

JRCS: Joint Routing and Charging Strategy for Logistics Drones

Muhammad Yeasir Arafat^{1b} and Sangman Moh^{1b}, *Member, IEEE*

Abstract—Unmanned aerial vehicles (UAVs), commonly known as drones, are currently being used to combat the COVID-19 pandemic through applications, including the delivery of medical supplies, aerial spraying, and public space monitoring. In a pandemic, drone-based delivery is a promising and highly efficient method to reduce transportation time, cost, and exposure to infection. However, owing to both the limited battery lifetime and the limited functions of UAV in-flight missions, it is difficult to implement multiple deliveries over long distances in a single transportation mission. In this article, we study how to extend the drone flight time with charging stations and ensure multiple deliveries in a single mission. For multiple long-distance deliveries, optimization methods are required to design the delivery area networks of customers, charging stations, and delivery routes. We propose a joint routing and charging strategy (JRCS) comprising three phases to perform multiple deliveries in a single mission. We first split the customers of a delivery area using a clustering algorithm according to their distance from the nearest charging station and the maximum flight range. The second phase provides flight segmentation and intersegment routes between the depot, customer locations, and charging stations based on the maximum flight range and safe flight distance. The joint consideration of drone routes with charging stations minimizes the number of charging stations and ensures safe delivery. Finally, we formulate mixed-integer linear programming to solve the drone delivery route problem. According to simulation results, the proposed JRCS outperforms existing delivery approaches in terms of various performance metrics.

Index Terms—COVID-19, drone, drone charging, drone delivery, drone routing, logistics drone, unmanned aerial vehicle (UAV).

I. INTRODUCTION

RECENTLY, unmanned aerial vehicles (UAVs), commonly known as drones, have attracted increased attention from academic and industrial research communities because of their wide range of potential applications in civilian domains, such as wildfire monitoring [1], search-and-rescue [2], surveillance [3], transportation [4], and traffic monitoring [5]. UAV applications have increased in popularity in recent years because of their ability to incorporate a wide variety of sensors while retaining cheap operating costs and excellent mobility [6].

Manuscript received 18 February 2022; revised 13 May 2022; accepted 6 June 2022. Date of publication 14 June 2022; date of current version 24 October 2022. This work was supported in part by the National Research Foundation of Korea (NRF) Grant funded by the Korea Government (MSIT) under Grant 2022R1A2C1009037. (*Corresponding author: Sangman Moh.*)

The authors are with the Department of Computer Engineering, Chosun University, Gwangju 61452, South Korea (e-mail: smmoh@chosun.ac.kr).

Digital Object Identifier 10.1109/JIOT.2022.3182750

Drone-based delivery is a promising and highly efficient component of logistics systems for cities because it requires less time and cost for logistic delivery [7]. Drone delivery has many advantages over ground-based delivery [8]. In particular, drones can provide delivery at a low-cost, on-demand, faster, and without human involvement. Several e-commerce platforms use drones for commercial package delivery, including Amazon, Google, UPS, and DHL [9].

Drone delivery is an efficient and reliable solution for relief distribution in a disaster area inaccessible to ground vehicles and rescuers on foot. Drones have shown significant potential to mitigate pandemic disease outbreaks, particularly during COVID-19 [10]. This is accomplished through crowd surveillance, delivery of emergency medical supplies, aerial spraying, and public space monitoring and guidance by law enforcement. During the COVID-19 pandemic, drones have provided safe and low-contract delivery that can minimize the spread of infection [8]. Many countries, governments, and companies offer drone-based delivery for distributing medicines, vaccines, and face masks to health care centers during the pandemic and lockdown [11].

A drone can deliver COVID-19 vaccines to remote areas quickly, safely, and at the required temperature. Last-mile delivery is a problem in the developing world, where it can take hours to reach remote villages on foot or by car. Medical supplies are often damaged during transit or do not arrive on time. However, rapid delivery is crucial for some COVID-19 vaccines such as the Pfizer/BioNTech vaccine, which needs to be stored at -70 °C and lasts for just 2 h at room temperature [12]. UNICEF recently used a drone in trials on the South Pacific island of Vanuatu to deliver vaccines to 19 remote health facilities [13]. To prevent the spread of COVID-19, many countries have decided to go into lockdowns and quarantine those who have had close contact with a confirmed COVID infection. Nevertheless, a timely supply of medicine and necessary goods to home-quarantined people is important to keep them alive and safe. Moreover, many people live on mountains or islands that are difficult to reach, making it a challenge to ensure delivery by traditional means. Furthermore, traditional home delivery has a major security risk, where delivery people can become infected and spread the infection to others without their knowledge.

Drone-based delivery can cut the journey time from days to minutes. Drone-based delivery can solve the problem of vaccine delivery to remote locations where medical supplies often fail to arrive on time or can be damaged during transit. Infrared technology guides the drones to dedicated landing

pads. If something goes wrong, drones have a parachute to land safely. Unlike other drones, medical drones can fly over urban areas, can carry up to five kilos, and have a range of 20 km [14]. Drones will make the transport of medicines and other supplies faster and more efficient. Drone delivery eliminates human contact, bringing significant benefits in the COVID-19 era. Drone-based delivery can improve consumer satisfaction, accelerate innovation in logistics, and be more convenient for people who live on islands or in mountainous areas.

However, because of the limited capability of power, weight, and functions, the transportation missions in a complex and dynamic environment cannot be implemented effectively. Most of the recent works on drone-based delivery have studied single-customer and short-range delivery owing to the limited flight range and battery power of available drones. The battery capacity, flight range, and payload capacity are crucial parameters for drone employment in package delivery. Several approaches have been proposed to overcome the problems, including truck–drone collaboration [15], independent drone delivery [16], and drone delivery with charging stations that enable drones to recharge their batteries [17]. In truck–drone collaboration, the trucks carry parcels and several drones, and the drones mainly concentrate on last-mile delivery. The drone carries the parcel from the truck and delivers it to the customer. The second approach, independent drone delivery, works on short-distance delivery from the depot to customers. In the third approach, several charging stations are deployed in the delivery areas, allowing drones to recharge mid-mission and continue deliveries with an energized battery. Drone delivery with several charging stations increases the delivery coverage significantly, which enables long-distance delivery to multiple customers in a single mission.

As drone delivery is an emerging technology in the field of transportation, significant efforts are being made to develop drone delivery through improvements. They include charging fast with high-capacity lithium polymer batteries, increasing the payload capacity, and extending the drone flight range. Recently, rotary-wing-based flying taxis or drones have shown significant potential for long-range drone delivery. Flying taxis can support a long flight range with a high battery capacity and payload. Moreover, many countries have recently tested drone taxis for commercial public transport [18]. Both fixed-wing and rotary-wing drones have been used for drone delivery. However, rotary-wing drones are more widely used. Rotary-wing drones enable vertical takeoff and landing, which do not require a runway. Furthermore, delivery drones have a global positioning system (GPS), which is generally used for drone localization.

Recently, drone delivery with multiple charging stations has attracted increased attention from academic and industrial research communities owing to its ability to provide long-distance delivery in a single mission. In this study, we consider the drone delivery with several charging stations approach as well. Charging stations can be installed on the rooftops of buildings, allowing drones to be charged from a charging pad. A drone can use a charging station if the customer location is outside its maximum flight range. Two neighboring charging

stations should be placed within a certain range so that the drone can reach the charging station before the threshold battery level. Generally, all charging stations need to connect with the depot to create a proper delivery route. Then, a drone can depart from the depot and reach any charging station before reaching the threshold battery level and can serve customers near the charging station. In this study, we divided customers into clusters or groups according to the nearest charging station. When a drone delivers a parcel to a cluster, it moves from one cluster to another. During intercluster transactions, drones must ensure a minimum charge level for safe delivery. Finally, after successful delivery, the drone can return to the same depot. This approach also improves safety by allowing a drone to return to a charging station in an emergency.

In truck–drone collaboration, the truck can carry high loads over long distances but is expensive. In the independent drone approach, a drone is less expensive than a truck and more flexible but can only carry a limited payload over a limited range. For drones with several charging stations, drone flight restriction can be minimized and long-distance delivery can be provided in a single delivery mission. However, route selection for drone delivery affects drone delivery efficiency. Efficient route selection has an impact on the drone delivery time, drone flight path length, and landing frequency at charging stations. Owing to the unique features of drones, drone delivery routing problems (DDRPs) are quite different from vehicle routing problems (VRPs) [19] as there are many uncertainties in DDRPs, such as weather effects, airspeed, payload, and flight range. The flight time of the drone is related to the total payload of the drone, including the battery and parcels payload. Drone energy consumption increases for additional batteries and payloads, which decreases the drone flight time [20]. Therefore, several parameters, including payload, battery capacity, drone energy consumption, maximum flight range, and maximum safe flight range need to be considered in the DDRP.

A. Contributions of the Present Study

In this article, as per the above limitations, we propose a joint routing and charging strategy (JRCS) to conduct multiple deliveries in a single mission. The major contributions of this study are summarized as follows.

- 1) We first split the entire delivery area into customer clusters with charging stations at their centroids. We develop a customer clustering algorithm based on both the distances between customers and charging stations and the maximum flight range. Our proposed clustering algorithm divides the customers of the delivery area efficiently and fairly between all clusters. The proposed approach minimizes the drone landing frequency for charging during mission.
- 2) Then, we formulate two critical concepts: a) maximum flight distance and b) maximum safe flight distance for drone delivery. We utilize these two critical concepts to construct flight segments between depots, customer locations, and charging stations. The proposed approach solves the routing problem between clusters and provides safe delivery.

- 3) Finally, we derive a mixed-integer linear programming (MILP) scheme to solve DDRPs. MILP optimizes the drone delivery routes, total path distance, energy consumption, landing on charging stations, and the total number of customers for long-distance drone delivery.
- 4) Our performance study shows that the proposed JRCS outperforms existing schemes in terms of average delivery time, algorithm computation time, delivery area coverage ratio, drone travel distance, the number of customers served, and energy consumption in a single mission. JRCS also enables drone delivery at a reasonable cost.

