\{0,1\}, \forall i\in N_0, j\in\{N_c : i\neq j\}, k\in\{N_+ : \langle i,j,k\rangle\in P\} \quad (39)$$

$$p_{ij}\in\{0,1\}, \forall i,j\in N_c, \quad (40)$$

$$p_{0j} = 1, \forall j\in N_c, \quad (41)$$

$$0 \leq u_i \leq n+1, \forall i\in N \quad (42)$$

$$t_i \geq 0, \forall i\in N \quad (43)$$

$$t'_i \geq 0, \forall i\in N \quad (44)$$

$$z^r_{ij}\in\{0,1\}, \forall i\in N_0, j\varepsilon\{N_+ : j\neq i\}, r\in R \quad (45)$$

5. Performance analysis

In this analysis, we choose one of JD's regular delivery routes of drones in Guang'an, Sichuan, and set up 10 demand nodes with different weights for cargo. These demand nodes can only be served by the drone or truck once; node 0 is the depot, nodes 1 to 10 are the demand nodes, and the demand requirements of these nodes are 6.5, 10, 8, 155, 50, 8.5, 7.5, 6, 60, and 100 kg. Table 4 defines all the symbols of unit measures in this study.

In the drone delivery case, we assume that the manager at the reception agency will receive and sort the packages, waiting for customers to pick them up. We combine the dual-objective mixed-integer linear programming model with these actual delivery situations; each demand node is regarded as a terminal parcel storage node. There may be more than one customer, so the unloading time of the driver must be considered. We consider the service time s_i of each demand node to be 0.15 h, while s_L and s_R for the time of launching and recovering the drone are counted as 0.05 h. According to market conditions, the driver's wage, p, is set at 30 Yuan/h. Depending on the total pre-set demand for packages, the standard box-type mini trucks currently available on the Chinese market are selected. The rated load is 720 kg, and the unloaded mass is 1520 kg. We assume that the speed of the truck is $v^r_- = 40$ km/h, the maximum speed is $v^r_+ = 50$ km/h, and the average speed is $\overline{v}^r = 45$ km/h. The selected drone is the JD Y-3 model, mainly used in the regular drone delivery route. According to the official data of the JD Business Department, the rated load of the Y-3 model is 10 kg, and the empty weight is 12 kg; in addition, the speed is set at 60 km/h, the flight radius is 20 km, and the endurance is approximately 0.278 h.

For truck carbon emission, δ, the average low calorific value of

Table 4
Symbols of unit measures.

Measure	Description
kg	Kilogram
kJ	Kilojoule
t-CO_2	Tons of carbon dioxide
kV	Kilovolt
tC/TJ	Emission factor
km	Kilometer
h	Hour
m	Meter
s	Second
kWh	Kilowatt per hour
kg-CO_2	Kilograms of carbon dioxide
kW	Kilowatt
L	Liter

gasoline is 43,124 kJ/kg (NEFMSTC, 2020). When the thermal efficiency is 30%, the actual mechanical work of 1 kg of gasoline is 12,937 kJ. According to the National Development and Reform Commission (2011), the carbon content per unit heating value of gasoline is 18.9 tC/TJ, and the carbon oxidation rate is 98%; then, the carbon emission coefficient of gasoline is 2.8391 kg-CO_2/kg. δ is calculated by dividing the carbon emission coefficient by the work done per unit mass of gasoline, and the value is 2.1946 $\times 10^{-4}$ kg-CO_2/kJ. According to IEA (2020) data, the carbon intensity of China's electricity in 2017 was 0.623 kg-CO_2/kWh and the grid loss rate was 6.48% in the same year, and e was 0.66 kg-CO_2/kWh. Following the vehicle model, premium gasoline is used with a density of approximately 0.725 kg/L, and the price in Sichuan is 7.02 Yuan/liter, then c_1 is 7.494×10^{-4} Yuan/kJ.

The unit energy-consumption cost c_2 of the drone is composed of electricity cost and battery cost. The value of general industrial, commercial, and other electricity below 1 kV is 0.7344 Yuan/kWh, and multiply it by f_{kwh} to obtain the electricity cost of 2.04×10^{-4} Yuan/kJ. The Y-3 drone model uses an A-grade polymer lithium-ion battery, and its cycle life is approximately 600 times. Each battery charge allows the Y-3 model to fly 10 km at maximum load and return to the depot without any load for 10 km. The drone energy consumption function in Eq. (5) is used to obtain a total energy consumption of 889.78 kJ from fully charged power to an exhausted state. The average market price for a battery is 600 Yuan. Then, the unit energy consumption cost is 1.328×10^{-3} Yuan/kJ. Assuming that the average carbon price is distributed at approximately 30 Yuan/t-CO_2, therefore, c_3 is 0.03 Yuan/kg-CO_2. Table 5 lists all the parameter values.

5.1. Results and analysis

Based on the parameter values above and setting the weight coefficients w_1 and w_2 of the two objectives to 0.5, we use MATLAB to call CPLEX to solve the model, Eq. (9). The solution yields that the carbon emission value is 13.42 kg-CO_2 and the total cost value is 103.62 Yuan. Fig. 2 shows the resulting distribution path diagram. The red and blue lines represent the drone and truck paths, respectively. The result shows that the total delivery time of the truck that leaves the depot until it returns is 1.94 h.

Regarding the traditional truck delivery model, the delivery route diagram is shown in Fig. 3. After calculation, the carbon emissions under truck delivery are 17.88 kg-CO_2, the total cost is 133.07 Yuan, and the delivery time is 2.45 h. Compared to truck delivery, drone-assisted delivery reduces carbon emissions, total cost, and delivery time by 24.90%, 22.13%, and 20.65%, respectively, as shown in Fig. 4. This drone-assisted commercial delivery model effectively reduces emissions and economically benefits logistics enterprises.

Next, a cost-benefit analysis is conducted to explore further the effects of drone-assisted commercial delivery. The unit damage cost of carbon emissions was 417 dollars per tonne of CO_2 suggested by Ricke et al. (2018). Therefore, the social benefit of unit carbon emission reduction was set as 2.87 Yuan/kg-CO_2. Compared with traditional truck delivery, drone-assisted delivery reduces 4.45 kg of carbon dioxide, with a social benefit of 12.77 Yuan. Meanwhile, the total cost of drone-assisted delivery decreased by 29.45 Yuan. Correspondingly, there is a 42.22 Yuan increase in net social benefit for drone-assisted delivery compared with traditional truck delivery.

5.2. Sensitivity analysis and discussion

First, the four parameters of the fuel price, drone battery cycle life, carbon price, and driver's wage will be changed individually, keeping the remaining parameters constant with the values shown in Table 5. The impact of each parameter on the total cost is analyzed, as shown in Fig. 5. According to historical data, the fuel price is based on the Sichuan 92 octane-rated gasoline market, which increases by a gradient of 1 (Yuan/L) from 3 to 9. The battery cycle life denotes the maximum number of times it can be recharged, assuming the same power hours after each full charge. Considering that battery research development would gradually extend the battery's durability, we assume that the battery could recharge from 100 times to 1000 times in 100 increments. The carbon price fluctuates in the range of 100 Yuan/t-CO_2 based on the carbon price in China's carbon market. According to actual market conditions, we consider increasing from 0 to 100 Yuan/t-CO_2 in the range of 10 Yuan/t-CO_2. Zero means that the carbon-emission cost is not considered. The driver's wage is set from low to high according to the different situations of the companies, which are 20, 25, 30, 35, 40, 45, and 50 (Yuan/h). Note that these four parameters affect the total cost and do not affect carbon emissions.