B. Outline of This Article

The remainder of this article is organized as follows. In Section II, recent related works and their respective limitations are reviewed in terms of DDRPs. In Section III, the motivation of the proposed approach, system model and assumptions, drone energy consumption model, and problem definition are addressed. In Section IV, the proposed algorithms are presented mathematically and formally. In Section V, the performance of the proposed scheme is evaluated through extensive simulations and compared with existing approaches. The conclusions of this study are presented in Section VI.

II. LITERATURE REVIEW

Routing problems in UAV networks have been reported in the literature. Arafat and Moh [21] reviewed and provided a comprehensive survey of routing protocols in UAV networks. The routing problem in UAV networks mostly focuses on multi-UAV-aided aerial communication, where drones need to communicate with each other as well as a ground station. However, the routing problem in drone delivery is not similar to that of UAV networks. Moreover, although VRPs have been studied thoroughly in the last decade, DDRPs are not similar to VRPs. Most of the VRP research focuses on truck-based VRPs. In addition, several studies have been conducted on truck–drone collaboration delivery. Classical VRPs are based on the traveling salesman problem (TSP), which is an NP-hard problem, where vehicles use the shortest path to visit all customers and return to the origin. Many VRPs have been developed based on the TSP, including heuristic, meta-heuristic, and exact algorithms. Kim *et al.* [22] provided an overview of different types of VRP solutions, algorithms, and approaches. However, our study is not related to VRPs.

Recently, some research has been proposed based on truck and drone collaboration for delivery problems (DPs). Wang *et al.* [23] proposed routing and scheduling algorithms for multiple delivery approaches, including truck–drone combinations, independent drones, and truck-carried drones. Ulmer *et al.* [24] proposed same-day delivery based on drones and vehicles using drones for short-range delivery and trucks for long-range delivery. They also presented a policy function based on geographical districting to choose the more suitable delivery approach. Hu *et al.* [25] proposed a routing and scheduling algorithm for vehicle-aided multi-UAV for DP. They utilized one vehicle with multiple drones to deliver

parcels in multiple areas at a time. The proposed approach reduces the delivery time and expands the delivery area. Recently, Wu *et al.* [15] proposed a truck–drone-collaboration-based delivery approach for contactless delivery during the COVID-19 pandemic. All deliveries are processed by drones, and the truck serves as a portable warehouse and charging station. The authors divided the delivery area into several clusters, which improved the efficiency of the delivery process. Reinforcement learning was used to solve the DPs. Boysen *et al.* [26] proposed a truck–drone-based delivery approach in which the truck serves as a moveable landing and takeoff station. Drones delivered parcels to customers on the route of the truck. To minimize the delivery time, the authors proposed an MILP for DPs. Recently, e-commerce company Amazon received a patent for a flying warehouse, also known as the airborne fulfillment center (AFC), to deliver packages to customers. The AFC is placed at a high altitude, and drones carry parcels from the AFC to customers. Amazon AFC-based delivery is intended to ensure that drone deliveries are made within 10 min and can provide services over a wide area. Jeong *et al.* [9] proposed an AFC-based drone delivery system in which an MILP is used to optimize the delivery operation between the AFC and drones.

At this point, we turn our attention to the recent literature on DDRPs. Owing to the huge development of the drone industry in the past few years, research has focused on long-distance drone delivery. The recent development of drones, including flying taxis [27], proved that drones can provide multiple long-distance deliveries in a single mission. To cover a long distance, a drone must charge during the delivery time. Recently, massive developments have been made in the battery industry. Currently, batteries have a high capacity and can charge quickly [28]. Drone delivery with charging stations can minimize the limited flight range problem and enable long-distance deliveries. Liu *et al.* [29] proposed an energy-efficient crowdsensing with the presence of multiple charging stations, where UAVs are used to collect data from ground sensor nodes. Oubbati *et al.* [30] proposed a wirelessly powered UAV network architecture to provide the energy supply to the mission-oriented UAVs. The authors utilized a multiagent deep reinforcement learning method to optimize the task of energy transfer between flying energy sources and UAVs. The approach optimizes the trajectories of flying energy sources, avoids collisions, and maintains a standard level of fairness when recharging UAVs. Lv *et al.* [31] proposed a charging scheme based on Lyapunov optimization. The scheme maintains the schedule for charging UAVs and manages the operation of charging stations without congestion. Moreover, a contract-based incentive scheme maximizes the operation profit by adjusting the charging time of UAVs.

Ito *et al.* [32] proposed an energy-aware routing for drone delivery that considered the effect of wind during delivery. A dynamic DDRP was proposed to solve drone delivery under windy conditions. As wind influences drone energy consumption, an energy-aware route is necessary for efficient delivery. Simulation results show that the proposed scheme is capable of selecting the optimal route, which minimizes the total flight length. Pinto *et al.* [16] proposed mission planning

for multi-UAV drone delivery under windy conditions. They implemented an MILP to optimize the delivery, with a focus on minimizing the drone flight time during delivery to multiple customers in a single mission. Song *et al.* [19] proposed a scheduling algorithm for drone-based delivery on islands that considered multiple service stations where the drone can charge its battery in the delivery area. By considering multiple service stations, drones can minimize battery limitations and provide long-range delivery services to customers. Moreover, the authors also utilized the receding horizon task assignment algorithm (RHTA) to obtain optimal or near-optimal routing decisions for drone delivery.

Hong *et al.* [33] proposed a range-restricted model for a drone-charging strategy to develop a delivery network. For long-range delivery, the drone must be charged multiple times. To optimize the drone charging station locations, the authors proposed a new model by considering the Euclidean shortest path (ESP) and obstacles between the delivery routes. Huang and Savkin [17] proposed an optimization method for setting up charging stations in the delivery area that mostly focused on wide area coverage and drone connectivity between the depot, charging stations, and customers. Charging stations are placed in a triangular pattern to cover the delivery area. Then, the charging station locations are adjusted based on the customer locations, which removes unnecessary charging stations from the delivery area. Khosravi *et al.* [34] investigated the performance of multitask UAVs in last-mile delivery under two different conditions. First, they considered a simple condition, where the neighborhood area is circular. Second, they considered a practical scenario, such as an arbitrarily shaped area. The proposed algorithms in both scenarios ensure uniform coverage for last-mile delivery.

Sorbelli *et al.* [35] investigated the challenges that a drone might face during delivery in extreme environments. They introduced the DP by defining a cycle consisting of two parts: one with payload and the other without payload. If the parameters can be known beforehand, the drone may choose a different route. In addition, routes can be changed during the mission. Therefore, depending on the changing behavior, the drone might choose to change its decision from what was initially planned. Moreover, the authors proposed an approach in which they convert the delivery map into a weighted graph where the costs are time dependent. As the routes change depending on the conditions, the edge weights change as well. Under this approach, the goal is to calculate the percentage of missions that are considered successful. To achieve this, the authors proposed a drone mission feasibility problem that mainly follows the relationship between the limited budget and changing weather conditions. Shahzaad *et al.* [36] proposed a novel framework for delivering packages in dynamic environments, including varying weather conditions, limited battery conditions, capacity, and drone speed. In addition, when a drone has failed to complete a mission, it is crucial to know the reason for failure. Their study suggested a dynamic approach that investigates the impacts of a previously failed drone and then restructures the primary approach using a heuristic algorithm. Moreover, another crucial point is that their study can find the next optimal station bearing in mind that

no deviation to the primary plan has occurred. Kim *et al.* [37] proposed rooftop-based drone delivery in a city area using an MILP-based mathematical model.

Hamdi *et al.* [38] proposed uncertainty-aware drone-based delivery services. The drone delivery approach consists of three components of scheduling, route planning, and composition. Based on the weather situation, drones are capable to calculate relative drone airspeed, distance, and flying duration. Zhang *et al.* [39] analyzed and classified the drone energy consumption models based on drone types, payloads, and speeds. From the authors' assessment, it is proven that drone weight, payload, and airspeed have an impact on drone flight range. Drone delivery has several external factors, such as flying obstacle and weather condition, to select the delivery route. Kim and Lim [40] proposed a real-time rerouting of drone flights under uncertain flight times. Benarbia and Kyamakya [41] provided a comprehensive literature survey on a set of relevant research issues, and comparatively highlighted the representative solutions and concepts that have been proposed thus far in the design and modeling of the logistics of drone delivery systems.

III. PRELIMINARIES

In this section, we describe the preliminary knowledge, including motivating scenario, system model, channel mode, drone energy model, and framework of our proposed drone delivery scheme.

A. Motivating Scenario

In this study, we consider drone delivery with several charging stations for long-range delivery over a large area, as shown in Fig. 1. A drone starts from a depot with a fixed payload for delivery to customers. Commercial drones have limited flight ranges, which we overcome using charging stations. A delivery drone can charge its battery at a charging station without having to return to the depot. A charged battery can increase the drone flight range and maximum safe flight distance. When the drone energy level reaches a predetermined threshold, the drone flies to a charging station for battery recharge. The locations of the charging stations must satisfy certain conditions, such as being within the flight range of a drone of at least one other charging station. Therefore, the drone flight range affects the locations of the charging stations.

The maximum flight range of a drone depends on its payload and weather conditions. To ensure safe delivery over a long range, we consider two types of flight ranges: 1) maximum flight range and 2) safe flight distance. A delivery control center monitors the drone location, charging level, payload, and list of customers.

B. System Model and Assumptions

In this study, we consider drones and charging stations for multiple long-distance deliveries in a single mission. A drone delivery network consists of a depot, customer locations, and charging stations. In this scenario, M drones are available to deliver parcels from the depot to customers. The delivery center distributes the mission across the set of drones

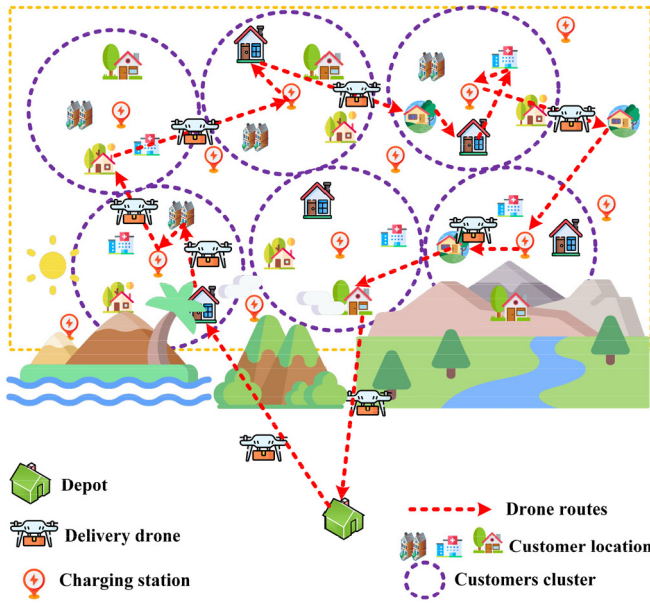


Fig. 1. Illustration of drone delivery with charging stations.

$\mathcal{M} = \{1, \dots, M\}$. The set of all customers is defined as $\mathcal{K} = \{1, \dots, K\}$. The positions of all customers are in a rectangular grid $\mathcal{A}(\ell, d)$, where ℓ and d represent the length and width of the delivery service area, respectively. The position of the depot (D) is fixed and defined as P_0 . In our work, we consider delivery in island or mountainous areas; therefore, our depot is placed far from the customer locations. The charging stations are placed in the delivery service area (S_a), and the set of charging stations is defined as $CS = \{CS_1, CS_2, \dots, CS_i\}$. The weights of the customers' parcels are $PL = \{PL_1, PL_2, \dots, PL_i\}$, where PL_1 is the payload of the first customer. The speed of the drone is v_d .

In general, our objective is to jointly optimize the placement of charging stations, flight segmentation, and route planning for drone delivery so that we can maximize the number of customers delivered within a minimum time. To achieve efficient drone delivery, we use a clustering algorithm to group the customers according to their nearest charging station. The output of clustering is denoted by a cluster set $C = \{C_1, \dots, C_k\}$, where C_1 denotes the first cluster, which covers a particular number of customers. Any customers that are far away from the other customers are defined as isolated customers and denoted by I_c . Each drone is equipped with a wireless communication interface, GPS, inertial measurement units, and cameras.

C. Channel Model

Our proposed drone delivery approach is free to assume any channel model. This is because we assume that drones and base stations are equipped with a single antenna and there is no obstacle between transmitter and receiver. However, to make our object more understandable in the simulation environment, we consider the communication path between the transmitter and receiver to endure both path loss and small-scale Nakagami- m fading. The Nakagami- m fading model is a

universal model that considers various fading environments between transmitter and receiver pairs ($m < 1$) for Hoyt, $m = 1$ for Rayleigh, and $m > 1$ for Rician). Therefore, the communication channel power gain mimics the Gamma distribution for m parameters as follows [34], [42]:

$$f_G(g) = \frac{m^m g^{m-1}}{\Gamma(m)} \exp(-mg). \quad (1)$$

D. Drone Energy Consumption Model

The flight duration of a drone depends on its payload and battery capacity. For drone delivery with charging stations, an energy consumption model is important to optimize the drone flight time and select the best routes. Most existing studies consider single-rotor or fixed-wing drones to derive an energy consumption model, but most studies consider multirotor drones for drone delivery scenarios. Therefore, in this study, we consider multirotor drones to derive a drone energy consumption model. In our model, we consider all possible scenarios for energy consumption, including hovering and flight. We assume that the power consumption for drone take-off and landing is roughly proportional to the energy consumed during hovering.

Generally, drones drain energy to maintain the flight by counteracting the forces of gravity, drag, and wind. In a multirotor drone, the control unit adjusts the speed of each rotor to obtain thrust and pitch, which is required for the drone to stay in the air and move forward at the desired speed. The thrusts from each of the rotors are approximately equal and help to balance the gravity and drag forces on the drone. The total required thrust for drone (D) can be calculated as

$$\mathcal{D}_T = \left(\mathcal{D}_{\text{body}}^m + \mathcal{D}_{\text{batt}}^m + \mathcal{D}_{\text{payload}}^m \right) g + F_{\text{drag}} \quad (2)$$

where $\mathcal{D}_{\text{body}}^m$, $\mathcal{D}_{\text{batt}}^m$, and $\mathcal{D}_{\text{payload}}^m$ are the masses of the drone body, battery, and payload, respectively, g is the gravitational constant, and F_{drag} is the total drag force. The angle needed to maintain a steady pitch is expressed as

$$P_\alpha = \tan^{-1} \left(\frac{F_{\text{drag}}}{\left(\mathcal{D}_{\text{body}}^m + \mathcal{D}_{\text{batt}}^m + \mathcal{D}_{\text{payload}}^m \right) g} \right). \quad (3)$$

The piecewise drag force can be estimated as follows:

$$F_{\text{drag}} = \sum_i \frac{1}{2} \rho v_a^2 C_{Di} A_i \quad (4)$$

where ρ is the air density, v_a is the velocity in air, C_{Di} is the drag coefficient, and A_i is the projected area of the i th component, which is the drone body, battery, or payload. The drag coefficient at various velocities is expressed as

$$C_D = \frac{2\mathcal{D}_{\text{body}}^m g * \tan(\alpha)}{\rho v_a^2 A_{\text{body}}}. \quad (5)$$

From (2), we obtain the total thrust, which aids in calculating the power requirements for a steady flight. However, theoretically, the minimum power depends on the area swept by the rotor. Usually, large propellers have higher efficiency, as they can cover large swept areas. Moreover, rotors must be placed in such a way that they avoid interfering with each

other. To avoid interference, the rotor size must be within a limit. For n rotors with diameters \mathbb{D} , the minimum power requirement for a hovering drone is expressed as

$$P_{\min, \text{hov}} = \frac{\mathcal{D}_T^{3/2}}{\sqrt{\frac{1}{2}\pi n \mathbb{D}^2 \rho}}. \quad (6)$$

Drone power requirements may vary when a drone moves at a significant speed or in significant wind. Airspeed and incident angle have a notable impact in such circumstances. With the help of the conservation of momentum [43], we can define the minimum power requirement for forward motion as

$$P_{\min} = \mathcal{D}_T(v \sin P_\alpha + v_i) \quad (7)$$

where v_i is the induced velocity for the required thrust and can be expressed as

$$v_i = \frac{2\mathcal{D}_T}{\pi n \mathbb{D}^2 \rho \sqrt{(v \cos P_\alpha)^2 + (v \sin P_\alpha + v_i)^2}}. \quad (8)$$

Therefore, the overall power efficiency (η) of a drone can be expressed as

$$P = P_{\min}/\eta. \quad (9)$$

We divide the drone power consumption by the average ground speed to measure the energy efficiency of travel e , expressed as

$$e = P/v. \quad (10)$$

Energy consumption for a drone delivery trip of distance d is defined by

$$E = (e_{\text{loaded}} + e_{\text{unloaded}})d \quad (11)$$

where e_{loaded} and e_{unloaded} are the energy efficiency during an outbound trip when the payload is present and energy efficiency during a return trip after the payload is delivered to the customers. Therefore, the drone maximum flight range may vary depending on the payload and is expressed as

$$f_R^{\max} = \frac{\mathcal{D}_{\text{batt}}^m \mathcal{D}_{\text{batt}}^s \delta}{(e_{\text{loaded}} + e_{\text{unloaded}})f} \quad (12)$$

where $\mathcal{D}_{\text{batt}}^s$ is the energy capacity per mass, δ is the depth of discharge battery factor, and f is the safety factor for storing battery power for atypical circumstances.

E. Problem Definition

Existing drone delivery approaches are not suitable for multiple long-range deliveries in a single mission. To solve the limited battery capacity of commercial delivery drones, we consider charging stations in delivery areas to enlarge the service area. Conventional drone delivery can only support a small area and a limited number of customers. When the size of the service area is increased, existing delivery routing approaches face difficulties in exploring the solution space, which indicates that large-scale drone delivery cannot be solved by the existing routing approach.

To improve the efficiency of drone delivery, we design drone delivery networks consisting of a depot, charging stations, and

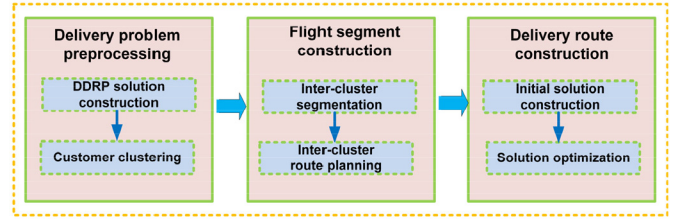


Fig. 2. JRCS framework.

customers' locations. We assume that M delivery drones depart from the depot, consecutively delivering parcels to S customers before returning to the depot. The location of the k th customer is defined in 3-D coordinates by $q_k = [x_k, y_k, 0]^T$, where $1 \leq k \leq \mathcal{K}$. Delivery drones fly at altitude H above the ground level. The location of the m th drone at time t is expressed as $q_m(t) = [x_m(t), y_m(t), h_m(t)]^T \in \mathbb{R}^3$, where $1 \leq m \leq \mathcal{M}$ and $0 \leq t \leq T$. The locations of drones and customers are determined using GPS. During the delivery process, drones need to visit charging stations to recharge their batteries. To ensure successful drone delivery over a long range, we consider JRCS. Our proposed JRCS consists of three phases, as shown in Fig. 2: 1) DP preprocessing; 2) flight segmentations; and 3) delivery route construction and optimization. We explain these three phases in Section IV.

IV. JRCS ALGORITHMS

In this section, JRCS for long-range drone delivery is presented in detail. We separated the problem into three sub-problems. First, owing to the large number of customers, we developed a clustering algorithm to partition customers into clusters according to their nearest charging station. Second, intercluster routing was planned based on the maximum flight range and maximum safe flight distance of the delivery drones. Finally, the DDRP was formulated based on MILP. The notation used in our study is summarized in Table I.