Furthermore, changes in fuel price and hourly wage significantly impact the total cost. When the fuel price is 3 Yuan/L, and the driver's wage is 20 Yuan/h, the total cost is approximately 80 Yuan. As the fuel price increases to 9 Yuan/L, the total cost reaches about 120 Yuan. Similarly, when the driver's wage is 50 Yuan/h, the total cost is approximately 140 Yuan. In addition, battery cycle life negatively correlates with total cost. The trend gradually slows down, indicating that the impact on the total cost decreases after the battery durability reaches a specific recharge time. In addition, the effect of changes in carbon prices is the smallest compared with the above three parameters. The total cost is 103.21–104.56 Yuan when the carbon price is 0–100 Yuan/t-CO_2. Although the carbon price generated by the domestic carbon trading market has varied in recent years, the overall low carbon price and small carbon emissions lead to a relatively small share of the carbon-emission cost, which is less than the share of energy cost and labor cost. Thus, the carbon-emission cost accounts for very little of the total cost. However, when the carbon price rises from 10 to 100 Yuan/t-CO_2, the proportion of carbon-emission cost changes from 0.13% to 1.28%. When the carbon price is low (such as 30 Yuan/t-CO_2), carbon-emission cost accounts for only 0.39% of the total cost, while energy consumption (fuel price) and labor costs (driver's wage) account for 43.44% and

Table 5
The parameter values used in this study.

Parameters	Description	Value
w	Truck curb weight (kg)	1520
v	Truck speed (km/h)	[40,45,50]
a	Acceleration (m/ s^2)	0
g	Acceleration of gravity (m/ s^2)	9.81
θ	Road angle	0
C_r	Coefficient of rolling resistance	0.01
C_d	Coefficient of aerodynamic drag	0.7
A	the frontal surface area of the vehicle (m^2)	3.436
ρ	Air density (kg/ m^3)	1.2041
δ	Carbon emissions index parameter (kg-CO_2/kJ)	2.1946×10^{-4}
v'	Drone speed (km/h)	60
w'	Drone curb weight (kg)	12
θ_s	Lift-to-drag ratio	4.25
η_p	Total power transmission efficiency	90%
η_r	Battery charging efficiency	98%
f_{kwh}	The coefficient from kJ to kW	2.78e-4
e	Carbon emissions emitted per unit of electricity (kg-CO_2/kWh)	0.684
ε	Flight endurance (h)	0.278
s_i	Service time in node i (h)	0.15
s_L	Launching time (h)	0.05
s_R	Receiving time (h)	0.05
c_1	Unit energy-consumption cost of truck (Yuan/kJ)	7.494×10^{-4}
c_2	Unit energy-consumption cost of drone (Yuan/kJ)	1.328×10^{-3}
l_b	Battery cycle life (times)	600
l_p	Battery price (Yuan)	600
s_e	Capacity of drone battery (kJ)	889.78
c_3	Unit carbon-emission cost (Yuan/kg-CO_2)	0.03
c_{3t}	Carbon price (Yuan/t-CO_2)	30
p_f	Fuel price (Yuan/L)	7.02
p	Driver's wage (Yuan/h)	30

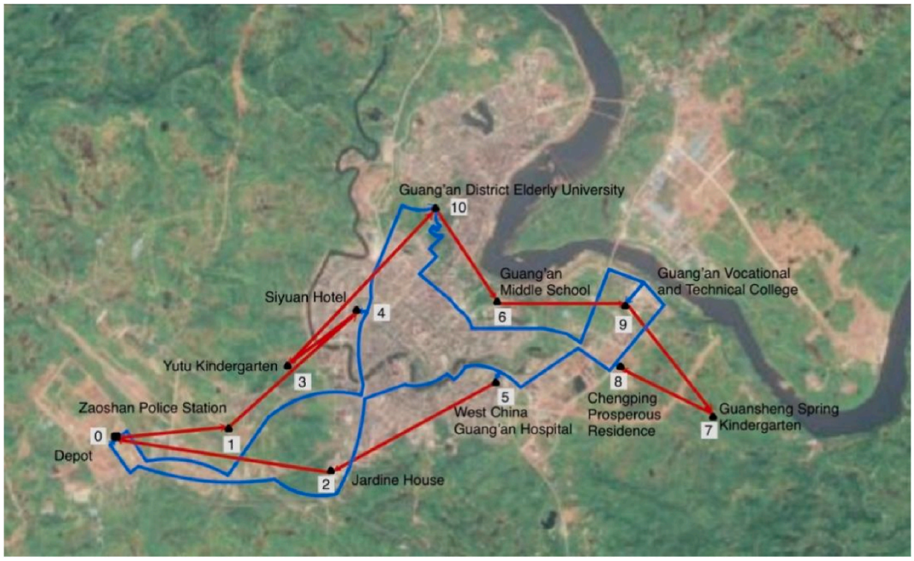

Fig. 2. A drone-assisted delivery route in Guang'an, Sichuan, China.

Fig. 3. The truck delivery route in Guang'an, Sichuan, China.

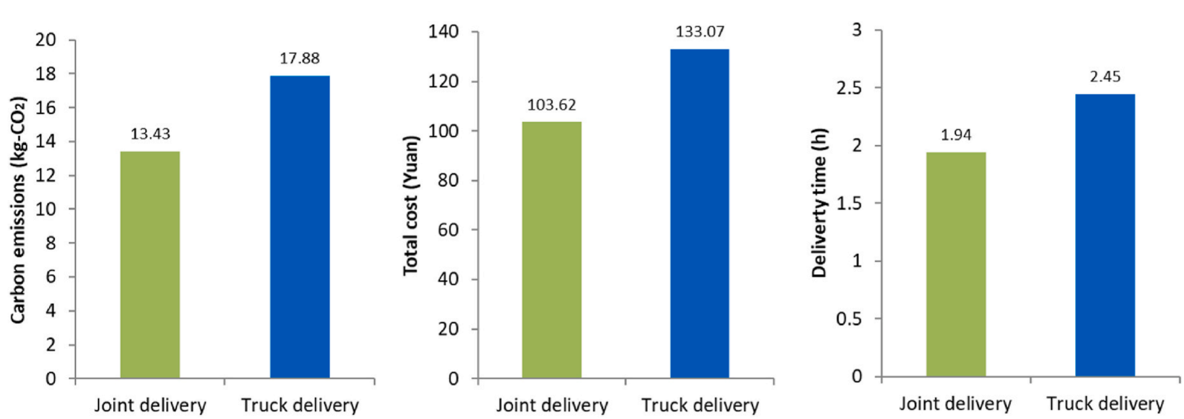

Fig. 4. Comparison of carbon emissions, total cost, and delivery time between drone-assisted joint delivery and traditional truck delivery.