A. Clustering of Customers

For the clustering of customers, we utilized the K -means clustering algorithm. The main benefits of using clustering are reducing the number of drones and completing the delivery task within the allocated time. Moreover, to enhance drone delivery, customers are clustered to build flight segments. Assume that the location of the depot is P_0 and the location of charging stations CS_i and CS_j is P_i and P_j , respectively, in the delivery area S_a . Some customers are within range of f_R^{\max} from P_0 and, thus, they can be served directly from the depot. In our model, most customer locations were outside of the P_0 delivery range. Therefore, we considered n charging stations in S_a . A clustering algorithm is necessary to split the customers based on the nearest charging station location and construct the flight segments between the depot, customers, and charging stations. Assume that \mathcal{G} represents the delivery network topology of n charging stations and the depot, where \mathcal{G} contain $n + 1$ vertices. To complete all deliveries successfully, all charging stations need to connect to the depot and

TABLE I
NOTATIONS USED IN OUR STUDY

Notation	Description
N	Depot and set of charging stations, where $N = \{n_i i = 1, 2, \dots, m\}$
L	Links between depot and charging stations, where $L = \{l_{ij} i, j = 1, 2, \dots, m\}$
T_i	Types of delivery network elements, where $T_i = \begin{cases} 0, D \\ 1, CS \end{cases}$
CS	Set of Charging stations, where $CS = \{CS_i T_i = 1, CS_i \in N\}$
d	Distance
\mathbb{E}	Reachability matrix of charging stations, where $\mathbb{E} = [e_{ij}], (CS_i, CS_j) \in N$
S_a	Service area
i, q	Indexes of S_a
K_i, K_j	Node of customer or customer index
D_t	Drone tour
D_{tc}	Set of all customers in a service area
A_t	Set of drone tours in a service area t
N_k	Candidate clusters within the drone safe flight distance sf_R of customer K_k
p	Number of charging stations to be located
CS_i, CS_j	Charging stations index
C_i	Set of candidate clusters within a distance of f_R^{\max} of cluster i
\mathcal{W}	Total number of candidate clusters sites
Z_{CS_i, CS_j}	A non-negative integer for tracking path flow between two charging stations
Z_A	Indexes of waypoints, where $Z_A = \{0, \dots, z + 1\}$
Z	The total number of waypoints including customers and charging stations, where $Z = \{1, \dots, z\}$
X_{ij}	Flight path between two waypoints
\mathcal{W}	Weight of drone
Q	Maximum payload capacity of the drone
T	Time required to deliver all parcels
\mathcal{W}_i^u	Weight offloaded at waypoint i
EC_{ij}	Energy consumption of drone between two waypoints
E_0, E_{\min}	Initial energy when departing from a depot and minimum energy level of drone
f_R^{\max}	Maximum flight range
sf_R	Safe flight range

need to satisfy the following condition:

$$\|P_i, P_j\| \leq f_R^{\max} \quad (13)$$

where i and j are two vertices ($i, j \in (0, n), i \neq j$) and $\|\cdot, \cdot\|$ represents the distance between two vertices.

A drone departs from the depot and can reach any charging station in the delivery area. The coverage of each charging station is a circular area centered at that charging station with a radius of $f_R^{\max}/2$. In Algorithm 1, the customer clustering process is presented step by step. In the first step, customers are clustered based on the average distance between the customer locations and the nearest charging station. If the customer is far away from other customers, we define it as an isolated customer (I_c). Assume that S'_i is the subset of customers allocated to charging station i where $i = \{1, \dots, n - 1\}$. In the second step, if a customer has the same distance between two or more charging stations, then that customer will be allocated to the charging station with a lower index.

Algorithm 1 Clustering of Customers

Input: Customers $\mathcal{K} = \{1, \dots, K\}$, R , and charging stations $CS = \{CS_1, CS_2, \dots, CS_i\}$

Output: S_a , clusters $C = \{C_1, \dots, C_k\}$, and I_c

Phase 1: Update the index of the cluster

1. **for** service area index i in range $(2 : n)$ **do**
 2: **while** charging stations no longer change;
 3: Randomly choose i charging stations;
 4: Calculate the distances between the customers and charging stations; // Allocate the customers to the nearest charging station

5: Divide \mathcal{K} into clusters C according to the distances;
 6: Modify the coordinates of CS to be the central coordinates of corresponding clusters;

7: **end while**

Phase 2: Update centroids

8: **for** each service area index i **do**

9: Compute \mathcal{F}'_i for each i by Equation (16);

10: Adjust the influenced customer allocation;

11: **break**

12: **end for**

13: **if** all clusters satisfy the drone flight range f_R^{\max}

14: **break**

15: **end if**

16: **end for**

In the second step, we introduce a virtual force $f(p, P'_i)$ for customer $p \in S'_i$ as follows:

$$f(p, P'_i) = w(p)(p - P'_i) \quad (14)$$

where $w(p)$ is a weight, and $f(p, P'_i)$ represents the distance vector between P'_i and p . The combined virtual force for charging station P'_i can be expressed as

$$\mathcal{F}'_i = \frac{\sum_{p \in S'_i} f(p, P'_i)}{\sum_{p \in S'_i} w(p)}. \quad (15)$$

After substituting (14) into (15), we can get

$$\mathcal{F}'_i = \frac{\sum_{p \in S'_i} w(p)(p - P'_i)}{\sum_{p \in S'_i} w(p)} = C'_i - P'_i \quad (16)$$

where $C'_i = \sum_{p \in S'_i} w(p)p / \sum_{p \in S'_i} w(p)$ represents the gravitational center of S'_i .

B. Flight Segmentation

The flight range of commercial drones is a crucial factor for ensuring long-range delivery. The drone flight range affects the delivery service area and limits the distance between the depot and charging stations. The drone flight range depends on the type of drone, maximum payload capacity, and weather conditions. For long-distance delivery, if the customers are out of the maximum flight range f_R^{\max} of the delivery drone from the depot, the drone needs to recharge the battery at a charging station within the safe flight distance sf_R . As shown in Fig. 3, f_R^{\max} and sf_R decrease as a drone carries out deliveries and increase after recharging at a charging station. From Algorithm 1, each cluster contains at least one charging

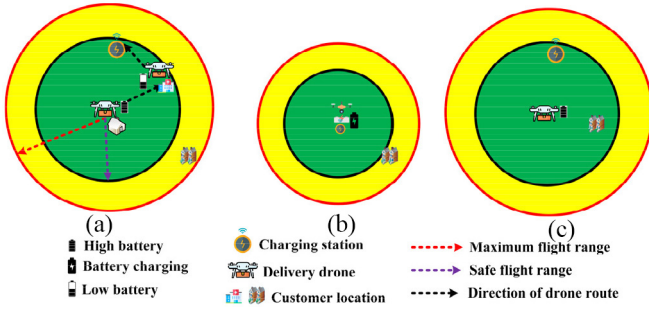


Fig. 3. Illustration of maximum flight range and safe flight distance (a) before making deliveries, (b) after making deliveries, and (c) after recharging.

station, and all customers in the cluster are within sf_R . The distance between two clusters should be within drone f_R^{\max} .

Assume that the drone delivery network is defined by $G(N, L)$, where N represents the depot and charging stations, and L is the links between the depot and charging stations. Therefore, N can be expressed as $N = D \cup CS$. Based on f_R^{\max} and sf_R , we defined conditions for long-range drone delivery. The maximum flight distance of the drone after a single charge must satisfy the following:

$$\begin{aligned} d(D, CS_i) &\leq f_R^{\max}, \quad d(CS_i, CS_{i+1}) \\ &\leq f_R^{\max}, \quad \text{and} \quad d(CS_m, D) \leq f_R^{\max}. \end{aligned} \quad (17)$$

In (17), the maximum flight distance is maintained between the depot and charging stations, one charging station to another, and the last charging station CS_m to the depot so that drones can return after all successful deliveries. To maintain a safe flight range for delivery, the drone must maintain the following conditions:

$$d(K_i, CS_i) \leq sf_R, \quad \text{and} \quad d(CS_i, CS_j) \leq sf_R \quad (18)$$

where $d(K_i, CS_i)$ is the distance between customer K_i and charging station CS_i and $d(CS_i, CS_j)$ represents the distance between two charging stations, which must be within the drone safe flight distance to mitigate any unexpected situations, such as sudden energy failures or bad weather conditions. Finally, the distance between two customers in a cluster must be satisfied as follows:

$$d(K_i, K_j) \leq (f_R^{\max}, sf_R) \quad (19)$$

where the distance between two customers within the cluster must be within the maximum flight distance and safe flight distance of the delivery drone. To deliver parcels to customers in a long-range delivery path, the number of landing spots must be minimized. The minimum flight path of the JRCS can be formalized as follows:

$$\begin{aligned} \text{Min } L &= \sum_{e_{ij}=1} l_{ij} * d(CS_i, CS_j) \\ \text{Min Max } \{ \text{rank}(l_{ij}) \} \end{aligned} \quad (20)$$

subject to

$$\sum_{j=1}^m l_{ij} - \sum_{j=1}^m l_{ji} = \begin{cases} 1, & i = 1 \\ -1, & i = m \\ 0, & i \neq 1, m \end{cases} \quad (20a)$$

Algorithm 2 Construction of Flight Segments

Input: Customers $K_i = \{1, 2, \dots, K_n\}$ in the clusters C_i and I_c

Output: Segments $S = \{S_1, \dots, S_k\}$

Initialization $S = \emptyset, k \leftarrow 0, \mathcal{K} \leftarrow C$

```

1: for  $K_i \in C_i$  do
2:    $K_i \leftarrow \text{unvisited}$ ;
3:  $K_{unv} \leftarrow K_i$ ;
4: while  $K_{unv} \neq \emptyset$  do
5:    $D \leftarrow f_R^{\max}$ ;
6:   form a circle with depot  $D$  as a center and  $f_R^{\max}$  as
   radius;
7:   obtain the customers in the circle;
8:   for  $i \in K_i$  and  $N \neq \emptyset$  do
9:     select  $i$  where  $d(P_0, i)$  is minimum;
10:     $i \leftarrow \text{served}$ ;
11:    form a loop  $\mathbb{L}$  with the  $D$ 
12:    if  $d(D, CS_i) \leq f_R^{\max}$  and  $d(K_i, CS_i) \leq sf_R$ 
13:    for customers  $j \in K_i$  do
14:      select the customer  $j$  which is nearest to  $i$ ;
15:      add  $j$  to the loop  $\mathbb{L}$ ;
16:       $j \leftarrow \text{served}$ ;
17:    end for
18:    else
19:      visit  $CS_i$ ;
20:    for cluster  $C_i$  to  $C_j$  do
21:      obtain the flight path by equation (20);
22:      select the path with  $d$  as a minimum;
23:      add it to the loop  $\mathbb{L}$ ;
24:       $C_j \leftarrow \text{visited}$ ;
25:    end for
26:    Update the served customers list  $K_{sur}$ ;
27:    Update the served cluster list  $C_{sur}$ ;
28:  end while