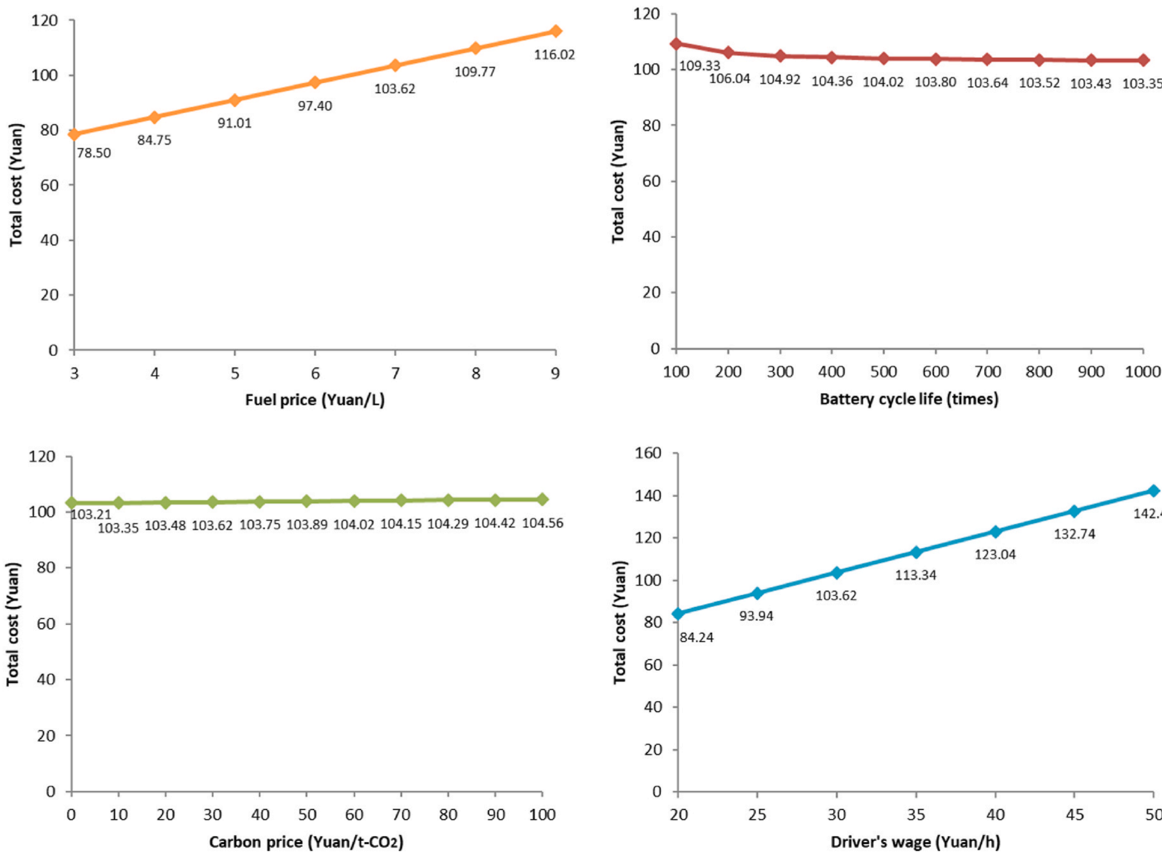

Fig. 5. The total cost based on fuel price, battery cycle life, carbon price, and driver's wage.

56.17%, respectively.

The apparent impact of driver's wage on the value shows that labor cost is critical. Fig. 5 shows that when the driver's wage is 20–50 Yuan/h, the proportion of labor cost in the total cost gradually increases from 46.06% to 68.01%. This pattern is consistent with the finding of Bektaş and Laporte (2011), who note that labor cost plays a leading role in the total cost. With the increasing carbon price in China, we assume that the carbon price of 100 Yuan/t-CO_2 will be increased from 100 to 1000 Yuan/t-CO_2. Fig. 6 indicates that a higher carbon price has a greater impact on the total cost. With the increase in the carbon price, the proportion of carbon emission cost in the total cost increases with an average growth rate of 29.83%. When the carbon price is 1000 Yuan/t-CO_2, the proportion of the carbon-emission cost reaches 11.51%.

The contributions to the literature.

Truck speed is affected by road congestion in the actual delivery

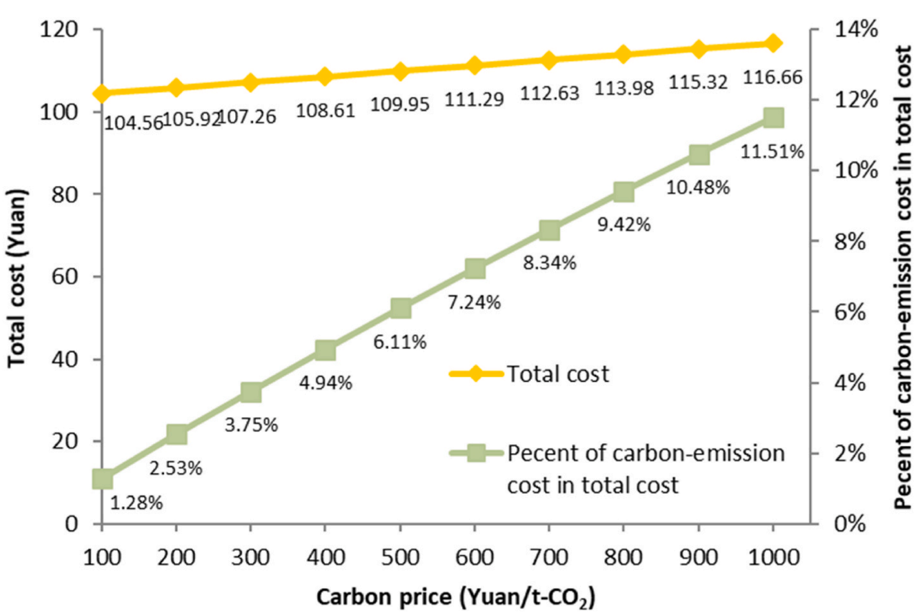

Fig. 6. The total cost change with a changing carbon price from 100 to 1000 Yuan/t-CO_2.

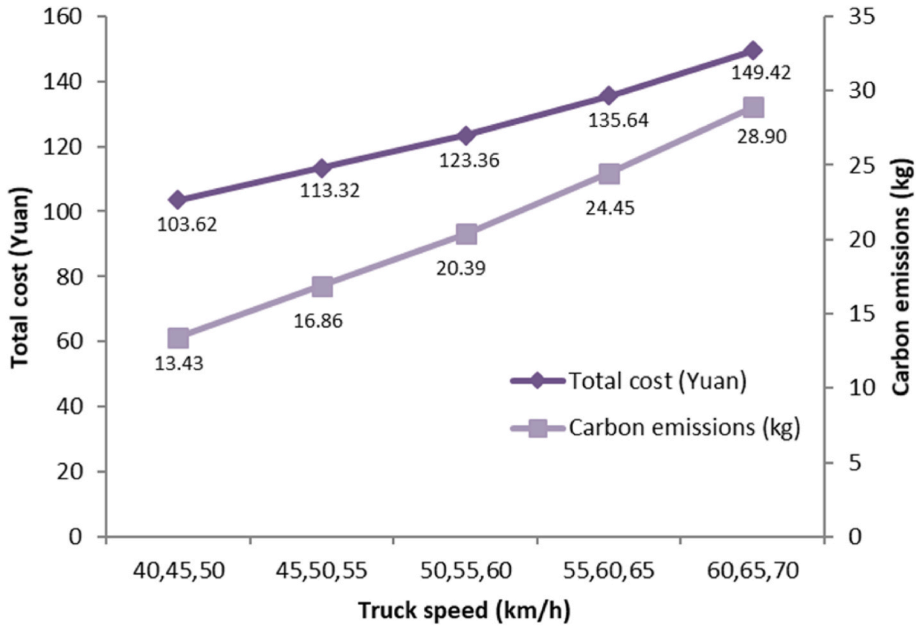

Fig. 7. Impact of truck speed on total cost and carbon emissions.

process. The load weight and the remaining battery power influence the drone's speed. Changing them will affect the total cost and carbon emissions. We increase the truck speed from the minimum speed of 40–60 km/h with a gradient of 5 km/h, and the maximum speed from 50 to 70 km/h. Meanwhile, the drone speed is 50, 55, 60, 65, and 70 km/h. Fig. 7 shows that truck speed positively correlates with the total cost and carbon emissions. The faster the truck speed, the greater the total carbon emissions., Therefore, it is necessary to reduce the truck speed to control emissions further. In contrast, drone speed has almost no impact on total cost and carbon emissions because it has very low carbon emissions, and the logistic cost of the drone is small. Therefore, the drone can serve as many qualified demand nodes as possible regardless of speed, indicating that the drone has played an essential role in reducing carbon emissions and the total cost.

6. Conclusions and policy implications

This study optimizes not only the economic impact but also the environmental impact of drone-assisted commercial delivery under the policies of the carbon trading market. First, we establish an innovative dual-objective mixed-integer linear programming model to make a trade-off between carbon emissions and the total cost of drone-assisted truck delivery, promoting the development of the method for low-carbon commercial delivery optimization. Then, using JD logistics in Guang'an, Sichuan as a case, we solve and compare carbon emissions, total cost, and delivery time between drone-assisted delivery and truck delivery. Additionally, we solve and analyze the sensitivity effects of carbon price, truck fuel price, drone battery cycle life, truck driver's hourly wage, truck speed, and drone speed.