```

$$l_{ij} \in \{0, 1\}, \quad \text{rank}(l_{ij} \leq m) \quad (20b)$$

$$d(D, CS_i) \text{ and } d(CS_m, D) \leq \min(f_R^{\max}, sf_R) \quad (20c)$$

$$d(CS_i, CS_j) \leq \min(f_R^{\max}, sf_R). \quad (20d)$$

In (20), our target is to minimize the drone delivery flight path and the number of landings. If a viable flight path between two clusters exists, then $l_{ij} = 1$; otherwise, $l_{ij} = 0$. The relation $\text{rank}(l_{ij} \leq m)$ indicates that at least one charging station exists between the links. The links from the depot to the first charging station and from the last charging station to the depot must fall within the maximum drone flight range and safe flight range. Moreover, two charging stations should be within the maximum flight range and safe flight range of the delivery drones. The flight segmentation procedure is presented in Algorithm 2.

In Algorithm 2, all customers in the clusters are first listed as unvisited. Then, drones are dispatched from the depot to deliver parcels. If the first customer is within the range of the depot, the drone delivers the parcel; otherwise, the drone checks its flight range capacity and visits the nearest charging station for recharge. After the first cluster is served, the drones visit the next nearest cluster. The intercluster length of the

flight path is minimized using (20). Moreover, the proposed approach minimizes the landing time for charging.

C. Drone Delivery Route Construction

We developed an MILP to solve the DDRPs. The objective of MILP is to minimize the delivery time. We define drone delivery routes that start and end at the depot. During delivery, the drone visits charging stations to recharge its battery before resuming delivery. To optimize the delivery route and solve the DDRPs, we derived the MILP as follows:

$$\text{Min } T = \sum_{i \in S_a \setminus \{0\}} \sum_{D_i \in A_i} \sum_{K_i \in D_{ic}} \sum_{K_j \in D_{ic}} y_{iD_i K_i K_j} / v_d \quad (21)$$

subject to

$$Y_{K_k} = \begin{cases} 1, & \text{if the customer } K_k \text{ is covered} \\ 0, & \text{otherwise} \end{cases} \quad (21a)$$

$$X_{C_j} = \begin{cases} 1, & \text{if the candidate cluster } C_j \text{ is selected} \\ 0, & \text{otherwise} \end{cases} \quad (21b)$$

$$\sum_{C_j \in N_k} X_{C_j} \geq Y_{K_k} \quad \forall K_k \in \mathcal{K} \quad (21c)$$

$$\sum_{C_j \in N} X_{C_j} = p \quad (21d)$$

$$\sum_{C_j \in C_j} Z_{C_j C_j} \leq (W - 1) X_{C_j} \quad \forall C_j \in N \quad (21e)$$

$$\sum_{C_j \in C_j} Z_{C_j C_j} - \sum_{C_j \in C_j} Z_{C_j C_i} \geq X_{C_j} \quad \forall C_j \in N \setminus D \quad (21f)$$

$$\sum_{C_j \in C_j} Z_{C_j C_j} - \sum_{C_j \in C_j} Z_{C_j C_i} \leq X_{C_j} - W \quad \forall C_j \in W \quad (21g)$$

$$\sum_{C_j \in S_a} X_{C_j q} = 1 \quad \forall q \in S_a \quad (21h)$$

$$\sum_{i \in Z_A, i \neq j} X_{ij} = 1 \quad \forall i \in Z \quad (21i)$$

$$\sum_{i \in Z, i \neq j} X_{ij} - \sum_{i \in Z, i \neq j} X_{ji} = 0 \quad \forall i \in Z \quad (21j)$$

$$\sum_{K_i \in D_{ic}} W_{iK_i} y_{iD_i K_i K_j} \leq Q \quad (21k)$$

$$\sum_{D_i \in A_i} \sum_{K_i \in D_{ic}} y_{iD_i K_i K_j} = 1, \quad i \in S_a \setminus \{0\} \quad (21l)$$

$$\sum_{K_i \in D_{ic}} y_{iD_i K_i} = \sum_{K_j \in D_{ic}} y_{iD_i K_j} \quad (21m)$$

$$\sum_{i \in Z, i \neq j} X_{ij} \cdot Q_{ij} - \sum_{i \in Z, i \neq j} X_{jk} \cdot Q_{jk} = W_i^u z \quad \forall j \in Z_A \quad (21n)$$

$$\sum_{i, j \in Z} X_{ij} \cdot EC_{ij} \leq E_0 - E_{\min}. \quad (21o)$$

The objective function (21) minimizes the total drone delivery time. In (21a) and (21b), customer locations and cluster coverage areas are defined by a binary function equal to 1 when coverage is confirmed and 0 otherwise. The objective of (21c)–(21g) is to ensure service area coverage. Equation (21c) indicates that the delivery area is covered with a minimum charging station within the safe flight distance of a drone.

Algorithm 3 Drone Delivery Route Optimization

Input: Area coverage S_a , set of drones \mathcal{M} , number of packages to deliver \mathbb{P} , charging station set CS , and drone delivery path L
Output: Task time to deliver \mathbb{P} packages $T_{\mathbb{P}}$

- 1: Define the drone speed v_{\max} and v_{\min} , where $v_{\min} \leq v_{ij} \leq v_{\max}$;
- 2: Divide the service area S_a into clusters $C = \{C_1, \dots, C_k\}$ by Algorithm 1;
- 3: Obtain the flight segments $S = \{S_1, \dots, S_k\}$ by Algorithm 2;
- 4: **for** drone delivery path $l = 1; l \leq L$ **do**
- 5: Generate the straight trajectory between the depot, charging stations, and customer delivery locations;
- 6: **end for**
- 7: **for** all drones \mathcal{M} **do**
- 8: **if** the conditions of equations (17), (18), and (19) are satisfied **then**
- 9: **for** ($K_i \in C_{sur}$) **do**
- 10: Run the DDRPs optimization model equation (21);
- 11: **end for**
- 12: **end if**
- 13: **if** a customer is visited by the drone **then**
- 14: Update the served customers list K_{sur} ;
- 15: Measure the drone current weight and energy level by equation (21n) and (21o);
- 16: Update the drone velocity;
- 17: **end if**
- 18: **end for**

Equation (21d) limits the number of charging stations in one cluster area. Equations (21e)–(21g) represent the flight path flow from one cluster to another by ensuring a charging station in the delivery area. According to (21h), drones that visit a charging station must visit only once. In (21i), all waypoints, including the locations of customers and charging stations, are visited exactly once. Equation (21j) represents that a drone arriving at a waypoint must depart from the same waypoint. The total carrying payload of the drone is restricted by the maximum payload capacity in (21k). Equation (21l) indicates that each customer in the cluster is visited only once. The flight flow from one customer to another is indicated in (21m). Equation (21n) indicates the weight difference when the drone offloads the payload at waypoint i . The energy consumption of drones is presented in (21o).

The drone delivery time was minimized by Algorithm 3. According to Algorithm 3, the total delivery region is clustered by a clustering subproblem (Algorithm 1). The flight segments between the clusters are obtained using Algorithm 2. Finally, the drone delivery routes are optimized by the MILP in Algorithm 3. The objectives of Algorithm 3 are to minimize the drone delivery time and increase the delivery area coverage.

D. Complexity Analysis

The time complexity of the customer clustering algorithm is $O(T \times C \times N)$, where T is the time required to find the

distance between customers and charging station, C is the number of clusters, and N is the total number of elements. The time complexity for flight segmentation is $O(K \times S)$, where K is the number of customers and S is the number of segments. The time complexity of drone delivery route optimization is $O(M \times 2^k k^2)$, where M is the number of drones, and k is the number of customers in one loop.

V. PERFORMANCE EVALUATION

In this section, we conduct an extensive simulation to evaluate the performance of our proposed JRCS. First, we evaluate the proposed approach in different scenarios. We then compare the proposed JRCS with two other delivery routing methods using TSP and the greedy approach.

A. Simulation Environment

All simulations were performed using MATLAB, MATLAB Toolbox, and MATLAB Simulink. We first considered a delivery area of 25 km² with 100 randomly placed customers or delivery points served by a single drone. We consider a single depot. The location of the depot is outside of the delivery area, which can allow drone delivery in remote areas, such as islands and mountains. To make the simulated delivery environment more realistic, we consider obstacles, such as high-rise buildings and void areas. We vary the delivery area from 25 to 50, 75, and 100 km², with the number of drones varying from 1 to 2, 4, and 6. The number of customers is also varied from 100 to 500. The altitude of the drone is varied from 100 to 150 m. The minimum speed of the drone is 10 m/s, the average speed is 15 m/s, and the maximum speed is 30 ms [33].

To maintain long-range communication between drones and the delivery center, we utilize 5G as a communication module. The maximum flight range of a commercial drone is approximately 16 km [44]. Therefore, the radius of each customer cluster is not more than 16 km to maintain the maximum flight range of the drone. The average airspeed is 8 m/s in random direction, which is equivalent to 28.8 km/h [38]. In general, daily wind speed is typically averaged between 10 and 19 km/h throughout the year. We consider the maximum and minimum of f_R^{\max} to vary from 16 to 8 km. The maximum and minimum of sf_R are varied from 8 to 4 km. The number of charging stations is varied from 5 to 25. The maximum drone payload is 21 kg [45] and the per-customer payload range is 0.1–2 kg. As our focus is on drone delivery in island or mountain areas, the simulated depot is far away from the location of customers. The energy consumption for the drone from flying and communication is 300 and 5 W, respectively. For communication, we use a directional antenna in the drone. The parameters used in our extensive simulations are summarized in Table II.

B. Simulation Results and Discussion

1) *Effectiveness of JRCS*: To demonstrate the effectiveness of the JRCS algorithms, we present our graphical simulation environment for single-drone and multidrone delivery. Fig. 4 shows the single-drone delivery for 200 customers in the 50-km² area. In the delivery area, all customers are clustered based on the nearest charging station. The drone visits all

TABLE II
SIMULATION PARAMETERS

Parameter	Value
Simulator	MATLAB
Delivery area	[25, 50, 75, 100] km ²
Drone altitude range	100–150 m
Number of drones	[1, 2, 4, 6]
Number of customers	[100, 200, 300, 500]
Minimum, average, and maximum speed of drones	10, 15, and 30 m/s respectively
f_R^{\max}	16 to 8 km
sf_R	8 to 4 km
Number of charging stations	[5, 10, 15, 25]
Number of depots	1
Maximum payload	21 kg
Drone flying power	300 W
Drone transmission power	5 W
Average airspeed	6 m/s

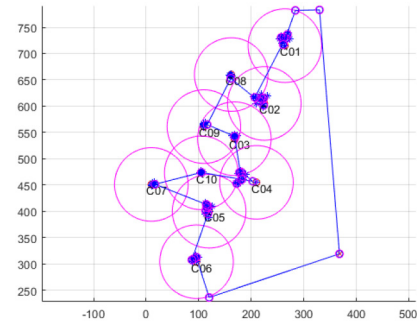


Fig. 4. Graphical representations of single drone delivery.

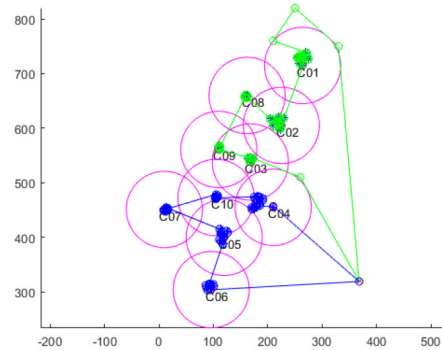


Fig. 5. Mission planning for multidrone deliveries.

waypoints, including clustered customers and single customers outside of the clusters. The depot is placed outside of the delivery area, clusters are marked by magenta, customers are represented by blue, and drone routes are illustrated in blue.

Fig. 5 shows the multidrone delivery by the proposed JRCS for 200 customers in the 50 km², with ten charging stations placed in the delivery area. Each cluster contains an approximately equal number of customers. The drone routes are planned based on the maximum flight range and safe flight distance.

We simulated the power consumption of the drone during flight, hover, and altitude changes. The average power consumption during these phases is displayed in Table III. According to Table III, the three operations have slightly different results in terms of voltage due to the residual battery

TABLE III
AVERAGE POWER CONSUMPTION DURING DELIVERY

Operation	Voltage (V)	Current (A)	Power (W)
Hover	18.3	21.1	315
Flight	17.9	20.8	307
Altitude change	16.5	22.7	296

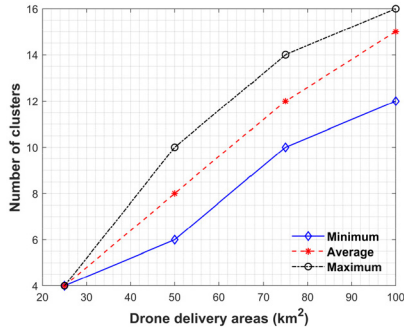


Fig. 6. Number of clusters for varying delivery areas.

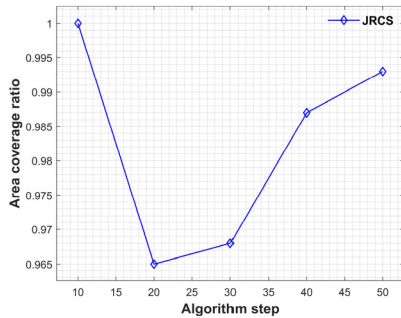


Fig. 7. Area coverage ratio versus algorithm step.

charge. During the altitude change, lower voltages were measured because that test was conducted last. During the straight flight, the current is relatively lower because airflow gives the rotors extra lift. However, the power consumption was relatively similar during the three operations.

Fig. 6 shows the number of clusters needed to serve 300 customers in different service area sizes. The expansion of the drone delivery area has an impact on the number of clusters.

The number of charging stations is another important parameter to cover the delivery area. Fig. 7 represents the delivery area coverage ratio versus algorithm (Algorithm 1) step, where 500 customers are deployed in the area of 100 km², f_R^{\max} is 16 km, and 25 charging stations are initially deployed to cover the entire area. In phase 1 (lines 1–7) of Algorithm 1, 21 charging stations are deployed based on both the distances between customers and charging stations and the maximum flight range. As shown in Fig. 7, initially, the delivery area coverage ratio is 100% since the entire area is covered by the 25 charging stations. When the number of charging stations is fixed on the basis of distances between customers and charging stations, some charging stations are removed and the coverage ratio drops to around 96.5%. Finally, phase 2 (lines 8–14) of Algorithm 1 fixes the number of charging stations by new positions and the area

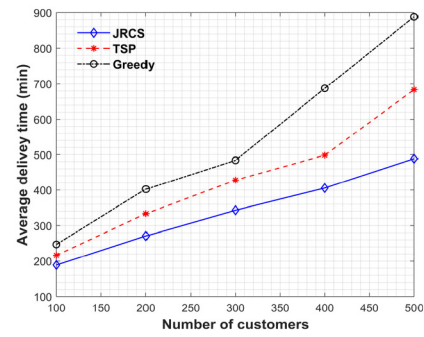


Fig. 8. Average delivery time for varying numbers of customers.

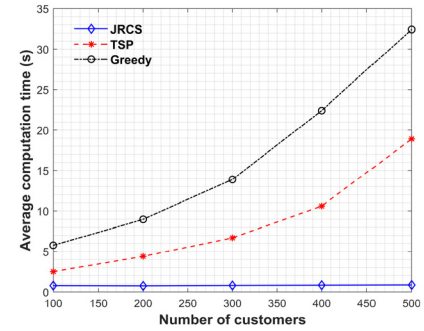


Fig. 9. Average computation time for varying numbers of customers.

coverage is increased to 99.3%. The final number of charging stations becomes 19 to cover the area, which indicates the efficiency of Algorithm 1.

2) Performance Comparison:

a) Impact of the number of customers and the delivery area size: In the simulation, we considered the number of customers and delivery area as major variables to evaluate long-range drone delivery. The average drone delivery time (including both flight and charging time) and average algorithm computation time are key parameters for the evaluation of delivery services. First, we varied the number of customers from 100 to 500 with delivery areas of 25–100 km² to evaluate the average delivery time. Fig.8 illustrates that the average drone delivery time of the JRCS algorithm is significantly less than those of the other two algorithms, particularly, when the number of customers is high and the area is relatively large. The proposed clustering scheme with charging stations helps to reduce the delivery time significantly.

We also studied the average algorithm computation time. As shown in Fig. 9, the computation time of the JRCS algorithm is significantly less than those of the TSP and greedy algorithms. The computational complexity increased exponentially for TSP and greedy as the number of customers and delivery area increased. The TSP and greedy algorithms are less effective for large numbers of customers. Customer clustering and flight segmentation aid JRCS to reduce the computation time.

Fig. 10 shows the average drone travel distance for a 100-km² service area while varying the number of customers from 100 to 500. According to Fig. 10, the drone traveling distance for JRCS increased owing to the drone needing to reach the charging station to recharge the battery. However,

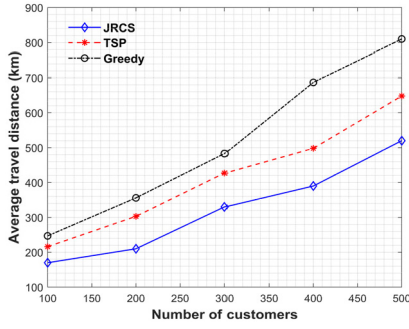


Fig. 10. Average travel distance for varying numbers of customers.

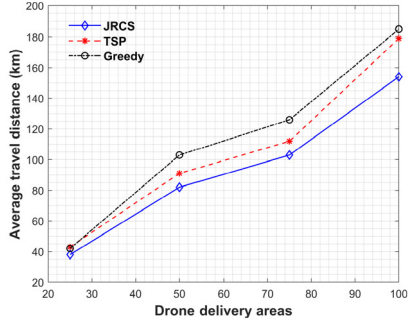


Fig. 11. Average travel distance for varying delivery areas.

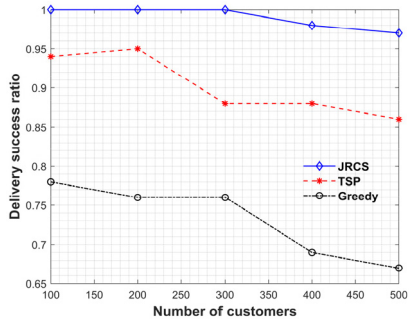


Fig. 12. Delivery success ratio for varying numbers of customers.

because of proper customer clustering, construction of flight segments, and routing optimization, JRCS outperforms the TSP and greedy algorithms. Moreover, JRCS minimized drone detours significantly.

Fig. 11 shows the average drone travel distance for 100 customers while varying the delivery area. As shown in the simulation output, as the delivery area increases, drones need to visit the charging stations more frequently; therefore, the average travel distance increases for the JRCS.

As shown in Fig. 12, we analyzed the drone delivery success ratio while varying the number of customers, with a constant delivery area of 100 km².

According to the simulation output, JRCS outperforms the other two algorithms. We observed that drone delivery failure had an impact on the average delivery time and average distance traveled. Our proposed approach optimizes the drone delivery routes, resulting in a higher delivery ratio.