Reducing carbon emissions is increasingly important as the negative greenhouse effect on humans becomes serious. The surge of carbon dioxide emissions from increasing road transport triggered by a rapid increase in stay-at-home shopping and home delivery in China during the COVID-19 pandemic poses a critical challenge to environmental protection. The carbon market plays a vital role in reducing global carbon emissions. Therefore, the government should improve carbon-emission standards and continuously promote the carbon market to provide an essential driving force for realizing carbon neutrality. In the carbon market, logistics companies should use drones to assist trucks in delivery to protect the environment and reduce carbon emissions. Compared with traditional truck delivery, drone-assisted delivery produces dual social benefits under the policies of the carbon trading market: curbing carbon emissions (the direct social benefit) and reducing the total delivery cost (the backhanded benefit). Correspondingly, there is a net social benefit increase of 42.22 Yuan for this drone-assisted delivery compared with traditional truck delivery. This study shows that drone battery cycle life, fuel price, driver's wage, and truck speed are critical to the total cost. Although the cost of carbon emissions accounts for only a minor proportion of the total cost, the government should regulate the carbon price and impose a strict policy on the carbon-emission level of every vehicle. This policy could continuously improve the living environment in China. Moreover, this study could inspire future related research in environmental policies and promote research on carbon emission mitigation in other transportation fields.

Furthermore, when the truck speed is not less than 40 km/h, the faster the truck speed, the more carbon emissions. In this vein, the road transportation industry is critical in the Chinese carbon trading market. Driven by the reduction of carbon emissions in the carbon trading market, a national policy should be enacted to encourage logistics companies to adopt drone-assisted low-carbon commercial delivery to gain competitive advantages effectively. In addition, higher carbon prices could reduce carbon emissions and minimize environmental impacts. Compared to traditional truck delivery, drone-assisted delivery reduces carbon emissions and the total cost of transportation, which is conducive to the green and sustainable development of logistics companies.

Finally, some practical implications are helpful to different stakeholders. For researchers, since this study innovatively establishes a dual-objective mixed-integer linear programming model to make a trade-off between carbon emissions and the total cost of drone-assisted truck delivery, they can further extend the proposed model to develop a low-carbon commercial delivery optimization method. For policymakers, they can further analyze environmental and economic impacts under other environmental policies by using the proposed model. Finally, managers of logistics companies can properly apply or adjust the proposed model to solve similar problems based on practical situations.

7. Limitations and future research

There are a few limitations of this study. First, only a truck and a drone are considered. As more and more large-scale deliveries are emerging, more research is needed on low-carbon commercial deliveries with multiple trucks and drones. Moreover, this study only analyzes the effects of several critical factors on drone-assisted truck delivery. A plausible extension would be to consider other factors (e.g., fuel efficiency, fuel type, and engine type) that affect a truck's fuel consumption, influencing carbon emissions and the total cost. Finally, this paper considers drone-assisted truck delivery under the carbon market price. Future research should consider more pricing policies and compare the corresponding results to adjust environmental policies.

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Submission declaration and verification

The authors formally declare that this paper's content is the original work. It has not been published previously in any media, including journals, conferences, or websites. It is not being reviewed by any editorial office of publishers. All cited materials have been properly credited with citations in the contexts and the References section.

CRediT authorship contribution statement

Zhiyi Meng: Project administration, Investigation, Visualization. **Yuting Zhou:** Investigation, Formal analysis, Writing – review & editing. **Eldon Y. Li:** Formal analysis, Visualization, Writing – review & editing. **Xinying Peng:** Data curation, Formal analysis, Writing – original draft. **Rui Qiu:** Conceptualization, Supervision, Investigation, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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