Fig. 13 illustrates the normalized energy consumption of drones while serving 100 customers in a 25-km² area. To

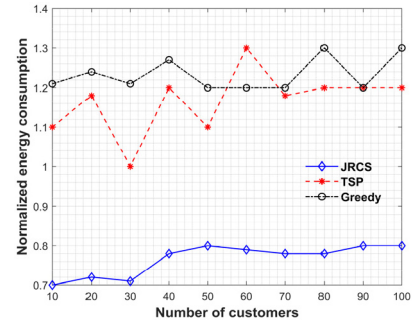


Fig. 13. Normalized energy consumption of drones for varying numbers of customers.

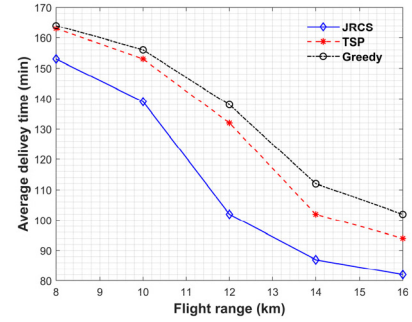


Fig. 14. Average delivery time for varying drone flight ranges.

obtain the energy consumption value for one functional unit of the delivered package, the energy utilized by the drone must be normalized for the number of packages it carries and delivers per kilometer. In our study, energy consumption was normalized as $\sum EC_{ij}/E_0$. Delivery routes have an impact on drone energy consumption. Moreover, drone payloads and wind effects influence the energy consumption of drones. We observed that the drone energy consumption was reduced after offloading the payload to the customers. Owing to the optimal delivery route selection, the JRCS energy consumption is less than those of the other algorithms.

b) Impact of drone flight range: Fig. 14 illustrates the impact of the drone flight range on the drone delivery time for 100 customers in a 25-km² area. According to the simulation outcome, the drone delivery time is significantly reduced when the drone flight range is maximum. The maximum drone flight range increased the number of deliveries in a single mission. However, to ensure a high flight distance, drones must have high battery capacities, which have an impact on the total payload of the drone.

VI. CONCLUSION

Over the last few years, drone delivery has attracted significant attention from academic and industrial research communities. Drones are promising and highly efficient tools for city logistics because they require less time and cost for logistic delivery. In the COVID-19 era, drones can transport medicines and other supplies faster and more efficiently than ground-based delivery services. Multiple long-distance deliveries in a single mission are quite difficult because of the limited battery capacity and flight range of delivery drones. In this article, we

have proposed a novel drone delivery approach called JRCS for long-distance drone delivery in a single mission. We utilize drone delivery with distributed charging stations that minimize drone flight range limitations and increase delivery area coverage. The proposed JRCS consists of three phases. In the first phase, we split the customers using a clustering algorithm. Next, we develop a flight segmentation based on the maximum flight range and safe flight range of the drones. Flight segmentation aids in maintaining connectivity between the depot, customer locations, and charging stations. Finally, we formulate a DDRP using MILP. According to our extensive simulation results, the proposed JRCS outperforms existing approaches in terms of average delivery time, algorithm computation time, drone travel distance, and drone energy consumption. In addition, the proposed scheme optimizes drone delivery routes using an existing routing approach.

In this work, we ignore the effects of weather uncertainties. Future extensions of this work may focus on including flying obstacles in the delivery route, the effect of weather uncertainties in drone delivery, and uncertainty-aware drone delivery route planning. In our future work, we will consider finding more optimal solutions by using different kinds of heuristic algorithms and the probability of drone failure with other mathematical models.

ACKNOWLEDGMENT

The authors give thanks to the editor and anonymous referees for their comments that helped improve the quality of this article.

REFERENCES

- [1] M. Y. Arafat and S. Moh, "Bio-inspired approaches for energy-efficient localization and clustering in UAV networks for monitoring wildfires in remote areas," *IEEE Access*, vol. 9, pp. 18649–18669, 2021, doi: [10.1109/ACCESS.2021.3053605](https://doi.org/10.1109/ACCESS.2021.3053605).
- [2] M. Y. Arafat and S. Moh, "Location-aided delay tolerant routing protocol in UAV networks for post-disaster operation," *IEEE Access*, vol. 6, pp. 59891–59906, 2018, doi: [10.1109/access.2018.2875739](https://doi.org/10.1109/access.2018.2875739).
- [3] N. Masmoudi, W. Jaafar, S. Cherif, J. B. Abderrazak, and H. Yanikomeroglu, "UAV-based crowd surveillance in post COVID-19 era," *IEEE Access*, vol. 9, pp. 162276–162290, 2021, doi: [10.1109/access.2021.3133796](https://doi.org/10.1109/access.2021.3133796).
- [4] A. Al-Hilo, M. Samir, C. Assi, S. Sharafeddine, and D. Ebrahimi, "UAV-assisted content delivery in intelligent transportation systems-joint trajectory planning and cache management," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 8, pp. 5155–5167, Aug. 2021, doi: [10.1109/tits.2020.3020220](https://doi.org/10.1109/tits.2020.3020220).
- [5] M. Y. Arafat and S. Moh, "A Q-learning-based topology-aware routing protocol for flying ad hoc networks," *IEEE Internet Things J.*, vol. 9, no. 3, pp. 1985–2000, Feb. 2022, doi: [10.1109/JIOT.2021.3089759](https://doi.org/10.1109/JIOT.2021.3089759).
- [6] B. Alzahrani, O. S. Oubbati, A. Barnawi, M. Atiquzzaman, and D. Alghazzawi, "UAV assistance paradigm: State-of-the-art in applications and challenges," *J. Netw. Comput. Appl.*, vol. 166, Sep. 2020, Art. no. 102706, doi: [10.1016/j.jnca.2020.102706](https://doi.org/10.1016/j.jnca.2020.102706).
- [7] D. Schneider, "The delivery drones are coming," *IEEE Spectr.*, vol. 57, no. 1, pp. 28–29, Jan. 2020, doi: [10.1109/mspec.2020.8946304](https://doi.org/10.1109/mspec.2020.8946304).
- [8] M. Alwateer and S. W. Loke, "Emerging drone services: Challenges and societal issues," *IEEE Technol. Soc. Mag.*, vol. 39, no. 3, pp. 47–51, Sep. 2020, doi: [10.1109/mts.2020.3012325](https://doi.org/10.1109/mts.2020.3012325).
- [9] H. Y. Jeong, B. D. Song, and S. Lee, "The flying warehouse delivery system: A quantitative approach for the optimal operation policy of airborne fulfillment center," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 12, pp. 7521–7530, Dec. 2021, doi: [10.1109/tits.2020.3003900](https://doi.org/10.1109/tits.2020.3003900).
- [10] R. Gupta, A. Kumari, S. Tanwar, and N. Kumar, "Blockchain-envisioned softwareized multi-swarming UAVs to tackle COVID-19 situations," *IEEE Netw.*, vol. 35, no. 2, pp. 160–167, Mar./Apr. 2021, doi: [10.1109/mnet.011.2000439](https://doi.org/10.1109/mnet.011.2000439).
- [11] Á. Restás, "Drone applications fighting COVID-19 pandemic—Towards good practices," *Drones*, vol. 6, no. 1, p. 15, 2022, doi: [10.3390/drones6010015](https://doi.org/10.3390/drones6010015).
- [12] A. F. Santos, P. D. Gaspar, and H. J. L. de Souza, "Refrigeration of COVID-19 vaccines: Ideal storage characteristics, energy efficiency and environmental impacts of various vaccine options," *Energies*, vol. 14, no. 7, p. 1849, 2021, doi: [10.3390/en14071849](https://doi.org/10.3390/en14071849).
- [13] V. Chamola, V. Hassija, V. Gupta, and M. Guizani, "A comprehensive review of the COVID-19 pandemic and the role of IoT, drones, AI, blockchain, and 5G in managing its impact," *IEEE Access*, vol. 8, pp. 90225–90265, 2020, doi: [10.1109/access.2020.2992341](https://doi.org/10.1109/access.2020.2992341).
- [14] E. Ackerman and E. Strickland, "Medical delivery drones take flight in East Africa," *IEEE Spectr.*, vol. 55, no. 1, pp. 34–35, Jan. 2018, doi: [10.1109/mspec.2018.8241731](https://doi.org/10.1109/mspec.2018.8241731).
- [15] G. Wu, M. Fan, J. Shi, and Y. Feng, "Reinforcement learning based truck-and-drone coordinated delivery," *IEEE Trans. Artif. Intell.*, early access, Jul. 1, 2021, doi: [10.1109/taai.2021.3087666](https://doi.org/10.1109/taai.2021.3087666).
- [16] V. P. Pinto, R. K. H. Galvão, L. R. Rodrigues, and J. P. P. Gomes, "Mission planning for multiple UAVs in a wind field with flight time constraints," *J. Control Autom. Electr. Syst.*, vol. 31, no. 4, pp. 959–969, 2020, doi: [10.1007/s40313-020-00609-5](https://doi.org/10.1007/s40313-020-00609-5).
- [17] H. Huang and A. V. Savkin, "A method of optimized deployment of charging stations for drone delivery," *IEEE Trans. Transport. Electrific.*, vol. 6, no. 2, pp. 510–518, Jun. 2020, doi: [10.1109/te.2020.2988149](https://doi.org/10.1109/te.2020.2988149).
- [18] A. Baltaci, E. Dinc, M. Ozger, A. Alabbasi, C. Cavdar, and D. Schupke, "A survey of wireless networks for future aerial communications (FACOM)," *IEEE Commun. Surveys Tuts.*, vol. 23, no. 4, pp. 2833–2884, 4th Quart., 2021, doi: [10.1109/comst.2021.3103044](https://doi.org/10.1109/comst.2021.3103044).
- [19] B. D. Song, K. Park, and J. Kim, "Persistent UAV delivery logistics: MILP formulation and efficient heuristic," *Comput. Ind. Eng.*, vol. 120, pp. 418–428, Jun. 2018, doi: [10.1016/j.cie.2018.05.013](https://doi.org/10.1016/j.cie.2018.05.013).
- [20] K. Dorling, J. Heinrichs, G. Messier, and S. Magierowski, "Vehicle routing problems for drone delivery," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 47, no. 1, pp. 70–85, Jan. 2017, doi: [10.1109/tsmc.2016.2582745](https://doi.org/10.1109/tsmc.2016.2582745).
- [21] M. Y. Arafat and S. Moh, "Routing protocols for unmanned aerial vehicle networks: A survey," *IEEE Access*, vol. 7, pp. 99694–99720, 2019, doi: [10.1109/access.2019.2930813](https://doi.org/10.1109/access.2019.2930813).
- [22] G. Kim, Y.-S. Ong, C. K. Heng, P. S. Tan, and N. A. Zhang, "City vehicle routing problem (city VRP): A review," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 4, pp. 1654–1666, Aug. 2015, doi: [10.1109/tits.2015.2395536](https://doi.org/10.1109/tits.2015.2395536).
- [23] D. Wang, P. Hu, J. Du, P. Zhou, T. Deng, and M. Hu, "Routing and scheduling for hybrid truck-drone collaborative parcel delivery with independent and truck-carried drones," *IEEE Internet Things J.*, vol. 6, no. 6, pp. 10483–10495, Dec. 2019, doi: [10.1109/jiot.2019.2939397](https://doi.org/10.1109/jiot.2019.2939397).
- [24] M. W. Ulmer and B. W. Thomas, "Same-day delivery with heterogeneous fleets of drones and vehicles," *Networks*, vol. 72, no. 4, pp. 475–505, 2018, doi: [10.1002/net.21855](https://doi.org/10.1002/net.21855).
- [25] M. Hu *et al.*, "On the joint design of routing and scheduling for vehicle-assisted multi-UAV inspection," *Future Gener. Comput. Syst.*, vol. 94, pp. 214–223, May 2019, doi: [10.1016/j.future.2018.11.024](https://doi.org/10.1016/j.future.2018.11.024).
- [26] N. Boysen, D. Briskorn, S. Fedtke, and S. Schwerdfeger, "Drone delivery from trucks: Drone scheduling for given truck routes," *Networks*, vol. 72, no. 4, pp. 506–527, 2018, doi: [10.1002/net.21847](https://doi.org/10.1002/net.21847).
- [27] S. Ong, "Electric air taxi flies over Singapore—[News]," *IEEE Spectr.*, vol. 56, no. 12, pp. 7–8, Dec. 2019, doi: [10.1109/mspec.2019.8913820](https://doi.org/10.1109/mspec.2019.8913820).
- [28] N. Kim, S. Chae, J. Ma, M. Ko, and J. Cho, "Fast-charging high-energy lithium-ion batteries via implantation of amorphous silicon nanolayer in edge-plane activated graphite anodes," *Nat. Commun.*, vol. 8, no. 1, p. 812, 2017, doi: [10.1038/s41467-017-00973-y](https://doi.org/10.1038/s41467-017-00973-y).
- [29] C. H. Liu, C. Piao, and J. Tang, "Energy-efficient UAV crowdsensing with multiple charging stations by deep learning," in *Proc. IEEE INFOCOM Conf. Comput. Commun.*, Toronto, ON, Canada, Jul. 2020, pp. 199–208, doi: [10.1109/infocom41043.2020.9155535](https://doi.org/10.1109/infocom41043.2020.9155535).
- [30] O. Oubbati, A. Lakas, and M. Guizani, "Multi-agent deep reinforcement learning for wireless-powered UAV networks," *IEEE Internet Things J.*, early access, Feb. 10, 2022, doi: [10.1109/jiot.2022.3150616](https://doi.org/10.1109/jiot.2022.3150616).
- [31] L. Lv *et al.*, "Contract and Lyapunov optimization-based load scheduling and energy management for UAV charging stations," *IEEE Trans. Green Commun. Netw.*, vol. 5, no. 3, pp. 1381–1394, Sep. 2021, doi: [10.1109/tgcn.2021.3085561](https://doi.org/10.1109/tgcn.2021.3085561).

- [32] S. Ito *et al.*, "Energy-aware routing of delivery drones under windy conditions," *IPSI Trans. Syst. LSI Des. Methodol.*, vol. 14, pp. 30–39, Jan. 2021, doi: [10.2197/ipsjtsldm.14.30](https://doi.org/10.2197/ipsjtsldm.14.30).
- [33] I. Hong, M. Kubly, and A. T. Murray, "A range-restricted recharging station coverage model for drone delivery service planning," *Transp. Res. C, Emerg. Technol.*, vol. 90, pp. 198–212, May 2018, doi: [10.1016/j.trc.2018.02.017](https://doi.org/10.1016/j.trc.2018.02.017).
- [34] M. Khosravi, S. Enayati, H. Saeedi, and H. Pishro-Nik, "Multi-purpose drones for coverage and transport applications," *IEEE Trans. Wireless Commun.*, vol. 20, no. 6, pp. 3974–3987, Jun. 2021, doi: [10.1109/twc.2021.3054748](https://doi.org/10.1109/twc.2021.3054748).
- [35] F. Sorbelli, F. Corò, S. K. Das, and C. M. Pinotti, "Energy-constrained delivery of goods with drones under varying wind conditions," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 9, pp. 6048–6060, Sep. 2021, doi: [10.1109/tits.2020.3044420](https://doi.org/10.1109/tits.2020.3044420).
- [36] B. Shahzaad, A. Bouguettaya, S. Mistry, and A. G. Neiat, "Resilient composition of drone services for delivery," *Future Gener. Comput. Syst.*, vol. 115, pp. 335–350, Feb. 2021, doi: [10.1016/j.future.2020.09.023](https://doi.org/10.1016/j.future.2020.09.023).
- [37] J. Kim, H. Moon, and H. Jung, "Drone-based parcel delivery using the rooftops of city buildings: Model and solution," *Appl. Sci.*, vol. 10, no. 12, p. 4362, 2020, doi: [10.3390/app10124362](https://doi.org/10.3390/app10124362).
- [38] A. Hamdi, F. D. Salim, D. Y. Kim, A. G. Neiat, and A. Bouguettaya, "Drone-as-a-service composition under uncertainty," *IEEE Trans. Services Comput.*, early access, Mar. 17, 2021, doi: [10.1109/tsc.2021.3066006](https://doi.org/10.1109/tsc.2021.3066006).
- [39] J. Zhang, J. F. Campbell, D. C. Sweeney II, and A. C. Hupman, "Energy consumption models for delivery drones: A comparison and assessment," *Transp. Res. D, Transport Environ.*, vol. 90, Jan. 2021, Art. no. 102668, doi: [10.1016/j.trd.2020.102668](https://doi.org/10.1016/j.trd.2020.102668).
- [40] S. J. Kim and G. J. Lim, "A real-time rerouting method for drone flights under uncertain flight time," *J. Intell. Robot. Syst.*, vol. 100, nos. 3–4, pp. 1355–1368, 2020, doi: [10.1007/s10846-020-01214-z](https://doi.org/10.1007/s10846-020-01214-z).
- [41] T. Benarbia and K. Kyamakya, "A literature review of drone-based package delivery logistics systems and their implementation feasibility," *Sustainability*, vol. 14, no. 1, p. 360, 2021, doi: [10.3390/su14010360](https://doi.org/10.3390/su14010360).
- [42] V. V. Chetlur and H. S. Dhillon, "Downlink coverage analysis for a finite 3D wireless network of unmanned aerial vehicles," *IEEE Trans. Commun.*, vol. 65, no. 10, pp. 4543–4558, Oct. 2017, doi: [10.1109/tcomm.2017.2722500](https://doi.org/10.1109/tcomm.2017.2722500).
- [43] J. K. Stolaroff, C. Samaras, E. R. O'Neill, A. Lubers, A. Mitchell, and D. Ceperley, "Energy use and life cycle greenhouse gas emissions of drones for commercial package delivery," *Nat. Commun.*, vol. 9, no. 1, p. 409, 2018, doi: [10.1038/s41467-017-02411-5](https://doi.org/10.1038/s41467-017-02411-5).
- [44] S. Kim and I. Moon, "Traveling salesman problem with a drone station," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 49, no. 1, pp. 42–52, Jan. 2019, doi: [10.1109/tsmc.2018.2867496](https://doi.org/10.1109/tsmc.2018.2867496).
- [45] B. Liu, W. Ni, R. P. Liu, Q. Zhu, Y. Guo, and H. Zhu, "Novel integrated framework of unmanned aerial vehicle and road traffic for energy-efficient delay-sensitive delivery," *IEEE Trans. Intell. Transp. Syst.*, early access, Jul. 14, 2021, doi: [10.1109/tits.2021.3095360](https://doi.org/10.1109/tits.2021.3095360).



Muhammad Yeasir Arafat received the B.Sc. degree in electronics and telecommunication engineering and the M.Sc. degree in computer networks and communication from Independent University, Dhaka, Bangladesh, in 2011 and 2014, respectively, and the Ph.D. degree in computer engineering from Chosun University, Gwangju, South Korea, in 2020.

During his Ph.D. study, he was a Korean Government Scholarship Program grantee. From 2011 to 2016, he has worked as the Systems Manager with Amber IT Ltd., Dhaka. Since November 2020, he has been an Assistant Professor with the Department of Computer Engineering, Chosun University. His current research interests include unmanned aerial vehicle networks and wireless sensor networks with a focus on routing and MAC protocols.



Sangman Moh (Member, IEEE) received the M.S. degree in computer science from Yonsei University, Seoul, South Korea, in 1991, and the Ph.D. degree in computer engineering from Korea Advanced Institute of Science and Technology, Daejeon, South Korea, in 2002.

Since late 2002, he has been a Professor with the Department of Computer Engineering, Chosun University, Gwangju, South Korea. From 2006 to 2007, he was on leave with Cleveland State University, Cleveland, OH, USA. Until 2002, he had been with Electronics and Telecommunications Research Institute, Daejeon, where he served as a Project Leader. His research interests include mobile computing and networking, ad hoc and sensor networks, cognitive radio networks, unmanned aerial vehicle networks, and mobile-edge computing.

Dr. Moh is a member of ACM, IEICE, KIISE, IEIE, KIPS, KICS, KMMS, IEMEK, KISM, and KPEA.